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An environmental decision support system for spatial assessment and selective remediation

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ABSTRACT

Spatial Analysis and Decision Assistance (SADA) is a Windows freeware program that incorporates spatial assessment tools for effective environmental remediation. The software integrates modules for GIS, visualization, geospatial analysis, statistical analysis, human health and ecological risk assessment, cost/benefit analysis, sampling design, and decision support. SADA began as a simple tool for integrating risk assessment with spatial modeling tools. It has since evolved into a freeware product primarily targeted for spatial site investigation and soil remediation design, though its applications have extended into many diverse environmental disciplines that emphasize the spatial distribution of data. Because of the variety of algorithms incorporated, the user interface is engineered in a consistent and scalable manner to expose additional functionality without a burdensome increase in complexity. The scalable environment permits it to be used for both application and research goals, especially investigating spatial aspects important for estimating environmental exposures and designing efficient remedial designs. The result is a mature infrastructure with considerable environmental decision support capabilities. We provide an overview of SADA's central functions and discuss how the problem of integrating diverse models in a tractable manner was addressed.

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Software availability

SADA is freeware: binaries for the full-featured installation files, documentation, databases, and examples are available for free download at: http://www.tiem.utk.edu/~sada/index.shtml. Minimum resolution is 1024 × 768 with 16 million colors (for 3-D viewing); processor should be a minimum Pentium 3 processor with 800 GHz, 512 MB RAM, and 800 MB hard disk space available for installation. The interface is constructed in VB.Net and leverages dynamic link libraries for algorithms constructed in other languages, including C and Fortran.

1. Introduction

Visualization is a key component of modern site assessments; however, visualization combined with spatial data analysis and assessment algorithms requires programming skills and budgets not always available for site assessments. These assessments require the integrated use of tools from multiple disciplines; including Geographic Information Systems (GIS), sample design, statistics, data management, two- and three-dimensional visualization, spatial modeling, uncertainty analysis, risk assessment, remedial design, and cost/benefit analysis. These diverse capabilities must then be used together in a coherent, defensible, repeatable decision process (Matott et al., 2009). Generally, this algorithmic integration is achieved through highly flexible implementations that require significant programming capability (e.g., command-line interface of *R* with contributed packages (R Development Core Team, 2010); plug and play model capabilities of FRAMES (Babendreier and Castleton, 2005)), proprietary software that may require significant financial resources and add functionality in response to market demand (ESRI), or even a sequence of individual models to handle each component separately. This situation creates a gap in software availability, decision support freeware for environmental assessment practitioners that does not require a significant investment in training and/or finances to apply at contaminated sites.

Spatial Analysis and Decision Assistance (SADA) is freeware that fills this gap. It has been developed at the University of Tennessee's Institute for Environmental Modeling in collaboration with other

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Universities, federal agencies, national laboratories, private sector companies, and individual consultants. The software has been funded by the U.S. Nuclear Regulatory Commission (USNRC), U.S. Environmental Protection Agency (USEPA), and the U.S. Department of Energy (USDOE). SADA has been in development for over a decade with its most recent release (Version 5.0) in 2009. Past versions have generated world-wide interest, over 20,000 downloads from 100+ countries, with the majority of users in North America and Europe. The software provides a tool that makes a direct, practical connection between data analysis, modeling, and decision-making within a spatial context (Stewart and Purucker, 2006). The target user is an environmental investigator interested in characterizing contamination for a particular site and designing selective remedial actions.

SADA has been used in a number of environmental modeling applications – including site assessments, academic investigations, and regulatory frameworks designed to streamline characterization processes. Direct application of the software, or discussion of its role in environmental investigations have appeared in a number of peer-reviewed articles. These include the assessment of contaminated sites such as underground storage tanks; landfill disposal sites (Butt et al., 2008a,b); contaminated land (Bardos et al., 2001; Carlon et al., 2007; Chung et al. 2007); surface water (Boillot et al., 2008); groundwater (Hornbruch et al., 2009); floodplains (Sauer et al., 2007); and applied spatial analyses for all these media (Goovaerts, 2010). Broader applications include investigations of microbial community structure (Franklin and Mills, 2003) and enzyme activity (Smart and Jackson, 2009); multi-criteria decision analyses (Linkov et al., 2004); boundary delineation of soil polygons for terrain analysis (Sunila et al., 2004); disease incidence (Ifatimehin and Ogbe, 2008); examination of interactions between habitat and contamination on ecological dose (Purucker et al., 2007); soil remediation frameworks (Norrman et al., 2008; Rügner et al., 2006); hot spot delineation (Sinha et al., 2007); landscape ecology (Purucker et al., 2009b; Steiniger and Hay, 2009); human health risk (Andam et al., 2007); and determining laboratory analytical support necessary to support field-level data collection (Puckett and Shaw, 2005).

In addition, SADA capabilities as an environmental management computational toolkit (Holland et al., 2003) have led its adoption within regulatory frameworks. Principal among these are the USEPA's Triad approach (Crumbling, 2001) and the USNRC's Multi-Agency Radiation Survey and Site Investigation Manual (MARSSIM). The USEPA has long recommended SADA as a tool for strategic site investigation and characterization (U.S. Environmental Protection Agency (USEPA), 2001a, 2005a, 2005b); however, recent developments in the Triad approach, a consensus-based decision-making approach for hazardous waste sites that maximizes use of innovative characterization tools and strategies (Crumbling et al., 2003), have increased its utility for larger-scale applications.

Construction of this type of software provides numerous opportunities for application and research. As a vehicle for deploying existing methods and developing new assessment approaches, SADA must meet several, sometimes conflicting, objectives successfully. A critical factor is the user interface. It is important to engineer an assessment environment that encompasses needed functionality, yet is also suited to specific users with specific goals. These objectives are met by a scalable interface that is visually consistent while providing access to the depth of available algorithms. The interface was created with four criteria in mind: (1) users should easily find an achievable assessment goal; (2) the interface should present only relevant tool sets and not clutter the computational environment; (3) the interface should provide open, flexible guidance through any interim steps required to achieve the assessment goal; and (4) the interface should be consistent across all goals. The primary modules and functions that help meet these criteria are encapsulated as objects that can be accessed for various decision-informing outputs (Rizzoli and Davis, 1999). For any given modeling task, the interface presents only the required steps and functional elements for that task; these methods range from simple statistical output to risk-based area of concern (AOC) maps based on ecological exposure models and geostatistical algorithms.

This manuscript describes the primary environmental assessment methods that are incorporated into the software, then presents the results of the integration with a focus on how the decision elements were accommodated into the interface, and a discussion concerning the elements of the scalable decision interface that both allows for added functionality in a scalable manner and guides the user through complicated, multi-step decision processes.

2. Methods

SADA's basic tool set encompasses many areas of environmental characterization and assessment. Fig. 1 shows how these tools are typically organized to facilitate decision support from the earliest phases of an investigation. In the following text, we briefly summarize available methods for: determining the number of samples needed to characterize a site; creating sample designs; data management; exploratory data analysis; and spatial modeling tools.

2.1. Sample design

Sampling is imperfect and subject to error (Christakos and Olea, 1992); uncertainty sources include the complex and dynamic processes under study, economic realities, and the technical limitations of available sampling and analytical methods (Thompson, 1999). Short of exhaustive sampling, investigators must use a limited set of data and accept uncertainty to characterize conditions at a site. An early decision when characterizing contaminated sites is determining how many samples to collect. For smaller sites this is often a function of the available sampling budget; however, statistical power curve methods recommended by the U.S. Environmental Protection Agency (USEPA) (2000, 2006) can be used to estimate sample sizes required to support decisions with specified error rates. SADA uses power curves based on the non-parametric Sign and Wilcoxon rank sum tests from MARSSIM guidance (Gogolak et al., 1998) and algorithms implemented in Gogolak (2001) to calculate required sample sizes and display power curves. Implementation requires specifying alpha and beta decision errors, a target concentration for the alpha decision error, a lower bound for the beta decision error, and an estimate of the standard deviation. After the data has been collected, a retrospective power curve can be constructed using the number of samples actually collected and the observed standard deviation to ensure that decision objectives were satisfied.

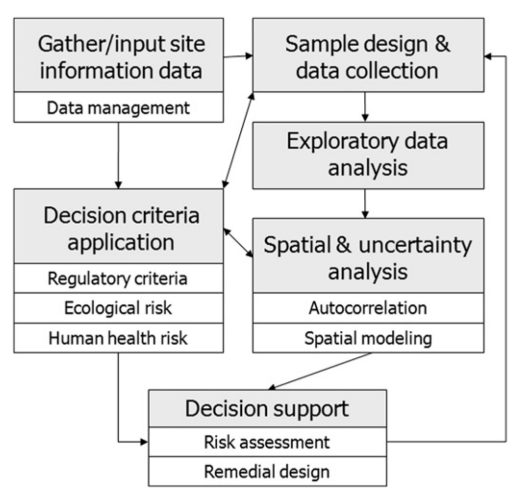

Fig. 1. Primary components of the graphical user interface that contain SADA software functions and a typical example flow path. Different chart elements are supported by decision support interview processes that guide the user through the relevant steps. The scalable and object-oriented nature of the components allows for new functions to be added to the software in a consistent manner and for existing modules to be recombined in useful ways, with new interview processes, to provide support for a range of decision support processes. Although environmental assessment decision processes are usually considered to be acyclic, decision support software must facilitate the ability to revisit earlier steps with update information. The presented components correspond to subheadings in the methods and results text.

The two broad categories of spatial sampling strategies are design-based and model-based (Brus and de Gruijter, 1997). Design-based strategies are used for collecting data where prior knowledge may not exist, or, if present, are ignored for statistical design purposes. Model-based sampling strategies utilize available information about the site, such as previously sampled data, historical information, or a spatial model, that allows for developing biased sampling strategies to achieve specific objectives. Because SADA permits users to import supporting data sets, construct spatial models, or create user-defined prior knowledge maps that support design-based strategies, these two categories are not mutually exclusive. A subset of sample designs in SADA is summarized in Table 1.

U.S. Environmental Protection Agency (USEPA) (2000, 2002) provides guidance on the selection of sampling designs. Grid approaches can be implemented in a triangular or square partitioning of the site (Yfantis et al., 1987) in which a sample point is located in the center of each partition. In addition, unaligned implementations of simple and standard grids are available that randomly place samples within each partition, not at a central point. This hybrid approach shares properties of both simple random and gridded designs: its samples are located with reasonably good spatial coverage, but still possess an element of randomness (Gilbert, 1987). Any sample design can be made into a stratified design using the standard drawing tools that allow users to aggregate sections of the site for purposes such as defining exposure areas or conducting stratified sampling.

Model-based sampling strategies can be based on hard data, soft data, or a data-driven model. These designs can incorporate the presence of spatial correlation, spatially delineated decision rules, and cost/benefit considerations. Geographical designs target particular areas of interest to refine local knowledge about spatial processes, rather than to estimate a population statistic. Among these are designs that place samples in high risk or boundary zones at a contaminated site, based on spatial modeling, subjective prior information maps, or Local Index of Spatial Association (LISA) statistics. Methods are also available to place samples in areas of insufficient data density, including adaptive fill, which sequentially places samples at a site location that maximizes the distance to the nearest sampled location, and Ripley's K, which sequentially places samples in neighborhoods with the lowest sample density.

Sample design variations are available in SADA based on a hot spot search routine discussed in Gilbert (1987) and implemented in the ELIPGRID model (Davidson, 1994). These methods take two of three user inputs concerning the grid specification, a probability of finding a hot spot, and the size of the hot spot to calculate the input that has not been specified. As an example, a sample grid can be produced at a contaminated site based on inputs of hot spot size and a desired probability of detecting that hot spot. There is also a search routine that combines spatially delineated prior knowledge to search more efficiently for elevated contaminated zones. Additionally, for all sample strategies, there is a Monte Carlo routine available that will estimate the probability of detecting a hot spot in two- or three-dimensions, given hot spot dimensions and a sampling design that has been implemented (or planned) at a site.

2.2. Data management and exploratory data analysis

A key aspect of successful decision support systems that combine different models is integrated data management. This provides the capability to pass information between models without extensive manipulation by users. Many current decision support systems employ a "null integration strategy" that shifts responsibility for data transfer between models to users (Denzer, 2005). While this may be acceptable for technical scientific users, it often limits access for other participants in the environmental assessment process and can create quality assurance/quality compliance issues in a regulatory setting. For sampled values, SADA requires an initial import of laboratory analytical data as either a comma-delimited text file or a Microsoft Access file; data must be pre-processed to handle laboratory qualifiers and to convert values to standard metric units for risk assessment purposes (mg/kg and mg/L). Modifications have been made to handle very large data sets such as those encountered in geophysical surveys. Import capabilities include gridded data in various standard GIS formats. In addition, the program imports two-dimensional and three-dimensional models created outside the code (e.g., digital elevation models or externally created contour maps). Once data are imported, no further data manipulation outside the software is needed to access program functionality.

Results of a sampling effort can be displayed in the program's internal GIS in two- or three-dimensions. GIS software provides several well-known advantages in conducting environmental assessments. SADA provides a set of tools for setting up the site of interest, including the ability to define a site by its horizontal/vertical boundaries and specified vertical layers. Individual sites can be defined using the polygon and layer tools, while sampling locations and analytical results can be displayed with GIS layers. Like other GIS systems, SADA can import popular layer formats such as shapefiles (.shp) and Data eXchange Format (.dxf) files, as well as photographic images that provide clearer spatial contexts for assessment. Standard drawing tools can further divide the site into areas of interest by specifying irregular site boundaries. These tools can be depth-specific, including or excluding areas of the subsurface for three-dimensional applications. Data can be displayed and queried according to separate sampling events, and options for handling non-detects imported at the analytical detection limit and for resolving duplicate data are available. This quickly identifies outliers or unexpected trends in the spatial distribution of contamination. In addition to visualization, a suite of summary statistics is available to help quantify what is occurring on the site. Many common statistical methods from USEPA guidance (1998) are available in the software for evaluating contaminated sites, including univariate measures of relative standing, central tendency, and dispersion. Graphical displays for posting plots, histograms, and ranked-data plots, and non-parametric hypothesis tests versus decision criteria or reference concentrations are also available.

Table 1
Subset of design- and model-based sample strategies available in SADA.

Sample design	Description
Judgmental	Users place samples on the map where professional judgment and/or prevailing objectives suggest their location.
Simple random	Random model for distributing a user-specified number of samples spatially.
Grid designs	Variations on simple, standard, and unaligned grids.
Hot spot	Grid methods take two of three user inputs concerning the grid specification, a probability of finding a hot spot, and the size of the hot spot to calculate the input that has not been specified.
Threshold radial	Resampling around particular points of concern in the data set at a user-provided radius.
Adaptive fill	Iterative selection of sample locations that maximize the minimum distance to the nearest neighbor.
Area of concern boundary	Specification of sample locations where models most unsure of criterion exceedance.
Local Index of Spatial Association designs	Evaluation of conditional samples for Ripley's K, Moran's I, Geary's C.

2.3. Spatial autocorrelation

Spatial autocorrelation exists when the similarity in measured values depends on separation distance or relative location in space. A common spatial correlation behavior occurs when data points that are close together are on average more alike than data points farther apart. Depositional and transport processes that control anthropogenic contamination in contaminated media can cause significant spatial correlation among contaminants as well as subsequent environmental exposures and effects. Spatial autocorrelation among data is often viewed negatively since it impacts various statistical assumptions normally used in site assessment, however, the presence of spatial correlation does not necessarily impact univariate statistics from site data that are compared to an established cleanup concentration (e.g., a confidence limit on the mean – Brus and de Gruijter, 1997). In contrast, autocorrelation can cause significant problems for hypothesis testing and sample size calculations (Griffith, 2005); nevertheless, for geospatial modeling, spatial autocorrelation is accepted and motivates the delineation of contamination and selective remediation.

Detecting, measuring, and visualizing spatial correlation can be a difficult process, further complicated by outliers, small data sets, and instrument detection limits. Considerable effort was, therefore, devoted to addressing this process in SADA, emphasizing on ease of use and intuitive visualization tools. Available tools include standard semivariogram plots, variogram maps, and standard correlation models. The code can recommend starting points for parameter values used in measuring and modeling correlation, improving tractability. Expansion of existing visual tools such as three-dimensional variogram maps (rose maps) greatly assist in identifying correlation trends, especially in subsurface applications.

LISA maps available in SADA are useful in identifying site sub-areas with marked differences in values of Geary's C (Geary, 1954) and Moran's I (Moran, 1950) spatial statistics for local neighborhoods (Anselin, 1995). For larger sites, global variography is insufficient to evaluate stationarity since it calculates average values for spatial subsets of the distance and may mask local patterns (Anselin, 1995). Plotting and analyzing LISA maps can identify areas of distinct spatial behavior, allowing additional subdivision or grouping of defined contaminated areas at the site before variography and interpolation procedures are performed.

The presence of spatial autocorrelation facilitates implementation of geospatial models that delineate contamination across the site, allowing for volume estimation and optimization of the remediation/removal area. SADA provides geospatial models with different approaches to utilizing spatial correlation, permitting model evaluation of contrasting spatial models and decision criteria for decision applications.

2.4. Spatial models

Environmental investigations often call for estimating concentrations at unsampled locations to create continuous spatial models of contamination. These spatial models, valuable in their own right, also serve as the basis for decision support and model-based sampling designs in SADA. The field is rich with estimation methods, many of which can be found in the public domain (e.g., Deutsch and Journel, 1992). Table 2 summarizes the available interpolation approaches in SADA. Available interpolants in SADA were selected to occupy a range from the simplest approaches that yield deterministic spatial predictions to geostatistical algorithms that are grounded in the theory of random function models (Christakos, 1992; Goovaerts, 1997; Isaaks and Srivastava, 1989). These more advanced routines can provide a solid statistical foundation for spatial uncertainty assessment.

The conceptual relationships between the interpolants in SADA are summarized in Fig. 2. While deterministic methods such as inverse distance produce a single estimate for each node, a geostatistical model builds a local probability distribution function at each node. From this node-specific distribution, representative values can be drawn (e.g., 50th percentile, mean, E-type estimate) for mapping. In addition, important features of each local distribution such as the entropy, mean, variance, and quantiles provide local measures of uncertainty. Advanced geostatistical simulation methods extend these local models to spatial models of uncertainty, permitting the use of a number of post-processing methods for determining joint exceedances. The process of geostatistical simulation yields multiple, equally probable realizations of an attribute across space. External models, such as fate and transport algorithms, can then use these realizations to produce a distribution of response values to quantify the contribution of spatial uncertainty to relevant modeling endpoints (Goovaerts, 1997). Unlike smooth kriging maps, simulation results are often more heterogeneous and thus more representative of the variability often seen in contaminated systems. Within SADA, these models of uncertainty are integrated with risk models or user-created decision criteria and participate directly in the decision process. Local and spatial models of uncertainty quantify uncertainty in concentration values (probability maps), uncertainty in the location and volume of affected media (AOC maps), and serve as motivations for certain secondary sampling design methods. The application of geostatistics in risk assessment and remedial design efforts is well documented in the literature (Thayer et al., 2003).

Often there is insufficient data to represent the site adequately, estimate the correlation structure, or produce a meaningful spatial model. Data can be limited by site accessibility or cost constraints such that neither deterministic nor standard kriging methods are appropriate. There may be available secondary forms of data that are well correlated with the primary attribute of interest. Secondary data can take many forms: in-field detection devices, surrogate contaminants, geophysical surveys, or expert judgment. For example, rainfall amount and elevation (Goovaerts, 2000), X-ray fluorescent results and inorganic concentrations, or gamma counts and radionuclide activity levels. Cokriging (Goovaerts, 1998) evaluates the correlation structure of the primary data and one or more secondary forms of data. A cross semivariogram model then captures the spatial relationship of the two data types. In some cases, there is insufficient data to evaluate the primary data correlation structure and specification of cross-variograms might be involved. Variations like the intrinsic model of coregionalization permit estimation of both primary and cross-correlation structures as a function of the estimated secondary structure that might be based on more abundant samples (Goovaerts, 1997). The reverse could also be true with the primary structure forming the foundation. In this manner, a potentially more defensible spatial model can be constructed where associated uncertainty is a function of the two data sets and strength of the inter-correlations. SADA provides a collection of cokriging functions, including linear model of coregionalization, intrinsic model of coregionalization, Markov, and Markov–Bayes models (Deutsch and Journel, 1992; Goovaerts, 1997). These are accompanied by tools for measuring and understanding the relationship among different variables, including correlation coefficient calculations and bivariate scatterplots.

Table 2
Selected spatial modeling approaches implemented in SADA.

Interpolant	Description	References
Nearest neighbor	Unsampled areas take on the value of the nearest sample location.	Franke, 1982
Inverse distance	Nearby sample locations are weighted according to an inverse power of the separation distance.	Shepard, 1968
Natural neighbor	Geographical weighting based on Voronoi tessellation areas of neighboring points.	Sibson, 1981, Watson, 1999
Ordinary kriging	Linear estimate of unsampled locations using a fitted variogram to weight sample locations; based on a constant but unknown mean and provides an error term.	Goovaerts, 1997
Indicator kriging	Variant of ordinary kriging, but performed on a data transform with binary variables for exceedance of multiple thresholds.	Deutsch and Journel, 1992.
Cokriging functions	Kriging implementation that uses a cross-semivariogram model to capture the correlation structure of the primary data and one or more secondary forms of data. Linear coregionalization models are used to estimate the cross-correlation.	Goovaerts, 1998, Wackernagel, 1998
Sequential Gaussian simulation	Grid sampling of node-specific Gaussian prior distributions to construct alternative, equally likely, distribution maps, with sampling conditional on the spatial model, observed data, and previously sampled nodes.	Goovaerts, 2001
Sequential indicator simulation	Similar implementation as sequential Gaussian simulation, but indicator variables are used instead of Gaussian distributions to transform data into dichotomous values for specified cutoff values.	Goovaerts, 2001

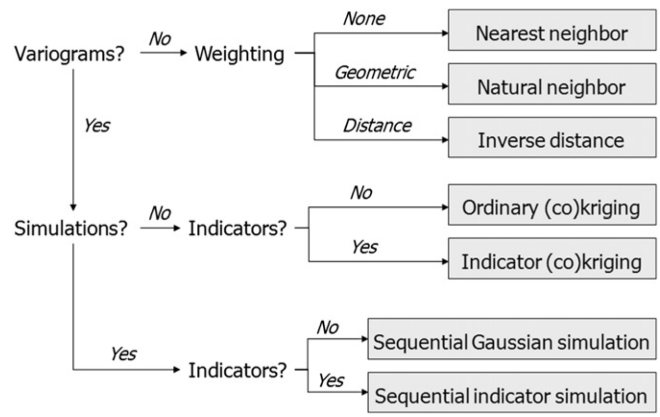

Fig. 2. Decision tree for use of spatial interpolant methods available in SADA. Interpolants were selected that span a range from simple weighting schemes, to flexible implementation of variograms for weighting purposes via kriging, to simulation approaches.

SADA provides two commonly used geostatistical simulation algorithms: sequential Gaussian and indicator simulation. Visualization tools for browsing through multiple simulations, storing the results, and processing the realizations are available. Several post-processing features are provided for calculating local and global uncertainties. The outcome of these post-processed maps can be used directly in the decision process (e.g., Juang et al., 2004) and exported for external models. Geostatistical methods of estimation and simulation are the basis for assessing and quantifying uncertainty with respect to remedial design, volume, and cost. Estimating and evaluating inherent uncertainty is important for informed risk management, especially as it relates to identifying areas of concern (Van Meirvenne and Goovaerts, 2001).

Moreover, the availability of multiple spatial interpolation methods and multiple parameterizations for each method requires model evaluation and selection approaches. Cross-validation algorithms compare the fit of alternative interpolation approaches to data (Legendre and Legendre, 1998). These methods can contrast different parameterizations of a prediction technique and compare interpolation algorithms. Comparisons are made by iteratively removing each sampled value, applying the interpolation model at that location, then observing the difference between predicted and measured values. SADA supplies typical model evaluation criteria, implemented via summary statistics and spatially, including mean error, absolute mean error, and mean squared error.

3. Results

Successful decision support tools provide information in a concise, relevant format. These tools do not make decisions for stakeholders, or exclude their expertise from the process. SADA provides a number of decision analysis tools, based on combining assessment tools and interpolation routines that are frequently the result of interactions between base components. For ecological and human health risk applications, interpolation routines can be combined with cleanup criteria to determine if action is necessary at a site, to identify specific areas of concern, and to evaluate the effects of the spatial heterogeneity of contaminant distribution and exposure (e.g., Barabás et al., 2001; Juang et al., 2001; Saito and Goovaerts, 2000; Purucker et al., 2007, 2010; Schipper et al., 2008). Applying these assessment tools in this manner can not only reduce decision errors, but also improve estimates of risk outcomes and assist in efficiently designing the risk management decisions that are ultimately implemented.

3.1. Scalable interfacing and decision support

As the functionality of SADA grew with each successive version, so did the number of potential interactions between components and the risk for the software to become increasingly complicated and hard to use. To address this, a highly scalable interface, referred to as the Interview-Steps-Parameters-Result (ISPR) approach, was developed. The majority of the interface design space is divided into steps, parameters, and results (Fig. 3). The ISPR provides a list of "interviews" that cover virtually every major function in everyday language, summarized in Table 3. The interface components are then organized, parameterized, and displayed based on the specific interview process chosen (Fig. 4). SADA uses the linear nature of inputs required to implement sequential models and classifies the most common outputs, represented by environmental decision support provided by the software, step-by-step. These interview processes contain all steps necessary to parameterize a particular type of decision support tool and are hyperlinked to the appropriate parameter windows for site-specific data entry. This allows users to input sequentially assumptions and parameters necessary to run the desired tool. Once input has been verified, users can run the requisite models to produce numerical output and/or a spatial result within the GIS window. Because the step and parameter windows reorganize themselves for each situation, the interface "real-estate" is not further cluttered by additional interviews. Furthermore, users are guided through complicated assessments by well-organized steps. Anecdotally, this has proven particularly helpful for new users of SADA and for educational applications.

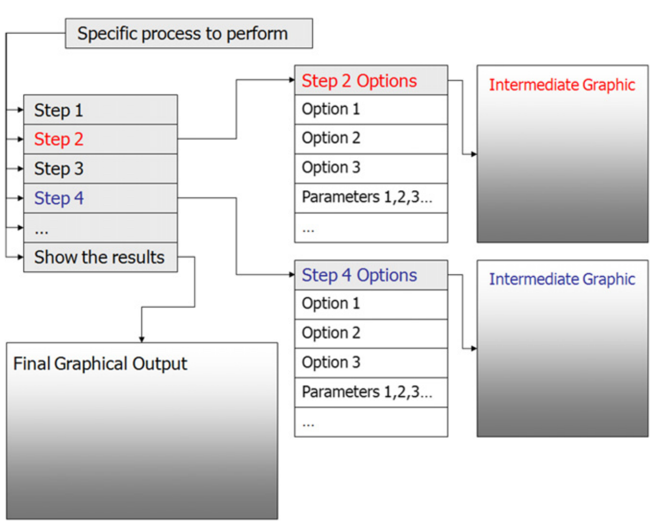

Fig. 3. Conceptual diagram of the ISPR design. The ISPR provides a list of "interviews" that cover most major functions. The majority of the interface space is divided into steps, parameters, and results. SADA uses the linear nature of inputs for these sequential models and classifies the most common outputs, represented by environmental decision support provided by the software, step-by-step. These interview processes contain all steps necessary to parameterize a particular type of decision support tool and are hyperlinked to the appropriate parameter windows for site-specific data entry. This allows users to input sequentially assumptions and parameters necessary to run the desired tool. Once input has been verified, users can run the requisite models to produce numerical output and/or a spatial result within the GIS window. Because the step and parameter windows reorganize themselves for each situation, the interface "real-estate" is not further cluttered by additional interviews.

Table 3
Subset of available interview processes.

Setup my site
Develop sample design
Plot my data
Draw a data screen map
Draw a ratio map
Model spatial correlation
Interpolate my data
Draw a variance map
Draw a probability map
Draw a contoured risk map
Draw an area of concern map
Calculate cost versus cleanup
Draw a LISA map
Perform geostatistical simulation
Smooth/reduce borehole data

This organization of the interface (Fig. 5) facilitates model documentation and transparency. Model transparency, the full reporting of model assumptions, inputs, and outputs, is critical for facilitating communication among decision participants and for meeting minimum documentation standards for environmental model implementation (Jakeman et al., 2006). SADA provides extensive information on its sub-modules and default parameters in a help file distributed with the program and in a comprehensive guide for users (Stewart et al., 2008). In addition, each module of the program contains self-documentation procedures that allow users to generate customizable HTML reports for modeling results. This feature documents all data, models, parameters, and other inputs that were used to generate any given graphical or tabular output; it allows full transparency of decision support processes and assists in model evaluation, algorithmic verification, and report generation.

3.2. Risk assessment

The strength of SADA's particular implementation of spatial modeling comes from direct integration with human health and ecological risk models; together these contribute directly to decision support. This is accomplished by using geostatistical methods that generate local distributions and calculating the probability that a threshold value is exceeded at each location on a prediction grid. This provides local models of spatial uncertainty based on a decision threshold value. The threshold can be based on human health risk, ecological risk, regulatory criteria, or a customized value provided by users.

3.2.1. Human health risk

Human health risk assessment results are used to evaluate concentration levels at a site to determine if risks are significant, whether remedial actions are needed, and to assist in determining remedial cleanup levels. Typically, these assessments focus on chemicals, land use scenarios, exposure pathways that are expected to occur at a site currently and under potential future conditions. The five land use scenarios considered in SADA include industrial, residential, recreational, excavation, and agricultural. Current contaminant concentrations are often used for the on-site assessment of future exposure; however, modeled results that represent future contaminant concentrations can also be imported. In the software, users select exposure pathways used to calculate total risk, and separate calculations are conducted for surface soil, sediment, groundwater, and surface water. SADA's risk models follow the U.S. Environmental Protection Agency (USEPA) guidance (1989 et seq.) and model input parameters can be modified to fit site-specific exposure conditions.

The human health analysis tools support screening and full baseline risk assessments. An important first step in both approaches

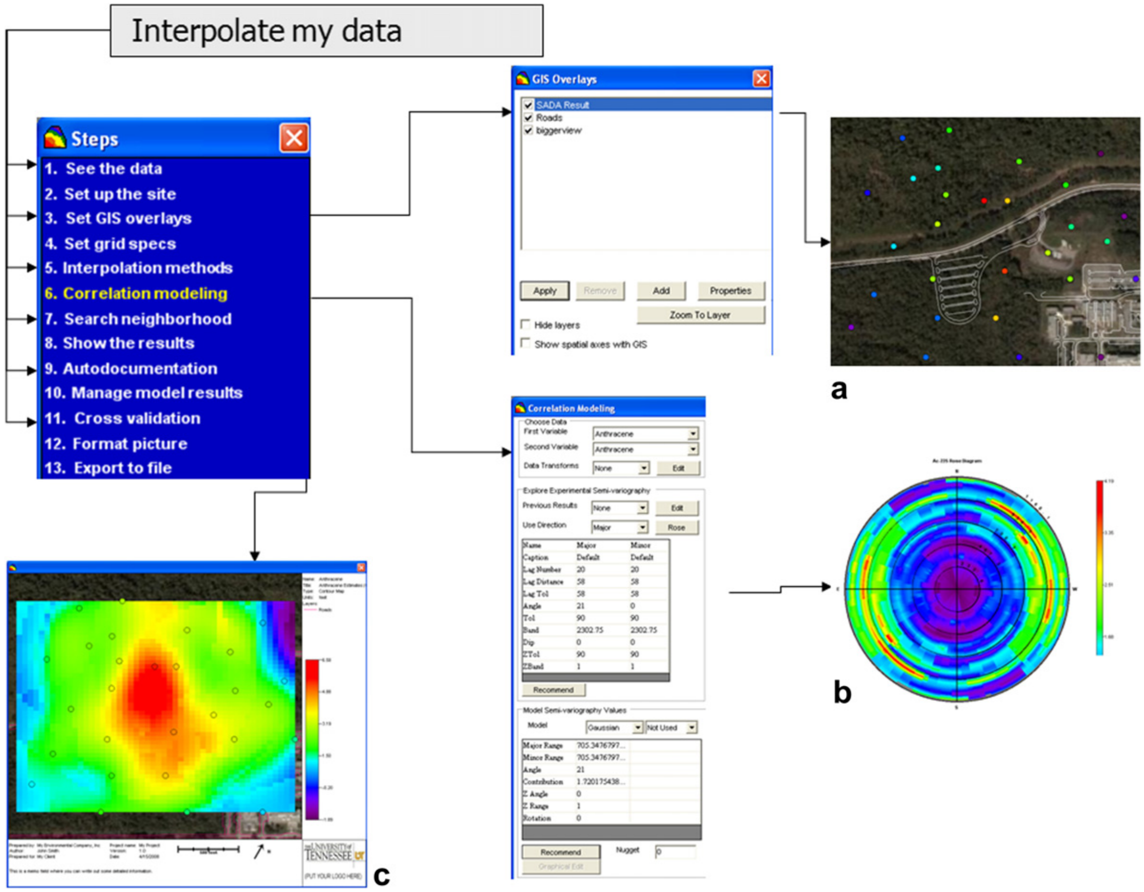

Fig. 4. Implementation of the ISPR design. After selecting the interview process "Interpolating my data", the user is provided with 13 steps to construct the site, parameterize the interpolation, create the graphic, and document the approach. Highlighted are the steps for; (a) setting up the site, including GIS layers, a background image, and specifying site boundaries; (b) fitting the correlation model for ordinary kriging and displaying a rose diagram; and (c) creating the final spatial interpolation graphic.

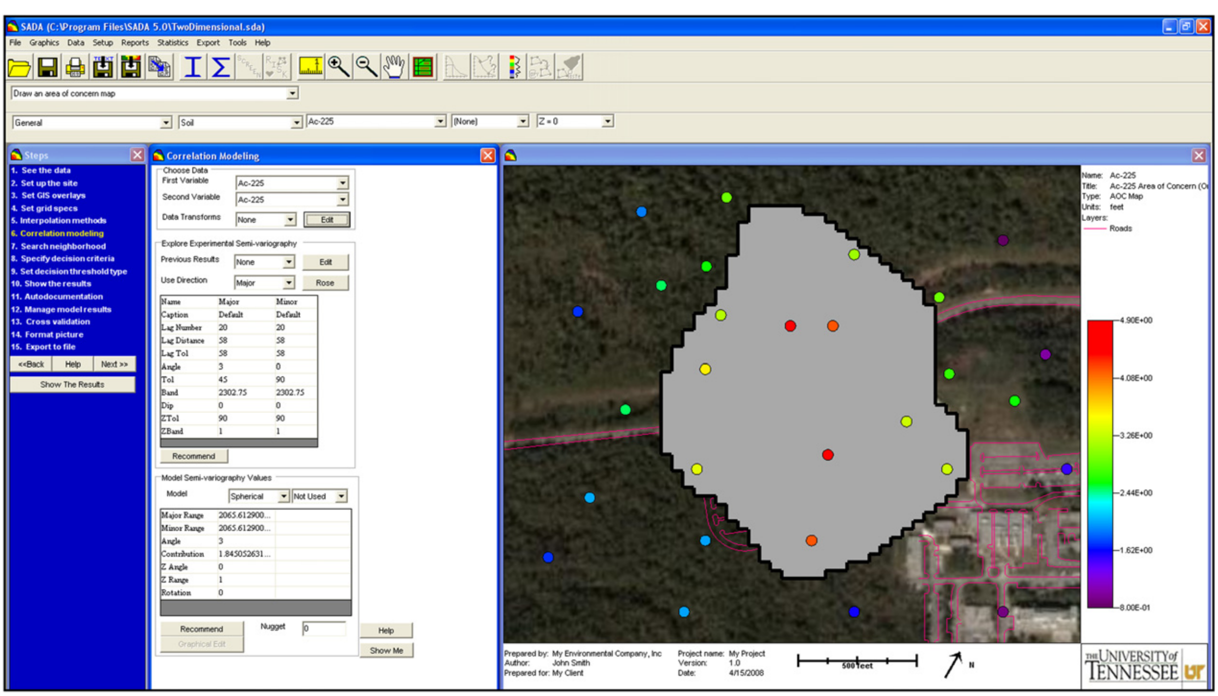

Fig. 5. A snapshot of the SADA interface is shown. One of the outcomes of a decision sequence, a visual depiction of the AOC is presented in relation to the geographic features of a contaminated site.

is the use of screening concentrations. A screening concentration limit can be back-calculated within the software for a target risk level or imported from an external file; these values then screen potential contaminants of concern. A lengthy list of detected contaminants at a site often can be reduced by such risk screening. SADA contains additional data screens and statistical tests that consider background, sample detection frequency, bioavailability, and whether detected contaminants are essential nutrients. Examples include univariate statistics and specific functions such as non-parametric comparison tests (e.g., Wilcoxon Rank Sum test for comparing data to background).

Additional decision support output includes tables of forward calculations of exposure and risk used to support a full baseline risk assessment for the contaminants of concern. The exposure concentrations are calculated based on statistical requirements of the data set, and scenario exposures and associated risks are generated. Detailed assessment of reasonable maximum exposure and central tendency exposure, cancer and non-cancer risks are then calculated for multiple contaminants using site-specific information. SADA produces tables of output that can be modified to support risk assessment documentation purposes (U.S. Environmental Protection Agency (USEPA), 2001b). For identified contaminants of concern, it also can provide spatial data screens to visualize where exceedances are found and risk can be mapped using the available interpolation functions.

3.2.2. Ecological risk

Ecological risk assessment encompasses a range of approaches to estimate the probability and magnitude of effects on ecological endpoints (Suter, 2008). Ecological risk assessment is a multi-step process that begins with screening and culminates in characterization of ecological risks from human activities (U.S. Environmental Protection Agency (USEPA), 1993, 1998, 2003a). Although there are well-established frameworks for performing these assessments, there are still many challenges and limitations that impact their implementation and usefulness (Kaputska, 2008), some of which can be addressed by freely available, competent decision support systems.

The ecological risk module allows benchmark screenings and gives users the ability to calculate forward dose for several terrestrial and aquatic receptors. Hazard identification consists of comparing (or screening) chemical-specific measurements to environmental effects concentrations derived from toxicity testing or other sources (benchmarks). Site contaminants that exceed these benchmarks are kept for further examination. SADA contains one of the most complete, publicly available compilations of benchmark sources and allows users to screen the data and site areas in a GIS view or tabular form. Benchmarks also can be adjusted for site-specific physical parameters. Exposure assessment determines the ecological receptors and pathways to model after considering account bioavailability, behavior, growth, and spatial distributions of contaminants and receptors. Exposure can also be measured directly via receptor body burdens or tissue residues. The software allows users to input toxicity reference values from the literature (e.g., California Department of Toxic Substance Control (CDTSC), 2002; U.S. Environmental Protection Agency (USEPA), 2007) as part of the dose response evaluation. SADA provides terrestrial exposure models to assist in modeling body burdens for over 20 species commonly found in North America (Purucker et al., 2009a). Each of these species can be parameterized as male, female, or juvenile (U.S. Environmental Protection Agency (USEPA), 1993, 2003b). The risk characterization integrates outcomes of the previous steps to estimate the likelihood that significant effects are occurring, or will occur, and to describe the nature, magnitude, and extent of effects on the designated assessment endpoints. Estimated and measured dose results can be displayed spatially or in tables to support selective remedial design or convention risk assessment documentation.

3.3. Selective remedial design

A central piece of SADA's toolbox is the process for delineating an AOC, one or more spatially identified site areas that are of interest in the assessment. An AOC can be based on a number of contamination scenarios, including plume definitions, source terms, and contamination footprints. An AOC necessarily will include a boundary and an associated volume specification, both of which may include a degree of uncertainty. Spatial models, therefore, occupy a central role in defining AOCs, as well as assessing uncertainty in their delineation. An AOC is defined through a set of decision parameters. These include decision criteria, uncertainty constraints, and specific engineering considerations (e.g., overburden calculations). Decision scale is also important in designating an AOC. In block scale, any estimated node value that exceeds a decision value is included in the AOC. At the site scale, the decision basis is applied only to the modeled site average; blocks are sorted from most to least contaminated and remediation is simulated by progressively replacing the concentrations in the highest estimated blocks with a post-remediation concentration until the site-wide average falls below the decision criterion.

A fully designated AOC includes the area, boundary line, and uncertainty bands around the boundary. In SADA, uncertainty bands include nodes on the prediction grid that may be improperly classified due to uncertainty in the spatial contaminant distribution (Fig. 6). This concept is also known as "thick lines" (Savelieva et al., 2005) and provides a spatial first order estimate on false positive and false negative decision errors when classifying contamination. SADA has two methods for quantifying uncertainty in the AOC: percentile intervals and value intervals. Recall that geostatistical methods generate contours by selecting a value, typically a central tendency statistic, from the probability distribution. Values other than the central tendency may also be used to create uncertainty bands. By choosing the 25th, 50th, and 75th percentiles uncertainty bands can be generated for an AOC. Value intervals provide an option for non-statistical models such as inverse distance. In this

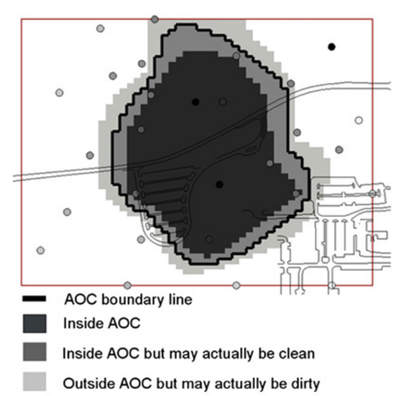

Fig. 6. Quantifying uncertainty in the AOC. The dark black line represents the boundary line for the current AOC. If no uncertainty were included in the analysis, everything inside this line would be part of the AOC. Conversely, everything outside this boundary would be considered clean. Application of the uncertainty bands shows there are actually three areas. The first area, shown in black, continues to be designated within the AOC even when uncertainty is considered. The dark gray area inside the boundary line is that portion of the AOC which may be improperly classified as contaminated; there is a reasonable chance that this area could be excluded from the AOC if more data were available (false positive). The light gray area outside the boundary line indicates the space classified as clean that may, in fact, be contaminated (false negative) after accounting for spatial uncertainty.

case, assessors account for spatial uncertainty in an ad hoc manner by choosing a lower and upper range for the decision criteria (e.g., criteria $= 3$ mg/kg ± 1). This type of uncertainty assessment can motivate a second round of sampling with the goal of reducing the uncertainty bands. The AOC boundary design (Table 1) is an appropriate tool for this task.

There is important inter-play between the decision criteria, the AOC boundary line, the uncertainty bands, the overburden, and the volume of removal. As decision criteria vary, so does the AOC, the uncertainty bands for failing that criteria, and the overburden. All these areas contribute to the volume of removal and overall cost. SADA provides a fairly comprehensive cost/benefit tool for calculating the relationship between spatial factors and total volume or cost. This tool can be useful in determining the tradeoff between taking additional samples to reduce uncertainty, adjusting the decision criteria, and accepting greater risk in the decision. Of particular interest are decision criteria ranges where small changes in the decision criteria yield large differences in volume for meeting as low as reasonably achievable remedial goals and for minimizing remedial costs. The cost/benefit tool in SADA shows the relationship between spatial factors and total volume or cost. This can be useful in determining the tradeoff between taking additional samples to reduce uncertainty, adjusting the decision criteria, and accepting greater risk in the decision.

4. Discussion and Conclusion

Some forms of output require a number of parameters to implement successive models. SADA takes advantage of the linear nature of input requirements for sequential models and presents them as step-by-step interview processes. The user interface conditions the display on the current interview step and presents only relevant variables for parameterization. The interview processes contain all steps necessary to parameterize a particular type of decision support tool, and are hyperlinked to the appropriate parameter windows for site-specific data entry. This allows users to input sequentially all the assumptions and parameters necessary to run the desired tool. Once input has been verified, users can run the requisite models to produce numerical output and/or a spatial result within the GIS window.

Model transparency, the full reporting of model assumptions, inputs, and outputs, is also crucial for an environmental decision support tool. Transparency facilitates communication among decision participants and assists meeting minimum documentation standards for environmental model implementation (Jakeman et al., 2006). SADA also provides extensive information on sub-modules and default parameters in a help file distributed with the program and in a comprehensive user's guide (Stewart et al., 2008). In addition, each program module contains self-documentation procedures that allow users to generate complete, customizable reports in HTML format for decision or modeling results. This feature documents all data, models, parameters, and other inputs that were used to generate a graphical or tabular output. It allows full transparency of decision support processes and assists in model evaluation (Oreskes, 1998), algorithmic verification, and report generation.

SADA is mature software for data visualization, processing, analysis, and modeling that is helpful to many areas of environmental assessment. It has robust applications for environmental sampling, spatial analysis, risk assessment, and remedial design for two- and three-dimensional data. Since few assumptions are made about input data, broad applications of its embedded functions are possible. Its strengths include a modern interface to facilitate parameterization of the assessment models and communication of underlying model assumptions and results to decision-makers. The SADA GIS is an assessment platform that accounts for spatial dependence, including spatially relevant descriptive statistics, moving window spatial statistics, correlation modeling, and interpolation methods. Collectively, these tools provide methods that minimize remedial action decision errors, provide efficient spatial designs under selective remediation conditions, and provide rationale for additional sampling efforts at contaminated sites.

Throughout the software design process there has been emphasis on ensuring that the user interface and contained algorithms are easy to implement, the assumptions behind the models are transparent and easily exportable, and that site information is collected in one SADA file (*.sda) that can be easily transported between personal computers and shared among assessors and decision-makers. Successful decision support software is accessible to all participants and can easily generate full sub-model documentation to maximize model transparency. Several methods allow accessibility to decision support software, from intensive interaction between modelers and decision-makers to web-enabled applications. Programs that require significant financial investment, multiple input files, or limit implementation to uncommon operating systems can impede portability and accessibility for decision-makers, thus complicating acceptance of a decision support tool in environmental applications. SADA is accessible by emphasizing an easy-to-use graphical user interface, free distribution on the operating system (Microsoft Windows) used by most environmental decision-makers, and including all site information in one file that is easily shared by different machines.

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