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ABSTRACT

Statisticians have a vital role to play in environmental restoration (ER) activities. One facet of that role is to point out where additional work is needed to develop statistical sampling plans and data analyses that meet the needs of ER. This paper is an attempt to show where statistics fits into the ER process. The statistician, as member of the ER planning team, works collaboratively with the team to develop the site characterization sampling design, so that data of the quality and quantity required by the specified data quality objectives (DQOs) are obtained. At the same time, the statistician works with the rest of the planning team to design and implement, when appropriate, the observational approach to streamline the ER process and reduce costs. The statistician will also provide the expertise needed to select or develop appropriate tools for statistical analysis that are suited for problems that are common to waste-site data. These data problems include highly heterogeneous waste forms, large variability in concentrations over space, correlated data, data that do not have a normal (Gaussian) distribution, and measurements below detection limits. Other problems include environmental transport and risk models that yield highly uncertain predictions, and the need to effectively communicate to the public highly technical information, such as sampling plans, site characterization data, statistical analysis results, and risk estimates. Even though some statistical analysis methods are available "off the shelf" for use in ER, these problems require the development of additional statistical tools, as discussed in this paper.

INTRODUCTION

The U.S. Department of Energy (DOE) has estimated that it will cost many billions of dollars to clean up its large volume of hazardous, radioactive, and mixed waste (DOE, 1990). As a consequence, the DOE is taking a close look at ways to reduce environmental restoration (ER) costs while still ensuring the scientific validity of the ER process. Achieving scientific validity begins by developing thorough plans for characterizing the waste site. These plans must specify both the quality and the quantity of site-characterization data required . That is, it is necessary to specify how much uncertainty in the nature and extent of contamination at the site can be allowed. Then efficient field sampling plans that will generate sufficient data of required quality can (and must) be developed.

In this paper, we discuss statistical issues and needs related to the planning and design of site characterization sampling studies and to the analysis of generated data. We begin by discussing how to deal with uncertainty (and cost) in the site-characterization process.

DEALING WITH UNCERTAINTY IN SITE ASSESSMENTS

It is impossible to remove all uncertainty about the nature, magnitude, and spatial patterns of contamination at a hazardous waste site, no matter how thorough sampling and measurement for the site characterization effort may be. We must therefore deal with the issue of uncertainty, which in turn means that we must deal with statistical concepts and methods that are related to the design of sampling programs so that we can quantify and/or reduce uncertainty. To deal with uncertainty requires careful planning even before any samples are collected. An important aspect of this planning process is the specification of data quality objectives (DQOs).

These DQOs are qualitative and quantitative statements that specify the quality of data that must be obtained. They are a tool to answer the questions: "What type and quality of data are needed to answer key questions?" and "How do we know when we have enough data?" (Neptune, et al. 1990). Specific DQOs are determined by the end use of the data and so are established to ensure that the data are both sufficient and of adequate quality for their intended use. Once DQOs are established by the ER planning team, they can be used by the statistician in developing a sampling design that will yield the necessary data at minimum cost.

The steps in establishing DQOs are as follows (Neptune, et al. 1990; EPA 1987a; EPA 1987b):

1. Carefully state the problem to be addressed or the decision to be made.
2. Identify the information required to select an appropriate course of action.
3. Articulate the specific role that data will play in selecting the course of action.
4. Specify the type of data needed.
5. Specify the way the data will be used.
6. Specify (by means of an iterative process that involves both the decision-maker and technical support staff) the degree of certainty desired in the conclusions to be derived from the data.
7. Optimize the sampling design for data collection to achieve the required degree of certainty in the conclusions at minimum cost.

Neptune, et al. (1990) have illustrated the procedure with a case study. The question addressed in the case study is whether a site at which railroad ties and creosote-soaked timbers were stored and burned posed an unacceptable risk to site workers and visitors as a result of exposure to polyaromatic hydrocarbons (PAH) in soil. After carefully considering the human health consequences and consulting with the toxicologist and site engineers, the project manager assigned acceptable decision error rates for various risk levels and associated levels of average PAH soil concentrations. Then a soil sampling plan was developed that was expected to achieve these DQOs at minimum cost. The sampling plan specified the number of composite soil samples that should be collected to estimate average soil PAH concentrations with sufficient precision to achieve the DQOs, i.e., such that the specified decision error rates were not exceeded.

DEALING WITH COSTS USING THE OBSERVATIONAL APPROACH

One lesson learned from ten years of experience of the U.S. Environmental Protection Agency (EPA) with conducting clean-up actions under the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) is that the clean-up process must be streamlined to avoid high costs and long delays in conducting remedial actions (EPA 1989a). The DOE and the EPA are currently evaluating the "Observational Approach" as a framework for streamlining the clean-up process while managing the uncertainty inherent in site assessment. Overviews of the method have been published by Smyth and Quinn (1991) and by Myers and Gianti (1989). The advantages and limitations of the method are discussed by Peck (1969). Brown, et al. (1989) discuss the application of the method to the remediation of hazardous waste sites. The method is a way of initiating remedial action at a waste site without full characterization of the nature and extent of contamination. The observational approach is intended to reduce costs by accepting greater uncertainty and allowing earlier selection of a remedial action approach based on probable conditions at the waste site.

The uncertainty in knowledge about conditions at the site is taken into account by making contingency plans for handling deviations from probable conditions if they occur during remedial action. In essence, the observational approach requires conducting thorough up-front planning to identify uncertainties and determine both possible and probable conditions at the site. The remedial action program is designed for probable conditions, but contingency plans are prepared in case deviations from the probable conditions occur during remedial action. As indicated by Smyth and Quinn (1991), the DOE has endorsed the concept (DOE, 1990), and the EPA has endorsed an equivalent approach (EPA, 1989b).

STATISTICAL NEEDS IN ENVIRONMENTAL RESTORATION

It is generally recognized that statistical methods should be used in ER projects. However, a number of problems associated with using statistical methods must be addressed. The following is a short discussion of some of these problems.

UNDERSTANDING THE ROLE OF THE STATISTICIAN

Frequently, statisticians are not brought into a study until after the data have been collected and analysis problems are encountered. However, the best time to get a statistician involved is at the very beginning of the study when initial plans are being made. The statistician should be a member of the ER planning team for the waste site, a collaborator rather than a consultant. As a member of the team, the statistician can help develop the sampling design (type, number, and location of samples) that will generate the data required to meet the DQOs.

DEVELOPING DATA QUALITY OBJECTIVES

Data quality objectives must be specified as part of the planning process. If this is not done, no one will know when to stop collecting data, and a lot of unnecessary or inappropriate data are likely to be the result. This idea of specifying a priori the quantity of data that is needed is a familiar concept to statisticians. For example, the method statisticians use to determine the number of samples required for estimating a mean involves specifying the required accuracy of the estimated mean and the confidence required in achieving that accuracy (Gilbert, 1987, pp. 30-42). The entire ER planning team needs to understand and support the use of DQOs and to take part in determining what those DQOs should be. The DQO approach will provide the information needed to develop efficient sampling plans and associated statistical analysis methods.

REDUCING COST

Ways must be found to reduce the cost of ER. Efficient planning via the Observational Approach and the specification of DQOs are two important tools for that purpose. But other methods are also available. For instance, the compositing of several field samples into one thoroughly mixed sample, which is then subsampled for analysis, can reduce analytical costs when the method is applicable (Gilbert, 1987; Bolgiano, et al. 1990). For example, concentrations of composite soil samples were used to evaluate the need for further removal of soil at sites contaminated with dioxin in the State of Missouri (Exner, et al. 1985). The use of in situ detectors in place of a portion of the environmental samples can also sometimes reduce costs. For example, in situ spectrometry was used in the United States on the Nevada Test Site, a nuclear weapons testing area, to estimate the spatial distribution and total inventory of the important anthropogenic radionuclides in the surface soil (McArthur, 1991). When in situ detectors are used to estimate environmental concentrations, it is usually necessary to quantitatively relate the in situ detector readings to concentrations in samples collected at the same locations. This quantification requires a statistical analysis of both the in situ and the sample data collected using a valid statistical design according to established DQOs.

COPING WITH SPATIAL VARIABILITY

Contaminant concentrations can vary greatly over space. Site characterization usually implies estimating what contaminants are present, where they are located, and their concentrations. If contaminant concentrations are not too heterogeneous over space, geostatistical techniques, such as kriging, can be used to estimate the spatial pattern by taking into account spatial correlations (Flatman, 1984; Gilbert and Simpson, 1985). The use of geostatistics for evaluating the attainment of clean-up standards is discussed in EPA (1989c). However, the presence of hot spots is another complicating problem. Although simple methods are available for determining the spacing between points on a sampling grid required to detect hot spots with specified probability (Gilbert, 1987), the number of sampling locations required can be prohibitively large. Sometimes it is possible to reduce variability by compositing and mixing samples. Also, in situ detector measurements can be less variable than those of single small samples because the in situ measurements measure relatively large volumes of soil. However, such smoothing out of sample spatial variabilities can also hide hot spots.

CHARACTERIZING HIGHLY HETEROGENEOUS WASTE

Many hazardous waste sites contain heterogeneous materials; e.g., concrete, clothing, liquids, bottles, tires, paper, and shredded autos may all occur at a site. These materials may be packed in barrels or lying loose. A given barrel may contain many different types of waste, unknown unless the barrel is opened and inspected, which is an expensive and possibly dangerous operation. The EPA is searching for techniques for obtaining representative samples of debris from hazardous-waste sites. As stated and discussed by Rupp (1990), the problems include 1) obtaining a representative sample from a mix of materials of various sizes and compositions, 2) characterizing the contamination of large items in a way that has meaning for a health risk assessment, and 3) subsampling from mixtures of large objects to produce the small-volume samples required by the analytical laboratory. The basic question is whether a defined unit of material, e.g., a barrel, contains areas of contamination that exceed action levels. A related problem is how to reduce the number of barrels that need to be opened and characterized. A sampling approach, such as acceptance sampling (Schilling, 1982), might be feasible to resolve the latter problem. But generally, the solution of these problems should be a team effort, wherein DQOs are established first, followed by studies to determine sampling and inspection approaches that meet the DQOs.

COPING WITH "LESS-THAN" DATA

Frequently the concentration of a contaminant in a field sample cannot be quantified, in which case it may be reported as a nondetectable or "less-than" value. When such less-than values are present, it is difficult to obtain valid estimates of important parameters, such as mean concentrations, or to conduct valid statistical tests to identify changes in concentrations over time or determine compliance with clean-up standards. The common practice of replacing less-than values with zeros or other fabricated values can lead to highly misleading results. To avoid this problem, it is necessary to use special statistical methods (Helsel, 1990; Gilbert, 1987). The need for additional statistical methods for such cases is discussed by Lambert, et al. (1991) who also introduce new tools (the "probability of acceptance" and the "probability of detection") to describe which measurements and field concentrations are detectable.

USING UNCERTAINTY AND SENSITIVITY ANALYSES

The assessment of risks associated with various clean-up scenarios and technologies requires the use of environmental transport and risk models, the predictions of which are often highly uncertain. Yet this uncertainty may not be explicitly taken into account when formulating DQOs and making decisions. User-friendly computer codes are available for conducting Monte Carlo uncertainty analyses (Iman and Shortencarier, 1984) and sensitivity analyses (Iman, et al. 1985) to quantify the uncertainty in model predictions and to identify model parameters that have a big impact on model predictions. Use of these methods may be considered if DQOs require precise estimates of uncertainty and when decisions must be made about which model parameters should be refined to reduce uncertainty. The use of uncertainty and sensitivity analyses has the additional benefit of clarifying the sources of uncertainty in the model and model parameters. This identification process also helps develop a more thorough understanding of the uncertainties present in the system and where they reside. IAEA (1989) has described procedures for evaluating the reliability of predictions made by environmental transport models, including uncertainty and sensitivity analyses and validation studies. Finkel (1990) has discussed uncertainty in risk management for decision-makers.

USING NONPARAMETRIC STATISTICAL TESTS

The standard assumption that underlies many statistical tests of hypotheses is that the data are normally (Gaussian) distributed, which is, however, not usually the case with waste-site data. In such situations, nonparametric statistical tests should be considered. For example, consider the problem of testing for attainment of risk-based or background-based soil clean-up standards at a remediated waste site. The nonparametric Wilcoxon Rank Sum test and Quantile test (Gilbert and Simpson, 1990) can be used for the background-based case. For the risk-based case, nonparametric tests for proportions based on the binomial distribution can be used (EPA, 1989c). Nonparametric tests are not a cure-all. For example, the data must be uncorrelated in order for the nonparametric test results to be valid, the same requirement as for standard parametric tests. However, nonparametric tests can be more powerful (i.e., have a smaller false-negative error rate) than parametric tests when the assumption of normality is not valid. Also, some nonparametric tests can be used even when a moderate number of less-than values are present (Gilbert, 1987), if all less-than values are less than the smallest detected value. The Quantile test can be used even when a large proportion of the data are less-than values. Regulators and the planning teams for ER need to become familiar with nonparametric tests and their advantages and disadvantages.

COMMUNICATING WITH THE PUBLIC

The public supports ER with tax dollars. Every effort should therefore be made to effectively communicate the plans, methods, results, and implications of results to the public in forms that the average person can understand. This is a formidable challenge. Statistical graphics and geographical information systems (GIS) are tools that can contribute to this communication effort (Tzemos, et al. 1991; Dangermond and Harnden, 1990). For example, a GIS can be used to integrate hazardous-waste site data with associated geographic information via map overlays. There is also potential for integrating statistical analyses and modeling of spatial data into GIS software, although present capabilities are limited (Bailey, 1990). This is an area where more work is needed to assess what is required and what the costs might be to develop the methodology. Also, statisticians can take mysticism out of statistical techniques by avoiding jargon, going back to first principles, and using intuitive descriptions and examples.

CONCLUSIONS

The problems of cost and uncertainty associated with ER can be tackled using data quality objectives, the observational approach, and statistical designs and analyses developed by the statistician in collaboration with other members of the ER planning team. A number of statistical tools are currently available, but the development of additional tools is needed. This paper has described a few of the issues and needs related to the application of statistics to site characterization and ER at hazardous waste sites.

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