Mojave GIOGEGIS Scaling Project Title Page

Project Title
Scaling, Extrapolation, and Uncertainty of Vegetation, Topographic, and Ecologic Properties in the Mojave Desert

Principal Investigators (PI)
David R. Bedford, Geologist. 345 Middlefield Rd MS973, Menlo Park, CA 94025 and Department of Geological Sciences, University of Colorado, Boulder, CO.
Phone: 303-735-4914
Email: dbedford@usgs.gov

Leila Gass, Geographer. 520 N. Park Avenue, Tucson, AZ 85719-5035
Phone: 520-670-5005
Email: lgass@usgs.gov

Sue Phillips, Biologist. 2290 S. West Resource Blvd, Moab, UT 84532
Phone: 435-719-2337
Email: sue_phillips@usgs.gov

Jayne Belnap, Biologist. 2290 S. West Resource Blvd, Moab, UT 84532
Phone: 435-719-2333
Email: jayne_belnap@usgs.gov

Primary Contact
Kevin Schmidt, Geologist. 345 Middlefield Rd MS973, Menlo Park, CA 94025.
Phone: 650-329-5302
Email: kschmidt@usgs.gov

Background
The Issues

Scaling issues remain one of the “holy grails” of natural sciences, and GIScience is the tool with which scaling issues will be resolved. Scaling is needed in order to take site-specific measurements or monitoring protocols and make them relevant to other places or in a wider context. Rarely does the USGS have the opportunity to have very fine details of physical and biologic properties are known and the larger (coarser) scale datasets are available with which to develop and test scaling methods. We propose a project to do just that, and this project would not be possible without an interdisciplinary project with a new source of funds.

Vegetation patterns, soil properties, and landforms, are tightly coupled as part of arid ecosystem functioning (Breshears and Barnes, 1999; Cross and Schlesinger, 1999; Ludwig and others, 2005; McAuliffe, 1994; Rodriguez-Iturbe, 2000; Sanchez and Puigdefabregas, 1994; Schlesinger and others, 1996). Examples of the close relationships between physical and biologic characteristics include increased infiltration rates and nutrient concentration around shrubs, higher topography under shrubs (shrub mounds), soil texture difference, and the nature in which overland flow moves through patchy vegetation. These relationships arise due to water limitations in drylands and the properties associated with vegetation and ecosystem function are generalized in a category of properties called ecohydrologic properties. These properties most commonly consist of soil texture, infiltration rates, microtopography, and other components of dryland ecology such as biologic soil crusts.

Vegetation pattern and associated patterns of ecohydrologic properties are closely correlated (e.g. Bhark and Small, 2003; Maestre and others, 2005; Puigdefabregas, 2005). Because ecologic pattern and process are intimately linked, especially in arid heterogeneous environments, detection of the patterns of any of these components can aid in assessing the ecologic function of an area. However, these patterns often occur over small distances that generally are not observable by datasets that cover wide areas, such as remote sensing.

Thus arises the predicament of managers and researchers in drylands, and indeed in many landscapes: small scale (often at a point), detailed, information is needed across the landscape, yet is only seldom even measured in a few locations. This information is used not only in assessing current pattern and processes of ecosystems, but in order to predict effects of future land use disturbances and the potential for rapid climate change. Thus, managers often need to make decisions (often at landscape scale) based on point observations and must rely on coarse datasets of differing sources and quality. Effective processes of scaling and extrapolating data are therefore needed in order to make prescient, effective decisions

Definitions

One of the problems encountered in scaling issues is the lack of consistent and concise terminology (e.g. Dungan and others, 2002). To ensure that our scaling research is

successful and transferable, we set out, and will elaborate on if necessary, the following definitions, some of which are illustrated in Figure 1:
Grain refers to the spatial extent over which a single measurement is made: typically this is considered equivalent to the cell sizes used in raster-based datasets. Fine grain refers to small (detailed) grain sizes.
Extent refers to the entire area that is analyzed.
Window refers to an area over which measurements over which neighboring cells or data points are analyzed.
Aggregation is the process of increasing grain size and analyzing the effects of increasing grain size. 'Scaling up' is also used synonymously with aggregation.
Disaggregation is the process of decreasing grain size and understanding its effects.
Extrapolation is the process of predicting data at unmeasured locations
Uncertainty is error involved in predictions.
Scaling – refers to the process of changing the grain size, accuracy, or extent of spatial data.

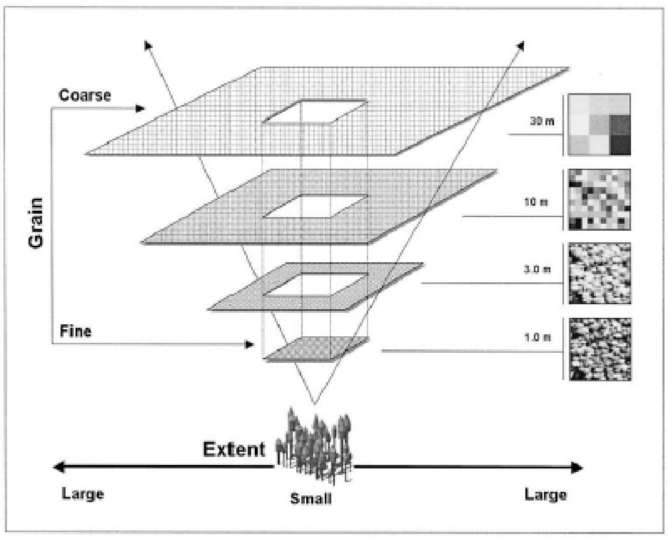

Figure 1. The relationship between grain and extent in remote sensing imagery.

Figure 1. Scaling definitions and relationships (From Hay and others, 2001)

Science Needs

There is a strong scientific need to develop scaling methods that best preserve the characteristics of fine-grained data, and yet can be used across a landscape at other areas or larger scales. This is even further needed in arid landscapes where the structure of spatial variability in physical and biologic properties and process are strong indicators of ecologic function. We propose to develop and test methods for scaling ecohydrologic data that accomplishes three goals: captures variability inherent in fine grained data, develop techniques to use datasets such as remote sensing and surficial geology to serve as proxy/extrapolation datasets, and quantify uncertainty involved in each of these processes. We feel that these techniques will serve as a framework for extrapolating similar or other properties in regions characterized by spatially structured ecosystem characteristics.

Hypotheses
This research will focus on three primary questions, with sub questions aimed at elucidating methods and contributions to scaling ecohydrologic properties. Primarily, for a suite of ecohydrological properties, we are interested in knowing to what extent coarse datasets, often from different data sources, can be used to infer and extrapolate fine-scale properties. The project will analyze data in an area in which the fine scale descriptions are known, and in which there are several datasets of differing sources and resolutions to scale to, and extrapolate with.

We propose to focus on properties that best describe ecohydrologic function of desert ecosystems: topography/terrain (including microtopography), soil texture, vegetation cover and pattern, and biologic soil crusts.

The research will be conducted in an area where mm to cm scale measurements of the above properties are known for several locations stratified by landscape position. The goal of initial data collection was to characterize the primary drivers of ecologic characteristics in the area: lithology, soil structure, and landforms. In association with the fine-grained data are coarse resolution datasets with which we will determine scaling and extrapolation relations. Most of the data has been collected, and is awaiting analysis that has not been possible to perform without a new funding source. The study site is on the Hayden Piedmont, in the Mojave National Preserve, a National Park unit in the Southern California Mojave Desert.

Topography data is from a variety of sources. At the finest scale, ground-based LIDAR is being acquired from cooperator funds to characterize sub-centimeter elevations associated with shrub mounds, rocks, and rills (microtopography). Across the area, we have airborne LIDAR at approximately 1-meter data postings. In addition, we have 5 meter topography from Master data, and 30 meter USGS DEMs. The 30-meter DEM resolution is the target scale at which we hope to extend scaling relationships.

We hypothesize that the best methods to scale topographic data will be those that quantify the spatial structure of topography. While the details of fine-grained spatial variability may be lost, there may be a self-similar nature to topography such that spatial variability at a coarse scale may be indicative of fine-grained variability.

Centimeter scale surveys and mapping of surface physical and biologic (including biologic soil crusts) characteristics, plant dimensions, and low-altitude (helium balloon and helicopter) air photography and color-infrared imagery are available to determine fine-grained characteristics of other properties. Coupled with the low-altitude color-infrared imagery are derived maps of vegetation (including green and senesced fractions) and lichens. Master and Landsat TM data will serve as the coarse grained remote sensing datasets.

We hypothesize that coarse-grained datasets will quantify vegetation and possibly biologic soil crusts amounts with some degree of accuracy, however much information on the spatial pattern of vegetation will be lost. Again, we hypothesize that vegetation patterns at a coarse scale may be indicative of the fine scale patterns, and that with ancillary datasets; there may be sufficient corrections or assessments of uncertainty.

Question 1. How does fine-grained data disaggregate (i.e. scale out)?
In order to assess how data at coarse resolutions from differing sources affects assessment of fine grain, we must first know what the original fine grain data "looks like" at coarse grains.

Question 2. How does high resolution data relate (translate) to coarse resolution data?

- Is there a signature of fine scale data in coarse scale data?
- Can you scale in (aggregate) from coarse data to fine?
- Role of ancillary data such as surficial geology

In order to transfer information between datasets (i.e. use one dataset as a proxy for another), it must be known how those two datasets are related. Typically this is done through statistical techniques that describe how sample means relate to one another. This however, is insufficient for studies involving heterogeneity where it must be known how the variability, spatial variability, and spatial patterns relate across datasets.

If there are "signals" of fine grained variability and patterns in coarse grain data, it also must be known how strong the signal is in order to ascertain uncertainty, and it must be known how much more the signal may be altered when going back from coarse data to fine (i.e. back-transforms of proxy datasets).

Other ancillary datasets may also be useful in scaling exercises due to the fact that the ancillary data may inform on patterns of variability, and may in fact have different scaling "rules" for them. For example in arid environments, soils characteristics, which are often best described by surficial geologic maps, have unique vegetation, texture, and topographic characteristics. Thus, it may often be useful to know which types of soils a given location is on before scaling out data from that location. However, as scales get larger, and window sizes or extents increase, soils of different types will be included in analysis, and thus some information of scale-limitations of ancillary data will be determined. Ideally, ancillary data also occurs and larger scales that can be used to quantify how the soil (for example) data may aggregate to large scales. These types of ancillary datasets should help to improve scaling methods, and (for example with surficial geology) may in fact inform us on processes that may be occurring on different types of soils.

Question 3. What role does scaling play in extrapolation and uncertainty?
Ultimately, data must be scaled out and extrapolated in order to make decisions across a landscape. This involves some sort of extrapolation process that takes data available across the area of interest, and applies a mathematical function that relates one or more datasets to the regionally available dataset. Typically this involves a new source of uncertainty introduced with often moderately significant statistical relationships between the datasets.

The uncertainty associated with the extrapolation techniques and datasets must also be quantified along with scaling uncertainties in order to quantify how accurate a prediction at unmeasured locations is. We intend to quantify that uncertainty, as well as develop techniques that minimize uncertainty associated with extrapolation techniques.

Objectives/Approach

The objectives of this research are for arid environments to understand how scaling of fine to coarse grain data and extrapolation techniques introduces uncertainty; and develop techniques to minimize this uncertainty. The rationale behind these objectives is discussed in the hypotheses section above. In this section we outline the general methodologies we anticipate using to achieve these goals.

Our approach is to quantify how univariate and spatial variation characteristics change with scale, and how these characteristics may be detectable by coarse grain datasets that are available regionally to provide extrapolation. Univariate characteristics such as the mean and variance are of obvious importance. For instance, we want to know how much vegetation is expected at a given location (the mean) and how well we know the expectation (variance). The spatial patterns of ecohydrologic properties are also an important characteristic due to the fact that the spatial pattern can inform on the effectiveness of ecologic and physical process.

We will focus our spatial analysis on using geostatistical and point pattern methods because these techniques allow assessments of heterogeneity, spatial dependence, and co-dependence in ecological systems (Dale, 1999; Rossi and others, 1992). Geostatistics are particularly appealing because they explicitly account for scale. Variograms and related functions quantify the spatial structure of data for explicit distances (scales). Techniques such as variogram scaling can be used to quantify how the spatial structure (heterogeneity) of data changes with different extents, grain/lags, and different scales (Atkinson and Tate, 2000). Other geostatistical techniques such as kriging and block kriging also account for spatial structure, assess uncertainty, and allow extrapolation.

We will also point pattern analysis to quantify the spatial structure of vegetation identified with different sources (with different grains, resolutions, etc) of remote sensing. We do this to determine how interpretation of vegetation pattern is affected by data sources and scaling operations. This is especially important in that coarse grain data will not be able to observe small, individual plants in patchy vegetation, but may identify large patches, or groups of plants. By knowing the true pattern, and quantifying the change in observed pattern with scale, we can further assess uncertainty in describing vegetation parameters such as cover and pattern. These techniques can also be used to infer community structure, such as contagion and dispersion characteristics for different vegetation types (Bowers and others, 2004; Brittingham and Walker, 2000; Fleishman and MacNally, 2006; Miriti and others, 1998; Wagner, 2003; Wu, 2004).

Part 1: Scaling fine grain data (Question 1)

Before we are able to relate fine-grain data to separate coarse grain data, we must first describe what the characteristics of the fine grain data are when it is scaled to coarse resolutions. Doing this enables a determination of disparities arising between data scaling and data source changes, and therefore quantify one source of uncertainty.

We will use a variety of univariate and spatial statistics to characterize the variability of data at different resolutions. For data that varies continuously over space, such as topographic and soil texture data, we will scale using block averaging (i.e. resampling), variogram scaling, and block kriging to characterize the structure of these variables at coarse grain sizes.

Block averaging is a simple scaling technique that quantifies how the mean and variance of data points changes with different window sizes. In general, variance always increases with window size, however, the mean may 'plateau' at certain window sizes that suggests that there is a domain of scale over which patterns do not change. At scales (window sizes) where mean and variance significantly change are referred to as scale thresholds and are critical in scaling exercises (Hay and others, 2001). Figure 2 shows and examples of scale relationships; determining the window sizes (grain) over which data is consistent or not is critical to determine how data scales from grains and data sources.

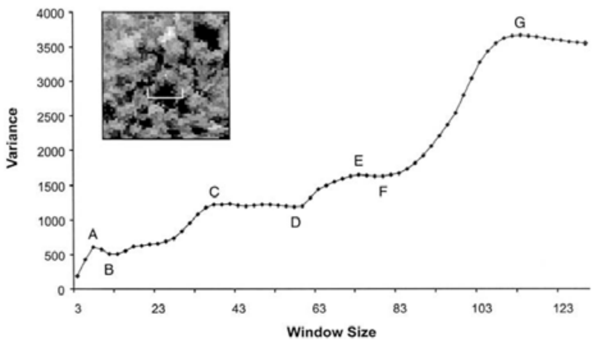

Figure 2. Example of univariate scaling relationships (from Hay and others, 2001)

Variogram scaling creates variograms based on support (windows), and therefore quantifies the spatial variability of data at coarser grains. By systematically increasing support windows (i.e. increasing grain) it is possible to quantify at which support sizes that scales of spatial variability may be lost (Atkinson and Tate, 2000). We will use these techniques on topography data, as well as soil texture, and any continuous derived vegetation characteristics to quantify at which scales portions of the spatial structure appear or disappear.

Block kriging is similar to variogram scaling in that it predicts values bases on the spatial variability of a given support. This technique is useful when point-based data must be interpolated to a grid-based dataset, and then compared with a separate dataset. The block-kriged data can either be directly compared with other datasets or used in block averaging.

For vegetation cover and pattern, we will use resampling and point pattern techniques. We use additional point pattern techniques for vegetation data in order to determine at what scales are individual plants detectable, and at what scales are only clumps of plants (or clumps of clumps) detectable. This type of analysis is important for maintaining vegetation structure/pattern information, as well as understanding how increasing grain sizes might bias the data. For example, Turner and others (1989) found that spatially rare or non-clumped data were preferentially not detected at larger grain sizes when compared to clumped data. This is important in desert ecology where shrubs of different sizes may show preferential clumping or avoidance patterns. Assuming that scale does not bias the detection of some shrubs can severely affect the power of scaling by introducing unnecessary uncertainty.

Part 2: Relating fine resolution data to coarse resolution data
Once we have quantified what information is lost or retained through changing grain size (scale) of individual datasets, we must then determine how those datasets relate to other datasets with inherently large grain sizes, but also large extents. We will perform this with traditional statistical techniques such as correlation analysis, linear and nonlinear regressions, to determine how the large grain size/extent data correlate to characteristics of both the small grain and coarse grain (scaled) data. Doing so will allow us to quantify uncertainty created by scaling and by switching dataset types.

We will also determine the effectiveness of using ancillary data, particularly, surficial geologic maps. This will be done with statistical techniques such as mixed effects modeling of linear and nonlinear relationships between datasets of different grains. Surficial geologic maps will serve as categorical datasets that may determine the best scaling rules/functions for a given soil-geologic deposit type.

Part 3: Extrapolation and Uncertainty
We will use the relationships identified in part 2 to develop extrapolation functions for ecohydrologic data. We will test the accuracy of these relationships by conducting validation surveys and analysis on predicted values. Validation will provide us with the total uncertainty that was involved in the scaling, data proxy transfer, and extrapolation processes. This sum uncertainty, or error, can be partitioned out into its respective components from these processes. We will have quantified scaling uncertainty in Part 1, and some degree of uncertainty in data proxy transfer will be quantified in Part 2 with statistical model performance. Finally, we can assess the extrapolation model performance and (ideally) quantify how much each of these processes contributes to the overall uncertainty.

Expected Results/Products
We expect to develop techniques to adequately scale fine-grained (known) data to larger grained data and extrapolate to new locations. We anticipate creating maps of ecohydrologic properties at larger scales that can be used by cooperating projects and agencies. We also anticipate developing a scaling framework for data in arid and semiarid heterogeneous systems.

Expected publications:

Bedford and others, 2007. Scaling and extrapolation of ecohydrologic properties on a Mojave Desert piedmont landscape. Journal Article.

Authors TBD, 2007. Scaling and Spatial patterns of vegetation on a Mojave Desert piedmont landscape. Journal Article.

Bedford and others. 2007/8. Methods for scaling and extrapolation of ecohydrologic properties in arid landscapes. Project Report.

Significance to the USGS Mission

One of the primary objectives of the USGS is to act as science support for Federal land management agencies such as the BLM, NPS, FWS, USFS, and DOD. In the arid western United States, these agencies are the primary landowners and managers, and must operate with a diverse set of land use and stakeholder demands.

In light of this, these "sister" agencies must be able to assess, and ideally predict, the functioning of their ecosystems as well as their vulnerability and recoverability to natural and anthropogenic dynamics. More and more, these agencies require monitoring strategies that inform about landscape-level processes. It is only with information about how site-specific monitoring data scales to landscape levels is the monitoring effective. Thus, scaling issues are a critical missing link in making monitoring successful.

In arid environments, the pattern of ecohydrologic properties can be used to asses its functioning. Methods that enable landscape-wide determinations of fine-scale patterns and form from coarse-scale data would provide an invaluable tool for cooperating agencies. Such methods would enable repeated measurements via remote sensing platforms that would not only asses ecohydrologic function via patterns, but to also asses the trends of changes that may be occurring.

References

Atkinson, P.M., and Tate, N.J., 2000, Spatial scale problems and geostatistical solutions: A review: Professional Geographer, v. 52, no. 4, p. 607-623.

Bhark, E.W., and Small, E.E., 2003, Association between Plant Canopies and the Spatial Patterns of Infiltration in Shrubland and Grassland of the Chihuahuan Desert, New Mexico: Ecosystems, v. 6, p. 185–196.

Bowers, J.E., Turner, R.M., and Burgess, T.L., 2004, Temporal and spatial patterns in emergence and early survival of perennial plants in the Sonoran Desert: Plant Ecology, v. 172, no. 1, p. 107-119.

Breshears, D.D., and Barnes, F.J., 1999, Interrelationships between plant functional types and soil moisture heterogeneity for semiarid landscapes within the grassland/forest continuum: a unified conceptual model: Landscape Ecology, v. 14, no. 5, p. 465-478.

Brittingham, S., and Walker, L.R., 2000, Facilitation of Yucca brevifolia recruitment by Mojave Desert shrubs: Western North American Naturalist, v. 60, no. 4, p. 374-383.

Cross, A.F., and Schlesinger, W.H., 1999, Plant regulation of soil nutrient distribution in the northern Chihuahuan Desert: Plant Ecology, v. 145, no. 1, p. 11-25.

Dale, M.R.T., 1999, Spatial Pattern Analysis in Plant Ecology: Cambridge, Cambridge University Press, 326 p.

Dungan, J.L., Perry, J.N., Dale, M.R.T., Legendre, P., Citron-Pousty, S., Fortin, M.J., Jakomulska, A., Miriti, M., and Rosenberg, M.S., 2002, A balanced view of scale in spatial statistical analysis: Ecography, v. 25, no. 5, p. 626-640.

Fleishman, E., and MacNally, R., 2006, Patterns of spatial autocorrelation of assemblages of birds, floristics, physiognomy, and primary productivity in the central Great Basin, USA: Diversity and Distributions, v. 12, no. 3, p. 236-243.

Hay, G.J., Marceau, D.J., Dube, P., and Bouchard, A., 2001, A multiscale framework for landscape analysis: Object-specific analysis and upscaling: Landscape Ecology, v. 16, no. 6, p. 471-490.

Ludwig, J.A., Wilcox, B.P., Breshears, D.D., Tongway, D.J., and Imeson, A.C., 2005, Vegetation patches and runoff-erosion as interacting ecohydrological processes in semiarid landscapes: Ecology, v. 86, no. 2, p. 288-297.

Maestre, F.T., Rodriguez, F., Bautista, S., Cortina, J., and Bellot, J., 2005, Spatial associations and patterns of perennial vegetation in a semi-arid steppe: a multivariate geostatistics approach: Plant Ecology, v. 179, no. 2, p. 133-147.

McAuliffe, J.R., 1994, Landscape Evolution, Soil Formation, and Ecological Patterns and Processes in Sonoran Desert Bajadas: Ecological Monographs, v. 64, no. 2, p. 111-148.

Miriti, M.N., Howe, H.E., and Wright, S.J., 1998, Spatial patterns of mortality in a Colorado desert plant community: Plant Ecology, v. 136, no. 1, p. 41-51.

Puigdefabregas, J., 2005, The role of vegetation patterns in structuring runoff and sediment fluxes in drylands: Earth Surface Processes and Landforms, v. 30, no. 2, p. 133-147.

Rodriguez-Iturbe, I., 2000, Ecohydrology; a hydrologic perspective of climate-soil-vegetation dynamics: Water Resources Research, v. 36, no. 1, p. 3-9.

Rossi, R.E., Mulla, D.J., Journel, A.G., and Franz, E.H., 1992, Geostatistical Tools for Modeling and Interpreting Ecological Spatial Dependence: Ecological Monographs, v. 62, no. 2, p. 277-314.

Sanchez, G., and Puigdefabregas, J., 1994, Interactions of plant growth and sediment movement on slopes in a semi-arid environment: Geomorphology., v. 9, no. 3, p. 243-260.

Schlesinger, W.H., Raikes, J.A., Hartley, A.E., and Cross, A.F., 1996, On the spatial pattern of soil nutrients in desert ecosystems: Ecology, v. 77, no. 4, p. 1270-1270.

Turner, M.G., O'Neill, R.V., Gardner, R.H., and Milne, B.T., 1989, Effects of changing spatial scale on the analysis of landscape pattern: Landscape Ecology, v. 3, no. 3/4, p. 153-162.

Wagner, H.H., 2003, Spatial covariance in plant communities: Integrating ordination, geostatistics, and variance testing: Ecology, v. 84, no. 4, p. 1045-1057.

Wu, J.G., 2004, Effects of changing scale on landscape pattern analysis: scaling relations: Landscape Ecology, v. 19, no. 2, p. 125-138.

Project Support

Southwest Surficial Processes and Mapping:
Project chief: David M. Miller, Geologist. 345 Middlefield Rd MS973, Menlo Park, CA 94025. Phone: 650-329-4924 Email: dmiller@usgs.gov
This project collected and continues to collect and maintain much of the data to be used in this project. The project provides datasets, computing, consulting, and partial salary for Bedford, Miller, and Schmidt. Field vehicles and other logistic support are anticipated but unquantifiable at this time

Recoverability and Vulnerability of Desert Ecosystems (RVDE):
Project chief: Jayne Belnap, Biologist. 2290 S. West Resource Blvd, Moab, UT 84532
Phone: 435-719-2333 Email: jayne_belnap@usgs.gov
This project is an integrated science project investigating desert ecosystem functioning. Project support is anticipated to be intellectual collaboration, and field personnel, as needed.

Budget
We propose a one-year project with the following budget. We anticipate that much of the costs will go to salary, and some to field work to collect data for validation sites.

FY2007 Budget	Bedford…	Gass…	Belnap…	**Total**
Cost Center	9937	9848	9398	
Personnel Salary	20000	20000	13000	**$53,000.00**
Other expenses travel, equipment & supplies, laboratory analyses, etc.	3000	1000	3000	**$7,000.00**
Total Direct	23000	21000	16000	**$60,000.00**
Gross Assessment Rate	18.50%	23.30%	25.00%	
Indirect Cost Estimate	4255	4893	4000	**$13,148.00**
TOTAL	**$27,255.00**	**$25,893.00**	**$20,000.00**	**$73,148.00**