Geospatial Decision Frameworks for Remedial Design and Secondary Sampling

Robert Stewart

University of Tennessee, USA

Wiespaden, Germany

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Introduction

This paper provides an overview of geospatially-based decision frameworks for remedial and secondary sampling design strategies. These methods were generated or implemented during the construction of Spatial Analysis and Decision Assistance (SADA), a freeware package for Windows. SADA is supported by the Environmental Protection Agency and the Department of Energy. For more information on SADA or on the methods described here, see http://www.sis.utk.edu/cis/sada/.

Although the remedial design frameworks are quite straightforward, they rely on geospatial and human health risk modeling results that are beyond the scope of this paper. Therefore, this paper only presents how output from the modeling practices can be used explicitly in a decision-making process. Additionally, a general overview of geospatial analysis provides context for the methods. Three remedial design approaches are presented: block scale, site scale, and site-block scale. Each framework has important implications for both risk assessment and remedial design, and in practice each has better defined the area of concern and ultimately saved valuable resources during the remedial process.

Similarly, the sampling designs in this paper rely on the same geospatial models. These secondary sampling designs assume that a round of sampling has already occurred, a geospatial model has been chosen, and a goal for taking another round of samples has been decided. Five distinct sampling strategies are presented, each with a separate goal.

Overview of Geospatial Analysis

For this paper, geospatial analysis refers to the modeling of concentration values or uncertainty at points that have not yet been sampled. Geospatial models estimate or predict the value of a contaminant at an unsampled point based on nearby sample values, spatial correlation, and a number of other possible parameters depending on the method chosen. These models are often called contouring algorithms and include well known methods such as inverse distance weighting and minimum tension gridding. Other increasingly popular methods for environmental characterization include ordinary kriging, indicator kriging, and co-kriging. These *geostatistical* methods contour concentration values and also provide a model of uncertainty about those predicted concentration values through the use of spatial covariance models. For more information on this subject, see *Applied Geostatistics*[1], *GSLIB*[2], or *Geostatistics for Natural Resources Evaluation*[3].

In most cases, a geostatistical anaylsis begins by defining a grid over the site.

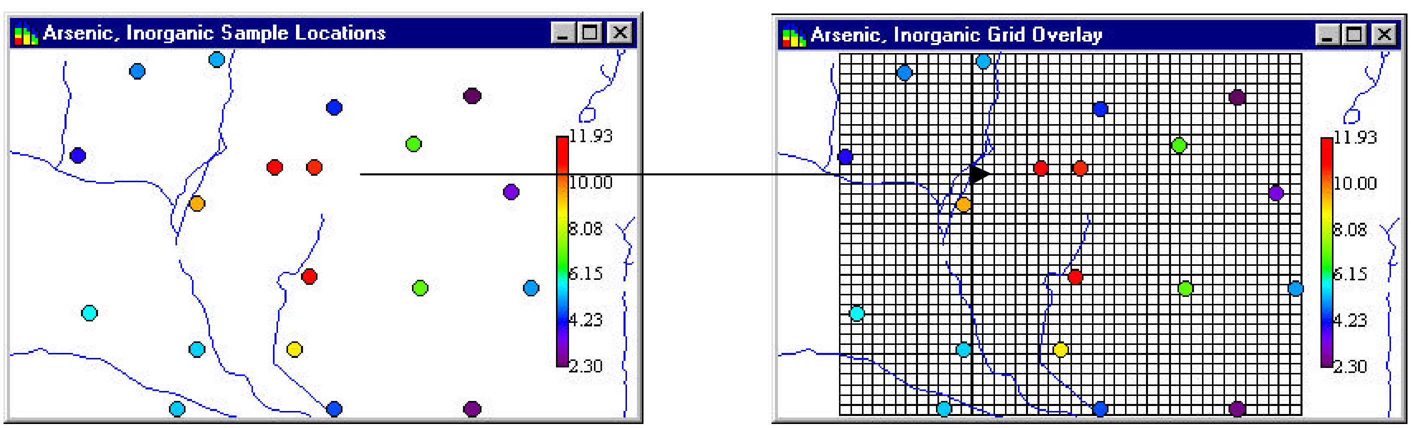

Figure 1. Defining a grid over a sampled site.

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[1] Issaks and Srivasta, *Applied Geostatistics*, Oxford University Press, 1990.
[2] Deutsch and Journel, *GSLIB*, Oxford University Press, 1997.
[3] Goovaerts, Geostatistics for Natural Resources Evaluation, Oxford University Press, 1997.

The blocks formed by this grid become the basis for remedial design and for secondary sampling strategies later. Once the grid is in place, a spatial model is run and the site is contoured.

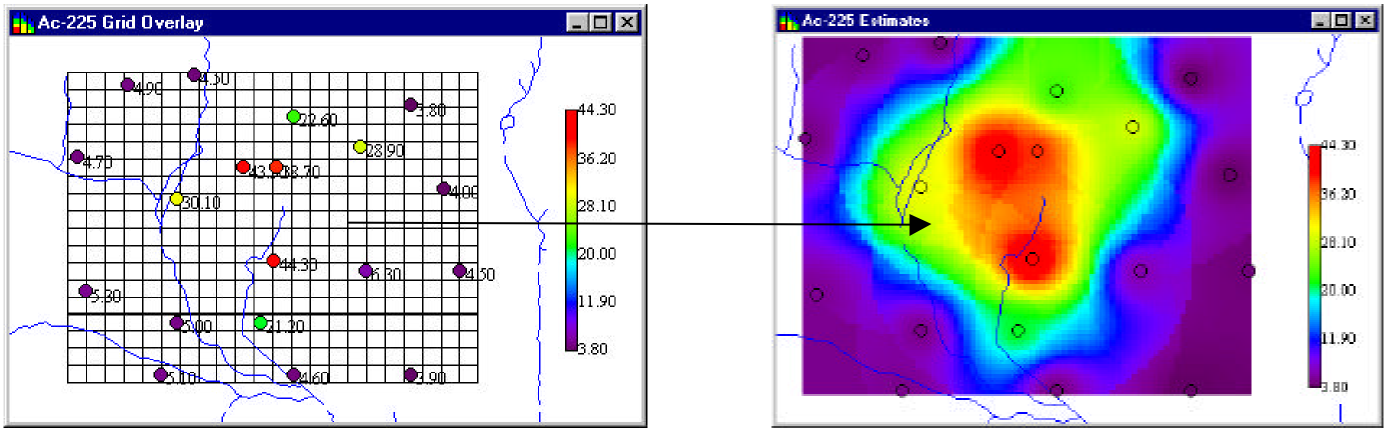

Figure 2. Contouring a gridded site with a geospatial model.

Remedial Decision Frameworks

Given a spatial model of concentration values, three frameworks are available for determining the remedial design: block scale, site scale, and the site-block framework. Each framework has a separate objective for remediation, can give a significantly different result depending on the spatial distribution of contamination, and is connected to a decision criteria. This criteria may include a cleanup concentration goal, a human or ecological risk goal, or a state or federal guideline for maximum concentration values. Depending on the geospatial model utilized, other goals may be a part of the criteria, including a confidence level about the remedial design. Once a criteria is available, it is straightforward to implement the following design strategies.

Block Scale

In the block scale framework, the decision criteria is applied to each block. In other words, each block must pass the acceptable criteria or be remediated. Choices for the block size include the exposure unit and the remedial unit size.

Site Scale

The site scale framework requires a region or subset of blocks to meet the decision criteria. In this case, the blocks may be equal in size to the remedial unit if the region is itself the exposure unit. In particular, if a representative statistical value of the blocks (e.g. average value or mean) fails to pass the acceptable criteria, then remedial action must be taken on the region. Under this system, the blocks are ordered from most to least contaminated. The blocks are then remediated from worst to best until the selected statistical value is below the acceptable criteria. This is a powerful approach that operates nicely under the concept of exposure unit within risk assessment . Under this concept, only the worst blocks are removed until the risk to an individual or species exposed to the entire site or exposure unit area is below a target risk level. This framework, however, may result in individual blocks exceeding the target risk value. This issue is addressed in the site-block framework.

Site-Block Scale

In this approach, there are two decision criteria. The first is the acceptable site value and the second is the acceptable block concentration. First, the site scale is applied to reduce the site wide exposure level to a suitable value. Next, a review of remaining block values is performed to determine if any single block value exceeds the maximum concentration value. If so, the block scale framework is applied until the maximum remaining block value is less than the second constraint. From a risk perspective, this may be the most appealing framework because the exposure unit risk is acceptable and unacceptable hot spots are removed.

Ultimately, this framework is reduced to either the site scale or block scale framework in practice. The site-block framework is effectively the block scale framework when the site scale fails to remediate far enough to meet block scale requirements. Conversely the site-block framework is equal to the site scale framework when enough blocks are remediated such that the maximum contamination remaining also satisfies the block scale framework.

Example

Consider the following site contaminanted with Arsenic. The human health risk assessment has established that for an industrial landuse scenario, the target carcinogenic risk will be set at 1E-6, corresponding to an exposure value 3.5pCi/g. The following figure shows the location of samples. Those enclosed by boxes exceed the target risk limit.

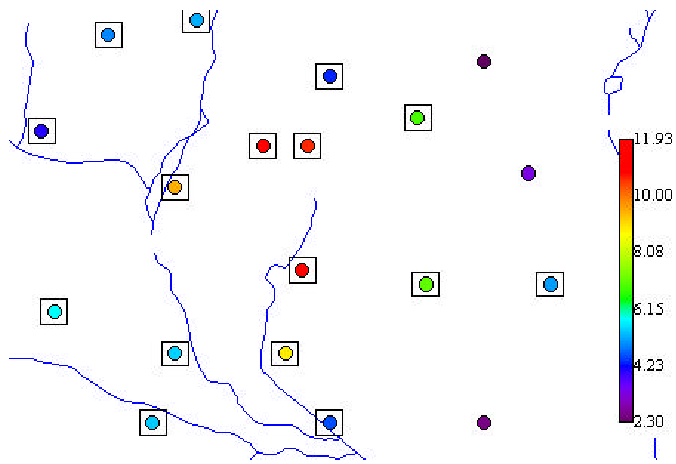

Figure 3. Location of sample points exceeding acceptable risk level

Through stakeholder discussions, the value 3.5 pCi/g becomes a cleanup goal. A geospatial analysis is performed on the site, yielding the following contour map.

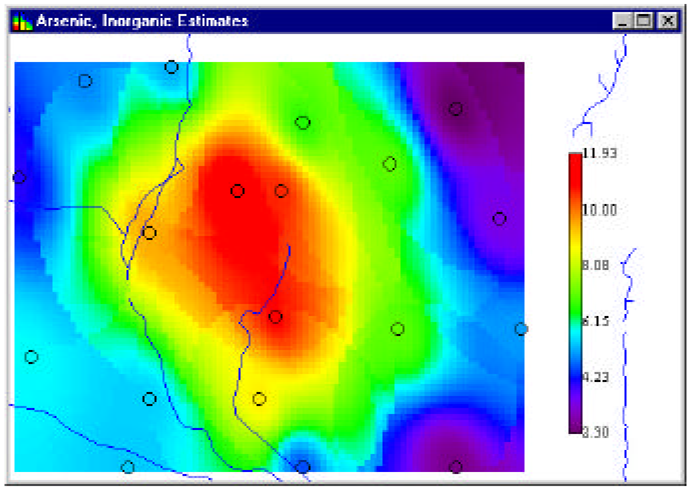

Figure 4. Geospatial contour of Arsenic concentrations across the site.

At this point, any of the decision frameworks may be applied. The framework must be chosen with a cleanup goal in mind.

In the block scale framework, any block exceeding 3.5pCi/g will be remediated. The following figure shows the remedial design for this framework. The areas shaded in gray must be remediated.

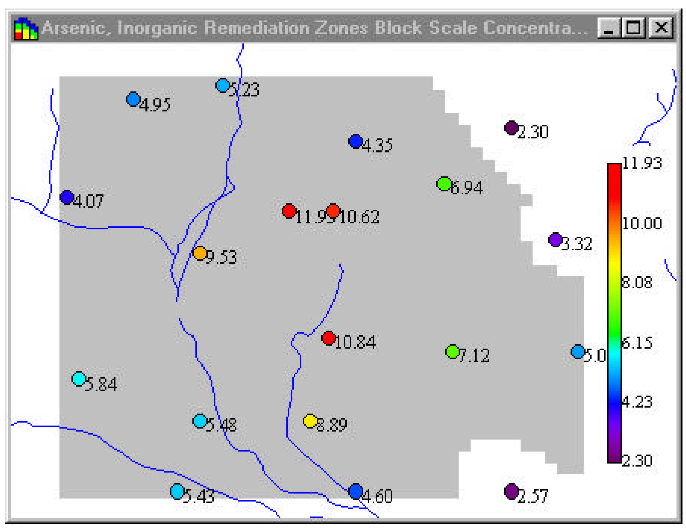

Figure 5. Remedial zone for the block scale framework.

Using the site scale framework, the worst areas are remediated until the site average concentration drops below the target risk value. This corresponds to the site-wide risk dropping below 1E-6.

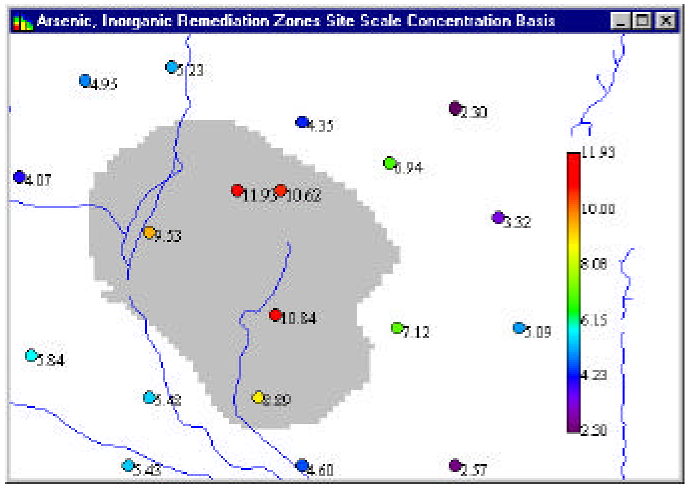

Figure 6. Remedial zone for the site scale framework.

For the site/block framework, stakeholders decided that the site-wide risk must be less than 1E-6 risk (which corresponds to a site wide average concentration of less than 3.5pCi/g) and the contamination for each block must be less than twice this concentration value. Thus our site scale goal is 3.5 pCi/g and our block scale goal is 7pCi/g. The site/block framework results in the following design.

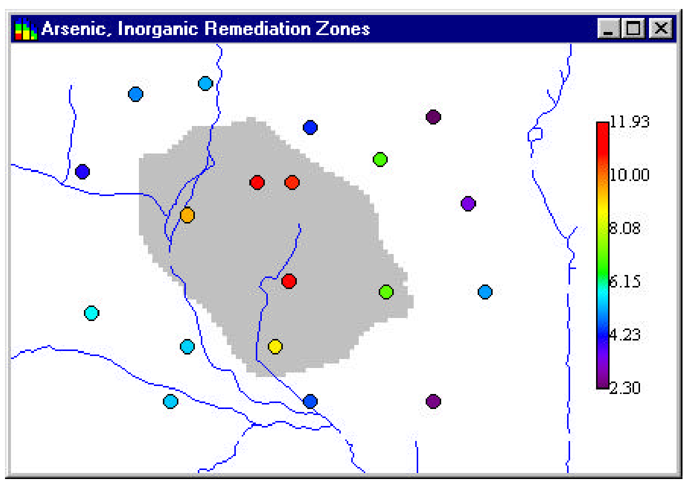

Figure 7 Remedial zone for the site-block scale framework.

By comparing Figure 7 with the site scale result for 3.5 pCi/g (Figure 6), the site/block framework is reduced to the block scale with a cleanup goal of 7pCi/g.

Secondary Sampling Strategies

Geospatial modeling routines open avenues into other decision frameworks in sampling design. In a geospatially based design, the contouring methods provide a model of concentration values or uncertainty at each point across the site. With this result, a suite of sampling strategies is available with unique goals for taking additional samples.

In an ideal situation, the sampling design strategies described here would select a location for a new sample, the sample would be taken, and the result would be analyzed and put back into the model to produce the next optimal sample location. Under this ideal situation, the following sampling strategies could drive a sampling effort in real time. This is possible for sampling devices with quick turn around capabilities and has been a useful option on some sites already.

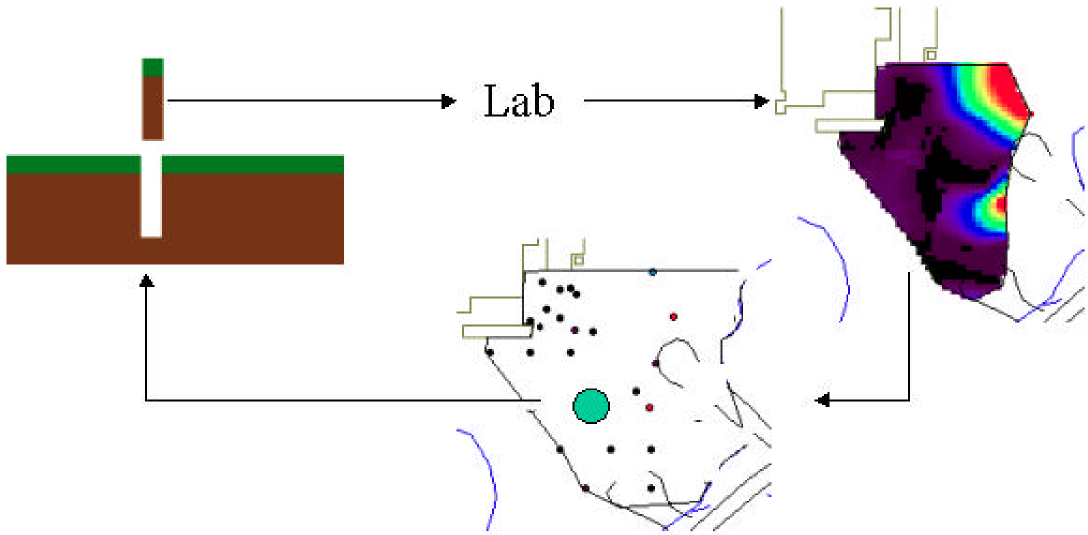

Figure 8. Flow for chart for using geospatial analysis to drive a sampling design in real time.

Without quick response time, the method must be able to predict the optimal location of several samples at once. This is achieved with simulated sampling. In other words, if multiple new samples are requested, the most optimal location is chosen first, and a modeled sample value is taken at that point and treated as if it where a true sample. The model is rerun, and the next optimal location is chosen for the second sample point. This is repeated until the number of samples requested is generated. Although the accuracy of each additional request is reduced as more and more dependency is placed on modeled values, this sampling is a valuable alternative when faced with producing a plan for multiple samples at once.

Five sampling strategies are demonstrated on the following sample site. The suggested new sample locations are highlighted with circles. Each block center becomes a candidate for a new sample location.

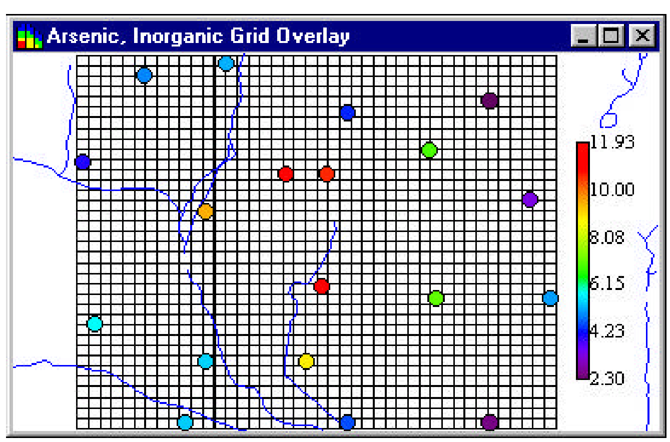

Figure 9. Gridded site used for building a secondary sampling design.

Adaptive Fill

The goal of this strategy is to fill spatial data gaps by sampling in those areas where data are far apart relative to the rest of the set. It is easy to implement this strategy because it is not dependent on a contouring method.

Adaptive Fill

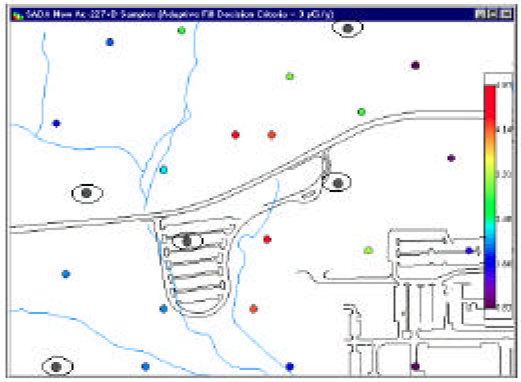

Figure 10. Adaptive fill results.

Estimate Rank

The goal of estimate rank is to place new sample locations where the highest concentrations are predicted to be. This corresponds to a confirmation type sampling design. The result is a design that will determine if the area has relatively high concentration values – hot spot confirmation.

Ordinary Kriging Results

Estimate Rank

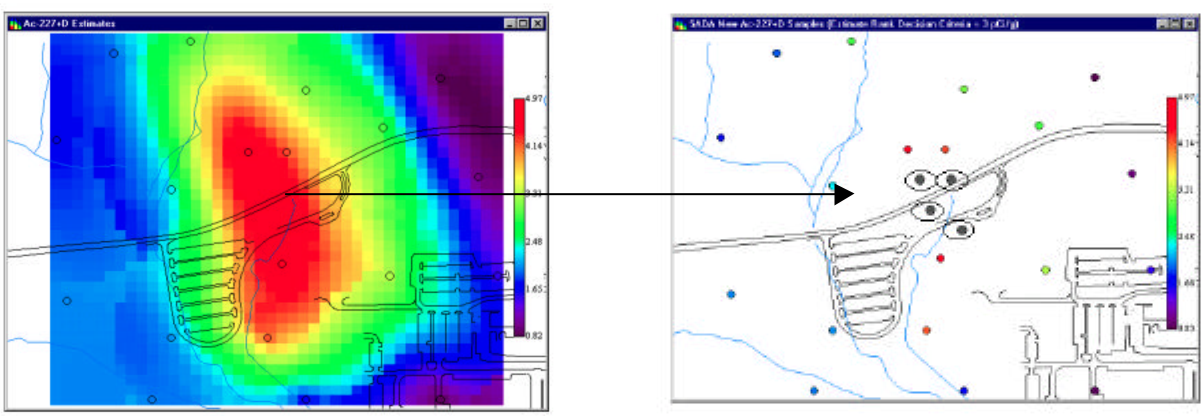

Figure 11. Concentration Contours and estimate rank results.

Variance Rank

This sampling strategy is based on the ordinary kriging method, where model variances are produced along side concentration estimates. These two quantities define a distribution of possible concentration values at each point. This sampling strategy will place new samples where the model variances are the highest and will result in a sampling design that reduces modeled variability.

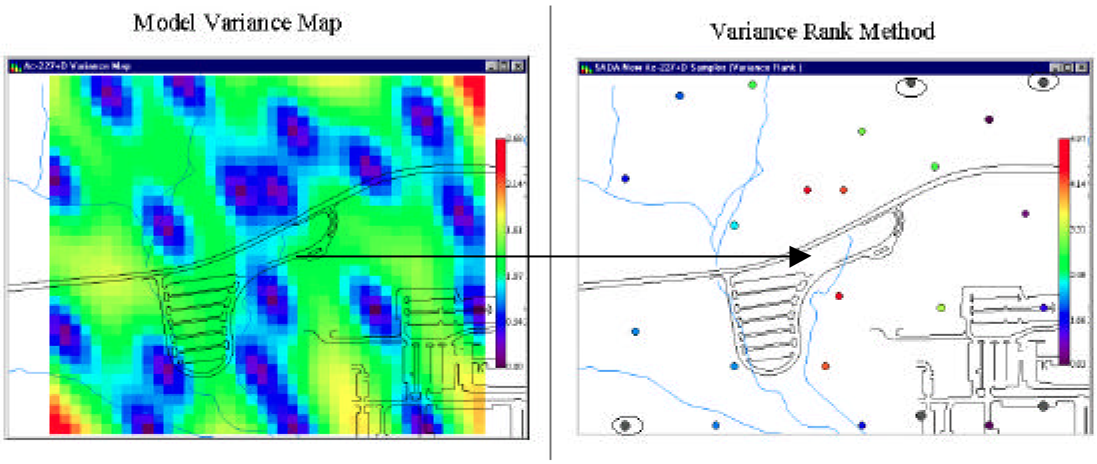

Figure 12. Model variances and variance rank sample design.

Percentile Rank

Geostatistical routines, such as ordinary and indicator kriging, will provide a distribution of possible concentration values at any unsampled point. This distribution describes the magnitude and variability in the modeled response to the sample data. In percentile rank, the goal is to identify those points with the potential to have extremely high value due to the span of the distribution rather than those points which have the highest predicted value (usually corresponds to the mean type value for geostatistics). This approach is useful to sample for potential hotspots. The following figure is based on the 90th percentile. Unfortunately, a graph of the 90th percentile map is not available.

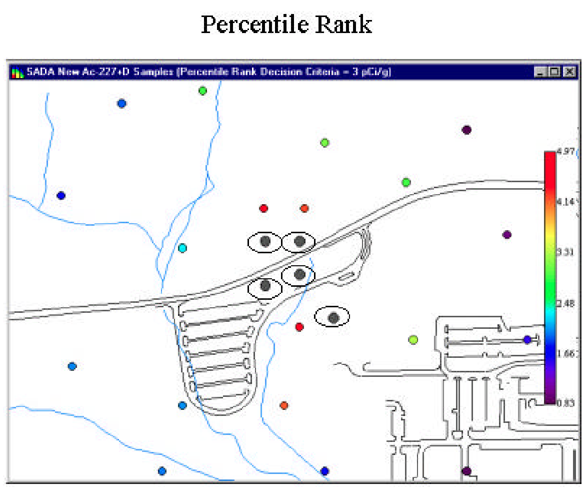

Figure 13. Percentile rank results

Uncertainty Rank

The uncertainty rank, like variance and percentile rank, assumes a geostatistical approach to contouring has been utilized. Uncertainty rank differs from the former methods in that it is directly connected to a decision criteria. In uncertainty rank, new samples are placed where the model is most uncertain about exceeding the specified criteria (i.e. Prob > Criteria ~ .50). This is primarily useful for delineating the boundaries of the area of concern.

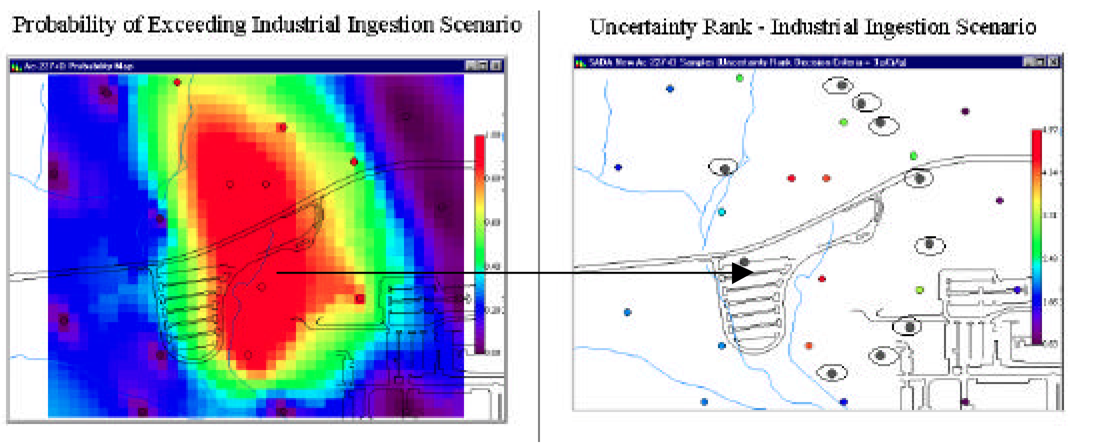

Figure 14. Probability of exceeding risk limit and resulting uncertainty rank sample design.

Secondary Engineering Constraint

For all strategies except adaptive fill, a secondary constraint is often required to create a viable sampling design. In each case, the mathematically optimal location is selected as the next new sample location. This location may be extremely close to another sample and therefore not practically optimal. As a result, a minimum distance constraint may be useful. In this secondary engineering constraint, new samples are forced to be separated from existing data as well as themselves by a specified distance. This results in sampling designs that optimize with respect to a design goal while spreading samples apart to also give better spatial coverage within the area of interest. A secondary constraint of 100 feet was used for all the examples in this section.

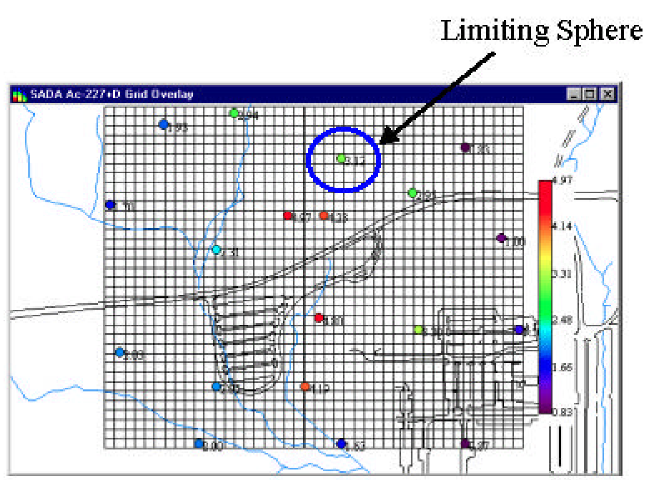

Figure 15. Secondary distance constraint. The limiting sphere applies to all new and old samples.

When to Stop Sampling: A Value of Information/Economic approach

A number of criteria for when to stop sampling are available. Most are statistically based and assume independence among the data or require the user to know something about the sampled object. A straight-forward "economic value of information" approach may provide another tool for determining when to stop sampling. This approach integrates the geospatial analysis, decision criteria, sampling design, and cost. Simply stated, when new samples are not producing new information, sampling may stop.

This approach is presented in this paper from the perspective of geospatial and decision analysis. The particulars of what is meant by "no new information" will vary widely within characterization studies.

In the following exercise, the concept of "value of information" is demonstrated with a simple geospatial analysis. The modeling results are shown for each round of sampling. As the number of samples increases, the model changes less.

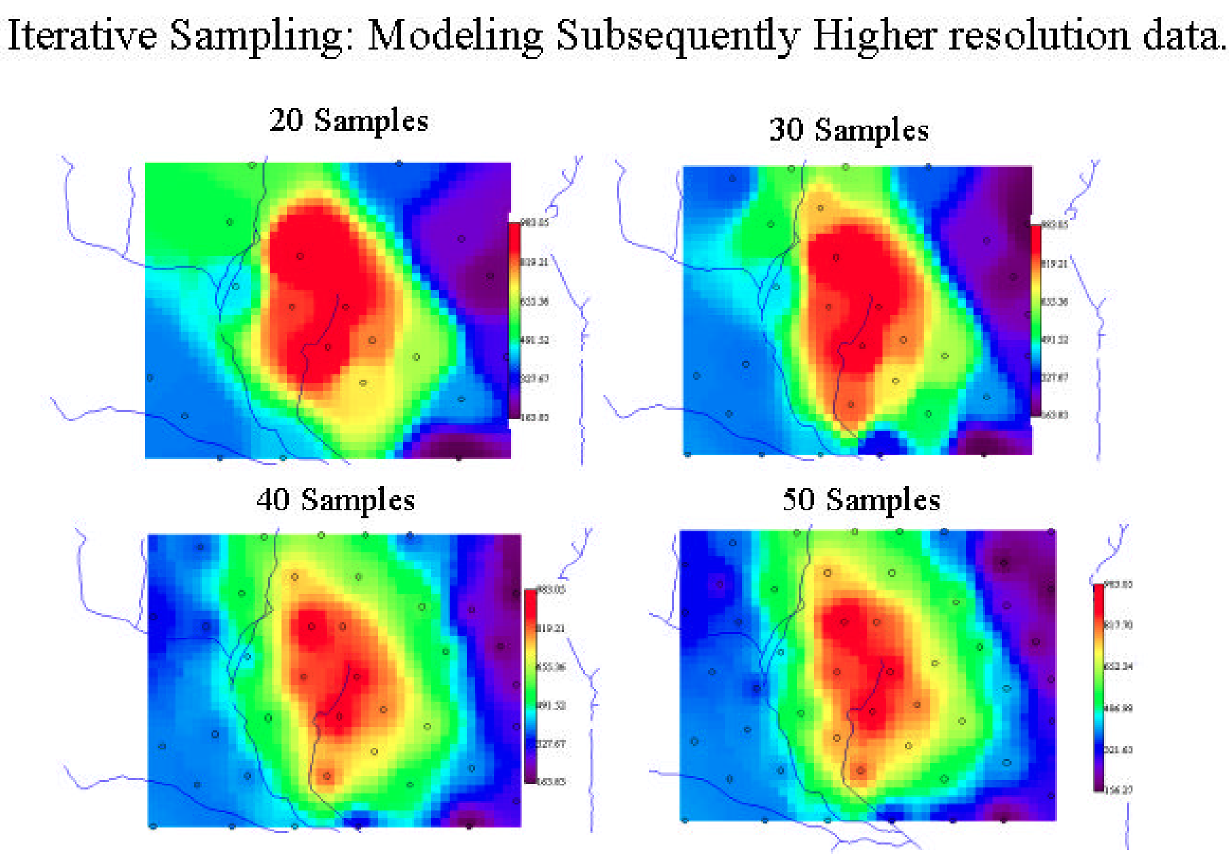

Figure 16. Subsequent analysis re sult with each round of new samples.

With each new sample, less new information is provided to the process. In fact, upon visual inspection, one can see that the difference between 40 and 50 samples if very little. The implications of using this approach are great for remedial design. For sampling designs that intend to refine the remedial process this approach is directly applicable.

Conclusion

Geospatial analyses can have an explicit and influential impact on environmental decision making processes. Delineating information within a spatial context aids in the definition of many decision processes and the quantification of their impact on cost and risk reduction. These impacts can result in enormous cost savings over traditional approaches. The methods presented in this paper represent the basic approaches in this area; more methods are being developed. All the described methods are available in the SADA software package, which can be freely downloaded at http://www.sis.utk.edu/cis/sada/.