A REVIEW OF METHODS FOR OPTIMIZING SURFACE AND GROUNDWATER MONITORING PROGRAMS GROUNDWATER MONITORING PROGRAMS AT MINE SITE[1]

by

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Abstract: Monitoring of surface and groundwater quality in the vicinity of mine sites is typically required to demonstrate lack of impact by mining activities. The monitoring programs, often instigated as part of the mine permitting process, can continue indefinitely. In addition to being costly, the accumulated data may be difficult to interpret. Several defensible techniques, based on statistical and geochemical principles, are available to optimize monitoring programs so that equivalent or better data are collected at reduced cost. Application of these techniques requires clear definition of the monitoring requirements and goals, evaluation of accumulated data, and optimization of the monitoring network. Elements of the network available for optimization include spatial distribution of sampling points, sampling frequency, and analytical parameters.

Surface and groundwater monitoring programs at two sites were evaluated to optimize sampling programs. Considerations for defining monitoring requirements and goals included removal of redundancy from sampling and clarify sampling results to enhance cost-effective monitoring. Data, often consisting of several thousand entries and spanning up to thirty years, were evaluated using parametric and nonparametric techniques to determine whether statistically dissimilar groups could be defined. Lack of dissimilar groups was used to reduce the number of sample locations. Geochemical relations and indicator parameters were considered when evaluating reduction of analytes. Optimization of the monitoring networks has resulted in reductions by 30 percent or more of groundwater and surface water monitoring points, as well as decreased monitoring frequency and analytes. Evaluations have also resulted in changing analytical techniques to fit monitoring goals.

Additional Key Words: geochemical evaluation, statistical evaluation, analytical parameters

Introduction

Monitoring of surface and groundwater quality in the vicinity of mine sites has become an integral part of environmental management. Monitoring typically starts as part of mine permitting and environmental baseline studies and continues throughout mine operations to demonstrate the nature and extent of impact by mining activities. After mine closure, monitoring often is continued with no provisions for its eventual elimination.

The accumulated analytical data may be difficult to interpret, in addition to being costly. Large quantities of data may contain seemingly conflicting results and clear patterns may not emerge. For example, more than one hydrogeologic unit may be sampled by a single monitoring well, yet well completion records do not always provide this information. Values above established standards may occur when standards are close to, or less than, detection limits. Seasonal effects can be difficult to interpret without graphical and statistical analyses.

This paper presents a methodology for optimizing surface and groundwater monitoring programs. Optimization primarily addresses the interpretation of analytical results from existing surface and groundwater monitoring programs. However, the methodology may also be applied at the planning stage of a monitoring program. Optimization assures that appropriate and defensible data are collected. Optimization of monitoring programs can result in

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The variability in the results is attributed to the affects of stress relief fracturing, full vs. partial extraction, etc. Some mines were mining near the subcrop whereas other mines were deeper and under more cover. An attempt was made to evaluate the data through regression by pairing discharge rates with linear feet of coal crop undermined, depth of cover, and barrier pillar distance. However, there are not enough data to do a reliable regression analysis. Hopefully with more data the variation in mine inflow rates can be better understood.

However, the present results do show a useful procedure and have provided OSM and the mining companies a method of predicting a range of mine inflows for their future operations.

Summary

Recent computer codes enable a quick analysis of hydrographs for estimating ground water recharge and discharge. Readily available USGS daily discharge records in computer format can be used in these models. The results of this study showed a median recharge rate of 20 inches/year for the Cumberland Plateau. The 90% confidence interval of the median was 16.4 to 23.8 inches/year.

Simplified water budget calculations can be made using approximate methods such as that of Thornthwaite to estimate water available for recharge. Results of calculations for the southern Tennessee coal fields by Skyline Coal Company showed about 19 inches of the yearly rainfall is available for recharge.

Spoil discharge measurements and calculation of premining aquifer recharge rates can help distinguish between infiltration that leaves the watershed as interflow along the soil/bedrock interface and water that actually percolated into underlying shallow bedrock aquifers. Preliminary calculations showed that premining infiltration rates of about 19 inches per year consisted as 17 inches of interflow and only about 2 inches of aquifer recharge for a flat site with little stress relief fracturing. Whereas after mining the spoil aquifer recharge rate was almost 19 inches with little interflow at the spoil/soil interface. I suspect rates for steep mines or for areas with stress relief fracturing wouldt be different from these results.

Underground mine inflow measurements were used to estimate recharge to the mine workings of 3.8 to 24.38 inches per year. This was used to estimate mine discharge rates of 0.07 to 1.26 gallons per minute per acre of mined out workings. Data showed variability resulting from various depths of cover, barrier pillars, partial vs. full extraction, and influence of stress relief fracturing.

Combined, these four methods can be used to evaluate both regional and local groundwater recharge and
discharge rates. Care must be exercised in applying results from one site to another given the variability in geology. However, they can contribute to the understanding of the hydrologic balance for an area and in quantifying the impacts from mining.

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increased cost effectiveness through the collection of equivalent or improved data at reduced cost. Examples of optimized monitoring programs are also presented.

Monitoring Optimization Methods

Monitoring optimization combines design of sampling plans, sample collection, and statistical interpretation (Myers 1997). As described by Myers (1997), the goals include:

- Integrating data assessment techniques which minimize uncertainty and error;
- Developing a defensible and logical decision-based approach;
- Maximizing use of resources;
- Establishing goal-oriented checkpoints for making decisions; and
- Minimizing costs and liability.

The process consists of three basic steps:

1. Define monitoring objectives.
2. Minimize sampling error.
3. Evaluate data.

Each step is discussed in the following sections.

Define Monitoring Objectives

Monitoring programs typically are designed to determine whether a mine site is impacting the groundwater or surface water. Specific objectives can vary from addressing regulatory requirements to monitoring background. Before a monitoring program can be optimized, a consensus on clearly stated objectives is needed. Monitoring objectives may be defined in terms of the decisions to be made and the required confidence level for those decisions. An example of a decision is whether to incorporate a monitoring well in the optimized program. Figure 1 provides a decision tree appropriate for this decision.

The U.S. Environmental Protection Agency (EPA) has published guidance for developing program objectives for site evaluations as part of their data quality objectives and data quality assessment guidance (EPA 1994; EPA 1996). The guidance provides a specific checklist for developing program objectives that can be used for optimizing the monitoring program. The list is includes the following components (EPA 1994) as applicable to groundwater or surface water monitoring:

- State the problem: What are the program goals, regulatory requirements, cost constraints, and other project limitations.

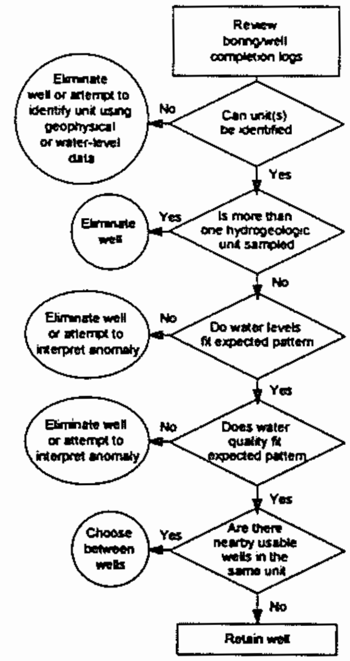


Figure 1
Decision Tree for Evaluating Groundwater Sampling Program: Determining Whether to Incorporate a Monitoring Well

- Identify the decision(s) to be made: Define the questions to be answered by the monitoring; such as, is the mine site impacting the groundwater?
- Identify inputs: What monitoring wells and surface sampling locations exist, and what water quality parameters have been collected?
- Define the program boundaries: Establish the spatial and temporal boundaries for the monitoring program.
- Develop a decision point: What is the endpoint of the monitoring and how will the decision be made that the endpoint has been reached.
- Specify limits on the decision errors: Determine the acceptable level of uncertainty, or confidence, for deciding the decision point.
- Optimize the design: Determine the optimum number and location of wells, surface water sampling points, and samples for the required level of confidence.

Development of program objectives ensures that only the appropriate data are collected and establishes a data-collection framework based on the scientific method by defining the criteria that the program must satisfy. These criteria address the timing, the number, and the location of the samples to be taken. A clear endpoint for the program is established, the existence of uncertainty is acknowledged, and a basis for specifying acceptable levels of uncertainty is provided. Such a basis provides a reproducible, defensible means of communicating and reaching consensus with the regulators and other concerned parties.

Minimize Sampling Error

The impact of sampling error needs to be addressed when evaluating existing data and when optimizing the monitoring program. Many different types of error can be introduced through the sampling process alone. Pierre Gy offers an analysis of sampling theory and guidelines for sampling practice which strive to obtain sample data that reflect as accurately as possible the true concentrations (Pitard 1993). Gy defines sampling error as separate and discrete from laboratory analytical errors.

Myers summarizes the principal goals for the minimization of sampling error (Myers 1997, pg 8):

- Distinguish the structural and circumstantial properties of sampling.
- Analyze the heterogeneities of the sample media.
- Select the appropriate dimensional module of observation.
- Separate sampling errors into the correct categories.
- Assess the correctness of sampling devices.
- Develop sampling protocols
- Reduce variability between duplicate and replicate samples.

Minimization of sampling error for the sampling of groundwater and surface water primarily relates to the use of established, standardized sampling protocols. Such protocols ensure that proper procedures are followed in the physical sample retrieval process. Failure to maintain consistent protocols can result in highly misleading results which can lead to unnecessary costs. For example, groundwater samples taken from improperly or inconsistently purged wells can show significantly different concentrations in an otherwise uniform distribution among wells. Mis-measured water levels in wells can cause similar problems. Protocols also ensure the proper documentation is recorded to assist in later evaluation of the data.

Unfortunately, far more emphasis is generally placed on the handling and analysis of samples, once retrieved. Errors introduced in the sampling process will compound exponentially with later errors related to the uncertainties of laboratory analysis and data evaluation. Minimizing sampling errors is critical to prevent the transfer and potential amplification of such errors in the later phases of the program. Investment in the sampling phase to minimize errors can lead to substantial cost savings in the long term. Detailed descriptions of methods to minimize sampling error are provided by Pitard (1993) and Myers (1997).

Evaluate Data

Monitoring data, by itself, offer little insight into the fundamental question of whether a mine site is impacting groundwater or surface water. Data need to be organized, presented, and analyzed to adequately evaluate the monitoring results and produce meaningful information. Monitoring data can be evaluated in a variety of ways, including: analytical and geochemical evaluation, statistical analysis, and geostatistical analysis. The level of evaluation required will vary depending on the size of the program and quantity of data available. Typically, large amounts of data have been collected, but little or no information has been developed. Each evaluation type is discussed in the following sections.

Analytical and geochemical evaluation. Evaluation of monitoring programs needs to consider analytical and geochemical factors during optimization, such as:

- Detection limits and their relation to regulatory limits, if any;
- Changes in parameters during sampling;
- Relation of total, total recoverable, potentially dissolved and dissolved concentration; and
- Geochemical interactions among parameters.

When detection limits are equivalent to or greater than regulatory limits, any detection may indicate noncompliance. Changing to a more sensitive analytical technique may not be a viable option due to cost or lack of an alternate method. Alternatives include reanalyzing the questionable sample, assuming the detection is reported within the sample holding time; instituting a field and laboratory quality assurance/quality control program that can include field replicates, trip blanks, and matrix spikes (EPA 1993); including the questionable sample in an ongoing statistical analysis that considers a measure of central tendency (such as the mean) rather than a particular sample. The field sampling method can be reviewed for consistency, particularly when total or total recoverable samples are analyzed. These samples can be impacted by pumping rates and bailing techniques (for groundwater samples) or depth and location of samples (for surface samples). For samples and sample locations that are to be compared to each other, the same analytical method needs to be used.

Parameters such as pH, alkalinity, and dissolved and total iron can change during sampling and during sample transport and storage. Field measurement of these parameters can provide more representative values. Field measurement kits are available that are inexpensive and easy to use. Values will not be representative, however, if samples are not collected and handled consistently. Herzog and others (1991) discuss sampling protocol for groundwater in detail.

Whether a concentration of an analyte is "total", "total recoverable", "potentially dissolved" or "dissolved" is based on operation rather than absolute definitions. EPA guidance (Puls and Barcelona 1989) recommends collection of unfiltered and filtered samples with the filter pore size less than 0.45 microns. Unfiltered groundwater samples alone can be representative of conditions if samples are carefully collected with dedicated sampling devices, limited purging, and low pumping rates (Kearl and others 1992). Optimizing monitoring programs can include reviewing sample collection protocols and clarifying written sampling programs to specify precise collection locations and methods.

Geochemical interactions among parameters can be used to designate indicator parameters in a monitoring program, thereby reducing the number of parameters to be analyzed. The indicator parameter depends on the geochemical setting, the potential contamination, and the expected interaction between contaminant and soils. For example, when sulfide weathering and acid rock drainage is expected, sulfate is a good indicator parameter that will increase in water samples before trace metals appear.

Statistical analysis. Statistical analysis covers a range of specific techniques, and includes simple procedures such as averaging, determining frequency distributions, mean concentrations, and standard deviations, and making simple or multiple correlations. Sara and Gibbons (1991) present a comprehensive guide to the statistical analysis of water quality data that includes statistical options for data that are normally distributed, a Poisson or parametric distribution, an unknown or non-parametric distribution, or a normal distribution with a significant proportion (between 50 and 90 percent) of non-detects. Methods for the analysis of data reflecting non-detects of between 90 and 100 percent are also discussed (Sara and Gibbons 1991).

Statistical methods for data evaluation are also described in numerous other publications (c.f., Helsel and Hirsch 1992 and Ross 1997). EPA guidance about available statistical analyses, which can be used in conjunction with their data quality objectives approach, is included in "Guidance for Data Quality Assessment" (EPA 1996). This approach fits the statistical data manipulations into an overall data quality assessment approach that includes:

- Reviewing the program objectives;
- Conducting a preliminary data review;
- Selecting the appropriate statistical test;
- Verifying the assumptions of the statistical test; and
- Drawing conclusions from the data.

Geostatistical analysis. Geostatistical techniques focus on mapping and analysis of spatial data. Such techniques can be used to estimate or interpolate the concentration of contaminants between data points and to calculate the related volume of contaminated media, such as groundwater. Geostatistical techniques can also provide estimates of error, or uncertainty, associated with the interpolated data based on the variability and distance between data points. Most importantly, geostatistical techniques can assist in cost benefit analysis to show where the addition of sampling locations adds no additional confidence to the interpolation estimate.

Geostatistics were originally developed for estimating ore reserves in the mining industry. Applications for geostatistics in the environmental field have grown steadily in recent years. Myers (1997) provides a comprehensive description of geostatistical applications in the quantification of uncertainty for environmental sampling and mapping.

The basic goals of geostatistical analysis include:

- Understanding the spatial relationship between the monitoring sample locations;
- Selection of an appropriate method for interpolating the data;
- Minimizing errors and uncertainty in the interpolation process;
- Delineating the levels and extent of contamination detected; and
- Minimizing the cost of decision errors.

Different types of interpolation methods include kriging, inverse squared distance, cubic polynomial regression, multiquadrics, and thin plate spines (Myers 1997). Kriging, the most commonly known method, relies on the variogram, which measures the relationship between distance and variance of sampled locations. The U.S. Army Corps of Engineers recently published a useful guide on the practical application of geostatistics at hazardous waste sites (U.S. Army Corps of Engineers 1997).

Geostatistics can be used to identify the optimum number of sampling locations. Depending on the variability between locations, adding locations will increase the confidence of estimates between points. However, increases in confidence gradually diminish as new locations are added, to a point where no additional confidence is gained by the additional sampling locations. This relationship follows the "law of diminishing returns". Regulators often require more

At a mine site in the Rocky Mountain region, a surface water monitoring program had been in place for approximately 30 years. The initial program had been expanded over the years due changes in the active mining area and in the regulatory environment. During that time, data had been collected from 19 surface water sampling stations, for up to 60 separate analytical parameters, and as frequently as monthly. Samples were obtained from several stream and reservoir locations and included voluntary and compliance monitoring.

The purpose of the optimization evaluation was to remove redundant monitoring locations and analytical parameters, and select an appropriate sampling time

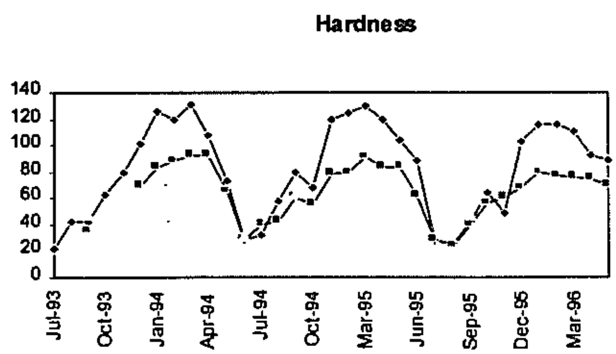
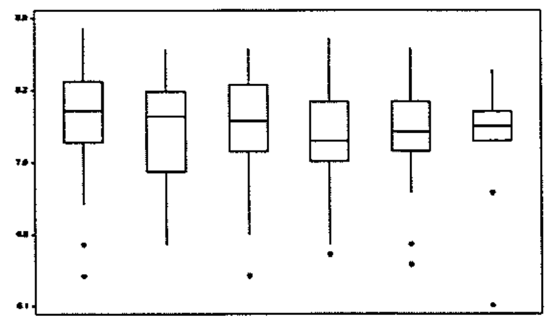


Figure 2
Example of Concentration Versus Time Plot



Explanation: Box encloses middle half of the data (25th to 75th percentiles). Twenty-five percent of the data fall below and above the box. The horizontal line inside the box is the median value. Fifty percent of the data are less than this value. The "whiskers" (vertical lines at the top and bottom of the box) indicate the range of typical data and end at actual data points. The lines end at values within 1 1/2 times the range within the box. "*" are possible outliers, which are more than 1 1/2 times the size of the box. "o" is a probable outlier, which is more than 3 times the size of the box. Concentrations shown on the vertical axis of the graph are in standard pH units.

Figure 3
Example of a Box and Whisker Plot for Field pH

monitoring locations (and related costs) than can be justified by the actual confidence gained.

Examples of Monitoring Optimization

Two examples of optimization of monitoring programs at mine sites are presented below. These examples illustrate the application of some of the concepts described in the previous section.

Statistically-Based Optimization of a Surface Water Monitoring Program

interval, with the end result being a more effective and cost-efficient monitoring program. The evaluation consisted of the following steps:

1. Define the monitoring objectives
2. Do an initial data review
3. Define a statistical approach
4. Perform the statistical evaluation
5. Evaluate the results and provide recommendations.

For this site, monitoring objectives included establishing background concentrations, tracking water quality improvements, documenting capture of water needing treatment, and providing monitoring to a nearby community as a public service. Compliance monitoring locations were fixed by agreements with the state, and therefore were not included in evaluation.

The initial data review consisted of dividing the sampling locations into geographically and hydrologicallyrelated groups (old mine site, upstream, downstream), focusing on voluntary, currently-monitored locations, and graphically comparing data for each parameter within each group. This review indicated some obvious patterns in the data, such as an improvement in downstream water quality after installation and startup of a water treatment plant. Therefore, the data evaluation was limited to post-treatment data.

tests of residuals for normal distribution and variances for equality. When outliers occurred, tests were done with and without outliers; however, there were usually no significant differences in results due to inclusion of outliers. Parameters with obvious differences among related sampling points were not evaluated statistically. A statistical confidence level of 95 percent (= 0.05) was chosen for the tests to determine whether differences occurred between sampling locations for different parameters.

The statistical evaluation was done using a statistical software package (Analytical Software 1996) and EPA guidance (1989). In addition to the statistical methods defined in Table 1, correlation coefficients of

Table 1
Basis for Choosing Statistical Method

Statistical Method	Basis
Test of Proportions	more than 50% nondetects
One-Way AOV	less than 15% nondetects no seasonality (1)
AOV - Ln transformation	less than 15 nondetects no seasonality (1) variances unequal or residual distribution not normal
Nonparametric AOV (Kruskal-Wallis)distribution not normal for transformed data	between 15 and 50% nondetects less than 15% nondetects and variances unequal or residual

Notes: AOV = analysis of variance
Ln = natural logarithm
1. seasonal patterns were the same at sites compared, and therefore, not evaluated separately

The initial data review also revealed that, except for the most recent sampling events, there had been no quality assurance/quality control program in place. Data had been recently entered into a spreadsheet format, but entries had not been checked. However, the large database and number of sampling locations permitted use of consistency as a check for precision.

Based on the initial review, the percentage of nondetects, and graphical evidence of seasonality, parameters for statistical evaluation were chosen and statistical methods defined. Table 1 lists the basis for choosing the statistical tests. When using parametric analysis of variance, nondetected values were replaced by half the detection limit. Data were transformed (natural logarithm transformation) as needed based on

parameters were determined. Data were also presented graphically using time versus concentration plots and box and whisker plots. Figures 2 and 3 are examples of these plots.

Where the evaluation indicated that there were no statistically significant differences among locations for different parameters, consolidation of the sampling program was recommended. Based on the statistical evaluation of eight surface sampling locations and 18 parameters, the following was recommended:

- Eliminate two locations
- Eliminate five parameters because results have been consistently below detection and no new sources or major operational changes are expected
- For the remaining parameters, limit analysis to

between two and four locations rather than sample at the remaining six locations

- Sample locations quarterly rather than monthly.

Correlation coefficients were examined to determine those that were meaningful based on geochemistry, such as the correlation between total recoverable iron and total suspended solids. This evaluation helped confirm the efficacy of removal of some of the parameters. Overall, the recommendations were for a reduction from a monthly sampling of 130 parameters to a quarterly sampling of 48 parameters.

Non-Statistical Evaluation for Optimization of a Groundwater Monitoring Program

The groundwater monitoring program at a site in the Grants Uranium District of the Colorado Plateau had expanded over approximately ten years based on the complex regulatory oversight of the area. Approximately 400 wells were monitored in a site of 100 acres. The resulting data were inconsistent, incoherent, and costly.

For evaluation of this groundwater sampling program, the key step was to determine what hydrogeologic zone was being monitored by each well. Therefore, the evaluation consisted of:

1. Review geophysical, borehole and well completion data
2. Review water-level and water-quality data, as available, for wells with known completion intervals
3. Recommend an optimized groundwater sampling program.

Well completion data were used to eliminate wells with obvious completion problems, such as screening across more that one hydrogeologic unit. Borehole data were inconsistent and generalized when available, so geophysical data, which were available for approximately one-third of the wells, were used to construct cross-sections of the site.

Water-level and water-quality information was used to confirm well completion data. First, data were reviewed to establish characteristics of each hydrogeologic unit. When water levels did not fit within the expected water table for a unit, the well was eliminated. Water-quality data were used in a similar manner. For example, large differences of pH values for nearby wells were used as an indication of completion within different units or contamination during well installation.

The recommended optimized monitoring program reduced the number of wells sampled to approximately 100 from the original 400. The optimized program was reviewed and accepted by the EPA and U.S. Nuclear Regulatory Commission.

Conclusions

Optimization of active monitoring programs includes defining the monitoring objectives, minimizing sampling error, and evaluating data that have been collected. Data evaluation can include geochemical and analytical data evaluation, statistical data evaluation, and geostatistical data evaluation. The method(s) used depend on the objectives and the decisions to be made. These methods are particularly effective when applied early in the investigative process.

Examples of optimization of monitoring programs for groundwater and surface water demonstrate that significant cost reductions can be achieved. For the sites discussed, the number of monitoring points were reduced, monitoring frequency and analytes were decreased, and improvements were made to the sampling and analytical protocol.

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