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[Article]

An Interpolation Method for Stream Habitat Assessments

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Abstract.—Interpolation of stream habitat can be very useful for habitat assessment. Using a small number of habitat samples to predict the habitat of larger areas can reduce time and labor costs as long as it provides accurate estimates of habitat. The spatial correlation of stream habitat variables such as substrate and depth improves the accuracy of interpolated data. Several geographical information system interpolation methods (natural neighbor, inverse distance weighted, ordinary kriging, spline, and universal kriging) were used to predict substrate and depth within a 210.7-m^2 section of a second-order stream based on 2.5% and 5.0% sampling of the total area. Depth and substrate were recorded for the entire study site and compared with the interpolated values to determine the accuracy of the predictions. In all instances, the 5% interpolations were more accurate for both depth and substrate than the 2.5% interpolations, which achieved accuracies up to 95% and 92%, respectively. Interpolations of depth based on 2.5% sampling attained accuracies of 49–92%, whereas those based on 5% percent sampling attained accuracies of 57–95%. Natural neighbor interpolation was more accurate than that using the inverse distance weighted, ordinary kriging, spline, and universal kriging approaches. Our findings demonstrate the effective use of minimal amounts of small-scale data for the interpolation of habitat over large areas of a stream channel. Use of this method will provide time and cost savings in the assessment of large sections of rivers as well as functional maps to aid the habitat-based management of aquatic species.

The measurement of habitat is central to the management of fish (Noss et al. 1997; Bain et al. 1999; Bain and Stevenson 1999; Murphy and Willis 1999). The structure of stream habitat, which is inherently spatial in nature, is often measured at multiple spatial scales (Frissell et al. 1986; Fisher and Rahel 2004; Brenden et al. 2006). Important stream habitat variables, such as bottom substrate (i.e., rock sizes) and water depth, that can be measured at small (microhabitat) scales manifest themselves at larger scales as riffle and pool sequences (Leopold and Maddock 1953, 1957; Yang 1971, 1996; Powell 1998). Although an understanding of habitat at both small and large spatial scales is useful for fish management, data collection at small scales is often avoided because of the time and high labor costs it entails. The importance of spatial scaling of habitat data has led to increasing use of geographical information systems (GIS) in fisheries, where new methods of spatial analysis of stream data are emerging, especially in the interpolation of habitat data (Rastetter et al. 1992; Childs 2004; Fisher and Rahel 2004).

Ultimately, GIS analysis of spatial habitat data results in visual maps at scales ranging from microhabitat to landscape (Brenden et al. 2006). Even when consistent and accurate spatial data are used, important details can be lost owing to coarse map resolution (Demers 2005). A map with a 1:100,000 resolution may indicate a river flowing through an area but completely miss details relevant to the management of fish populations. Finer resolution is important for ecological studies, in which data are often collected at small (i.e., microhabitat) scales. The term "small" typically refers to resolutions of 1 m^2 or less (Greenberg 1991; Simonson 1993; Welsh and Perry 1998a, 1998b; Bunte and Abt 2001). Collection of small-scale data over large geographic areas is difficult; data at resolutions finer than 1:24,000 are only available for limited geographic areas (Fisher and Rahel 2004). Aerial and satellite methods can provide resolutions as fine as 0.2 m, but the use of such methods is expensive and they have some important limitations. Because of the reflective nature of water surfaces and varying water clarity, aerial surveys are not yet capable of consistently classifying stream variables below the 1-m scale. And because of the periodic or constant turbidity of streams, field sampling is often the only practical method for collecting accurate microhabitat data.

Geographical information systems such as ArcGIS provide interpolation methods for creating predictive maps. These methods include the trend, spline (SP),

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TABLE 1.—Size ranges used to categorize substrate type within the study site at Aaron's Creek. An additional category, land, was used to represent dry land within the streambed.

Substrate category	Diameter (mm)
Boulders	>250
Cobble	76–250
Gravel	2–76
Sand	0.1–2
Silt	0.002–0.100

inverse distance weighted (IDW), pointinterp, ordinary kriging (OK), universal kriging (UK), and natural neighbor (NN) methods. The trend and SP methods minimize the curvature of interpolated surfaces and would thus not be appropriate for predicting the (curved) topography of depth and substrate. The IDW and pointinterp methods assign weights to cells as a function of distance; they work well when the data points are dense and are able to clearly delineate a complex surface. Ordinary and universal kriging are well suited to mapping directional influence on a surface with adequate data. The various types of kriging, including cokriging, UK, and OK, are based on similar statistics but have unique strengths. Universal kriging in particular is able to address the issue of directional influence in a data set (Childs 2004). The IDW and NN methods are closely related and use similar formulas for their calculations. The main difference is that the latter weights spatially close, known values more heavily, whereas the former weights values further away more heavily. The advantages of the NN method include the ability to handle large data sets and clustered (nonrandom and spatially autocorrelated) data well.

Interpolation of stream habitat is possible owing to the patchiness and spatial correlation of variables such as water depth and substrate size. In streams, environmental influences produce differentially sized patches of specific habitat types (Yang 1971, 1996; Knighton 1998). Certain aspects of these patches are predictable, such as rock size sorting (Komar and Carling 1991) and the presence of velocity-controlled depositional areas with abrupt substrate transitions (Smith and Ferguson 1995; Purkait 2002). Stream habitat is predictable because two samples of habitat within adjacent areas of a habitat patch are likely to be similar and spatially correlated (Armstrong 2000). Spatial autocorrelation is a concern in some spatial studies (Liebhold and Gurevitch 2002), but it is an important element of predictability and accuracy in habitat interpolation methods (Robertson 1987). Autocorrelation in stream habitat structure creates the potential for elimination of redundant data collection. Optimizing sampling strategies has long been a goal of those using GIS (Atkinson 1996). By nonrandomly selecting habitat patch edges when collecting physical spatial data and using interpolation to predict stream habitat structure, one can create accurate maps using a small subsample of the total stream habitat area.

Our overall study objectives were to examine the applicability and accuracy of stream habitat estimation using interpolation methods. The focus was on interpolating the habitat of a stream section using data from a small subsample of the total stream habitat area. Interpolated maps will reduce the costs of habitat assessments if the habitat over long sections of streams can be accurately predicted from a small number of habitat samples. Additionally, accurate microhabitat maps of stream sections provide the option to scale up to larger habitat scales; hence, the data would be available at multiple scales. This is an important point because data collected at coarse scales cannot be accurately scaled down to the microhabitat scale (McPherson et al. 2006). Further, an accurate map of microhabitat data would provide location and area estimates of specific habitat types, an important need for the management of species with specific habitat requirements.

Methods

Study area.—Our study site was a 30-m reach (surface area, 210.7 m^2) of Aaron's Creek, which lies within the Monongahela River system in Monongalia County, West Virginia (NAD 1983; Universal Transverse Mercator [UTM] zone 17N; −79.933465, 39.619004). There is sparse to moderate urban and suburban development along approximately 70% of this 13.5-km stream. The riparian area of the stream (5–50 m wide) is a mixture of field, lawn, and mixed hardwood forest. Canopy cover was calculated using a densiometer at the upstream and downstream borders of the site and averaged 25% overall. The study site was selected because it contains a complete riffle and downstream pool and exhibits natural flow and sinuosity characteristics that are representative of the stream as a whole.

Data collection.—The study site was represented as two data layers, one for substrate and one for water depth. Two people collected the data; one sampled while wading in the stream, and the other recorded the data. For the digital representation of substrate data, the study site was divided into a grid of 2,268 cells, each 1/3 m^2. The predominant substrate type was recorded for each cell (quadrat; Table 1). Substrate values were not recorded on dry land. Quadrat sampling of the predominant substrate at a resolution 0.3048 m^2 accurately represented the boundaries of the substrate

TABLE 2.—Interpolation methods used to estimate water depth and substrate size at the Aaron's Creek study site. The input data used for these interpolations covered from 2.5% to 80% of the total area of the site.

Interpolation method	Percent of site area	Total number of interpolations
Natural neighbor	2.5, 5.0, 10, 20, 40, 80	12
Inverse distance weighted	2.5, 5.0	4
Universal kriging	2.5, 5.0	4
Spline	2.5, 5.0	4
Ordinary kriging	2.5, 5.0	4

TABLE 3.—Number of 1/3-m^2 sample quadrats (points) at Aaron's Creek used to interpolate substrate for a total stream area of 2,268 quadrats and number of 0.6096-m^2 quadrats used to interpolate water depth for a total stream area of 1,188 quadrats. Interpolations were based on data from 2.5% to 80.0% of the total study area.

	Points per interpolation	
Percent of site area	Substrate	Depth
2.5	56	29
5.0	113	59
10.0	226	118
20.0	452	236
40.0	904	472
80.0	1,808	944

patches. For the representation of water depth data, the study site was divided into a grid of 1,188 cells, each 0.6096 m^2. The spatial scale for depth was larger than that for substrate because depth is more homogenous over a given area. Water depth was measured in centimeters at the center of each cell.

Data analysis.—The site grids of 2,268 substrate values and 1,188 depth values represented the real-world site digitally (hereafter called the actual coverage of substrate or depth at the before-mentioned resolutions) and were used in to assess the accuracy of the interpolated values. Using the values for depth and substrate, we created separate data layers for conducting UK, OK, SP, IDW, and NN interpolations (Tables 2, 3). The data were prepared and analyzed in Microsoft Excel. ArcMap was used for georeferencing the site location, interpolation, and map creation. Site corner locations were entered into ArcMap, georeferenced for accuracy, and adjusted to match the size of the study site. Because the size of a sample quadrat was less than the accuracy of the global positioning system, study site corner values were assigned UTM coordinates corresponding to the center of each cell. This allowed us to create an even distribution of the (x, y) coordinate points at the specified resolutions using the series fill function. Although real-world coordinates are useful in locating a site on the geographic plane, interpolations would be possible without a link to them as long as the scale is consistent within the GIS.

Interpolation of substrate and depth.—Points (cell quadrats) within the study site representing 2.5% and 5.0% of the total site area were selected with which to interpolate substrate and depth for the entire study site. These percentages were chosen to provide an initial baseline for the accuracy of interpolations using 97.5% and 95% less field data. Separate interpolations were conducted with each of five interpolation methods: IDW, NN, OK, SP, and UK. Point selection is the crucial element for successful interpolation of maps; the fewer points used to make a map, the more important each of those points should be to minimize the loss of accuracy. We expected that choosing a combination of habitat patch boundary and substrate anomalies would be the most effective approach. Our point selection was accomplished by a three-step process. We first focused on macrohabitat features, such as bank and overall site definition, then on overall habitat structure (termed median features), and finally on microhabitat features, such as an atypical boundary curve of a patch of sand. Approximately one-third of the available data points were utilized in each of the three steps. Each interpolation created a new map representing water depth or substrate that was the same size as the map of the study site.

Calculating the accuracy of interpolations.—Several methods were used to estimate the accuracy of the interpolated values of water depth and substrate size. In general, the methods compared the estimates of the cell values of the interpolated maps with the corresponding known cell values from the actual coverages of water depth and substrate size. For comparisons, all of the interpolated cell values of the predictive maps were created by using the extract values to points function in the spatial analyst toolbox in ArcMap. In this way, there was a direct comparison of the predicted map and the actual coverage for each data point. For substrate, these methods included the percent of area match and total exact coordinate match rate, accuracy trends, and the root mean square error (RMSE); for depth they included threshold values, RMSE, and accuracy trends.

The percent of area match was calculated for each substrate type by comparing the area of predicted substrate with the area of actual substrate. Thus, if an interpolation predicted 10 m^2 of sand and the actual site contained 100 m^2 of sand, the percent area match would be 10%. The exact coordinate match rate was calculated as the percentage of coordinate points from the substrate and depth interpolations that matched the actual coverage. If point number 2,264 was interpolated as land and listed as land on the actual coverage, it was assigned a match.

TABLE 4.—Substrate interpolations at Aaron's Creek by the ordinary kriging (OK), universal kriging (UK), inverse distance weighted (IDW), spline (SP), and natural neighbor (NN) methods using 2.5% and 5.0% of the available data, and the resulting exact coordinate and total area match percentages.

Interpolation (% data)	Exact coordinate	Total area
OK (2.5)	22	16
UK (2.5)	29	13
IDW (2.5)	30	14
UK (5.0)	31	41
SP (2.5)	33	57
OK (5.0)	35	6
IDW (5.0)	43	31
NN (2.5)	46	45
SP (5.0)	46	72
NN (5.0)	61	79

The accuracy of depth interpolation was assessed based on the assigned threshold values because depth is a continuous variable. Actual site depths ranged from 0 to 60 cm, and we created 5, 10, and 20% threshold values, which corresponded to interpolated values within 3, 6, and 12 cm of the actual values. Therefore, if an interpolated value fell within 3 cm (5% or less) of the actual coverage value, it would be assigned a match for the 5% threshold (e.g., actual depth = 59 cm and predicted depth = 58 cm). Each successive threshold would have more matches under its umbrella.

The RMSE was used because it indicates the dispersion of data. To calculate it, we used the formula $\sigma/\sqrt{n}$, where σ is the standard deviation of the sample and n is the sample size. Comparing the dispersion levels of interpolations is another way of determining which interpolation best matches the digital representation of our study site's substrate values.

The substrate interpolation method with the highest accuracy was further evaluated based on input from 10, 20, 40, and 80% of the total stream area in addition to the initial 2.5% and 5%. The depth interpolation method with the highest accuracy was further evaluated based on input from 10, 40, and 80% of the total stream area in addition to the initial 2.5% and 5%. Trend curves showing accuracy were created from these evaluations. These curves indicated the extent to which there were increases in accuracy with increases in data collection.

Results

Raster maps of the interpolated values had degrees of accuracy ranging from 6% to 79% for substrate and from 19% to 95% for depth (Table 4; Figures 1–3). In all cases, the 5.0% interpolations were more accurate than the 2.5% interpolations. Natural neighbor interpolations achieved the highest level of accuracy for both variables (Table 4; Figures 1–3). As a result, trend curves were created to further explore this method's performance (Figures 3, 4).

Interpolated maps provide a visual comparison with the initial coverages and aid in the assessment of accuracy (Figures 1, 2). For instance, the SP method, which performed very well in substrate area prediction,

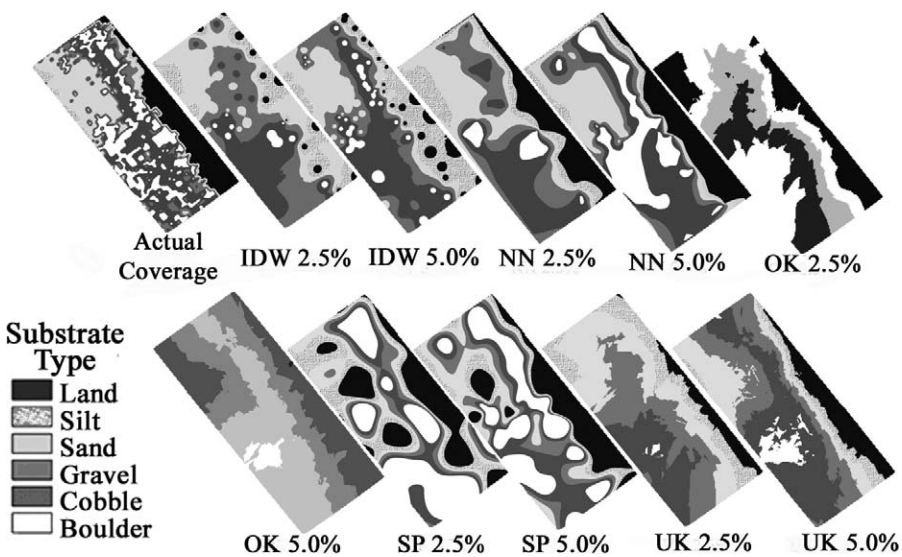

FIGURE 1.—Maps of the substrate at Aaron's Creek as determined by detailed measurements and as interpolated by the inverse distance weighted (IDW), natural neighbor (NN), ordinary kriging (OK), spline (SP), and universal kriging (UK) methods from 2.5% and 5.0% of the area of the study site.

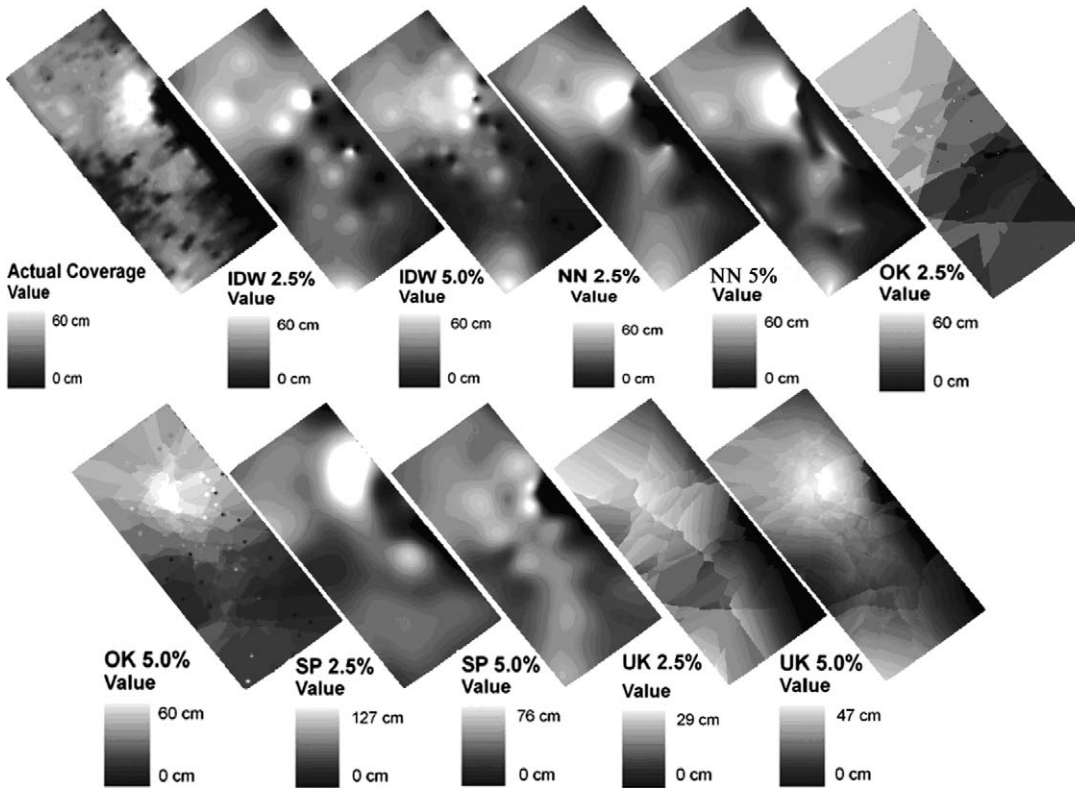

FIGURE 2.—Maps of the water depth at Aaron's Creek as determined by detailed measurements and as interpolated by the methods indicated in the caption to Figure 1.

did not produce accurate maps of the study site (Table 4; Figure 1). The NN method performed about as well as the SP method yet was able to produce maps of much higher quality (Table 4; Figure 1). Visual inspection of the predictive maps shows that NN interpolation produced the best likeness of the initial site (Figures 1, 2). Although the more intricate details of the habitat patches are lost, the overall structure, size, and location are conveyed. The NN interpolations were the most accurate for both depth and substrate when input data from 2.5% and 5.0% of the study site were used. As noted above, we also obtained interpolations based on 10, 20, 40, and 80% of the data; the resulting trend curves showed that the greatest gain in accuracy was achieved by expanding the input data from 2.5% to 5% (Figures 3, 4).

Substrate Interpolation

Natural neighbor interpolation returned the highest matched results (61% exact coordinate and 79% area match) when comparing the predicted values of substrate with the actual site values (Table 4). The values of the RMSE (Table 5), percent exact match, and percent area match (Table 4) were also best with NN interpolation. Both the NN and SP interpolations typically showed less than a 5% difference between the actual and predicted values when the models were separated by substrate type (Table 6).

The trend curves for the exact point and percent area of the site predicted correctly show that the gains in accuracy decreased markedly when data for more than 20% of the site (452 of 2,268 points) were used (Figure 4). The majority of the gains for exact (61%) and area match (79%) were achieved by the 5% interpolation; the remaining 39% and 21% were achieved only by adding the remaining data points. The RMSE values for substrate (Table 5) depict varying levels of difference between the different types of interpolation. The best performing method in comparison to the 0.039 RMSE value of the actual site was the NN method for 2.5% interpolations. Universal kriging produced the closest among 5.0% interpolations, followed closely by the NN method.

Depth Interpolation

The NN depth interpolations most accurately predicted the actual coverage of the study site (Figures

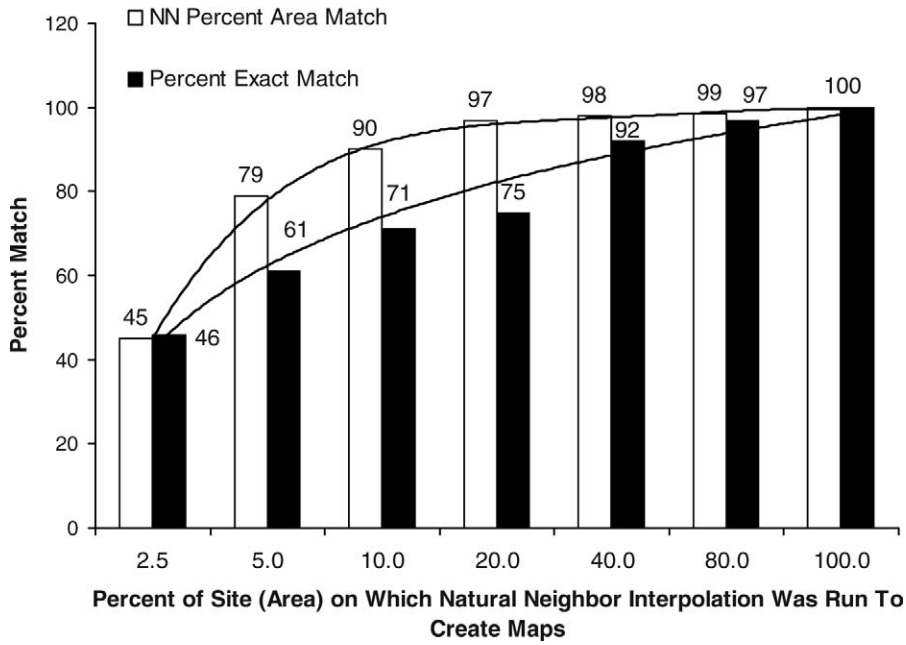

FIGURE 3.—Accuracy trend curves for substrate interpolations by the natural neighbor (NN) method using 2.5, 5, 10, 20, 40, and 80% of the data available for the study site at Aaron's Creek. The upper curve shows the percentage of the areal predictions that matched the actual site; the lower curve shows the percentage of exact substrate coordinates (x, y) that matched the actual site. The numbers above the bars are the actual bar values.

2, 5); both the 2.5% and 5.0% NN interpolations outperformed all other methods (Figure 5). For the NN interpolations based on 5% of the depth measurements (59 data points), 57% of the interpolated depths were within a 5% threshold (3 cm) of the actual values, 83% percent within 10% (6 cm), and 95% within 20% (12 cm). There was lower accuracy in the values interpolated from 2.5% of the depth measurements; 49% of these values were within a 5% threshold, 71% within 10%, and 93% were within 20%. The least accurate interpolation was that of the spline, which attained an accuracy of only 79% for the most liberal

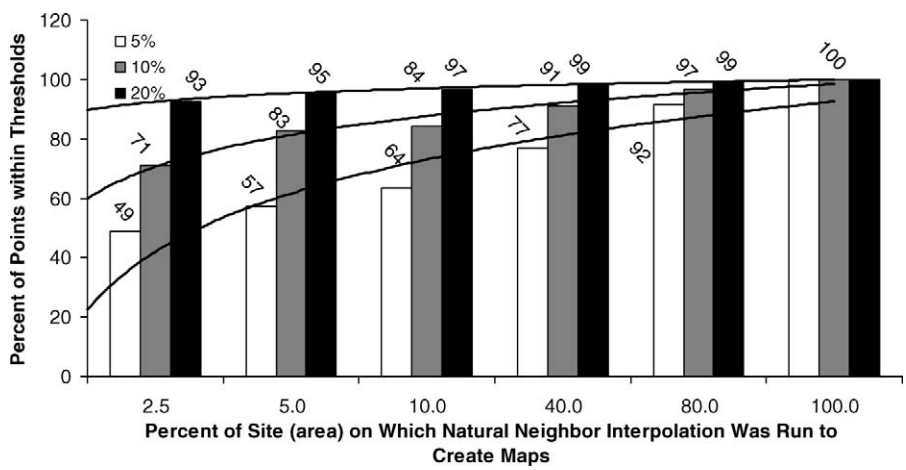

FIGURE 4.—Accuracy trend curves for depth interpolations by the natural neighbor method using 2.5, 5, 10, 40, and 80% of the data available for the study site at Aaron's Creek. The numbers above the bars are the actual bar values. Curves represent the percentage of predicted points within 5 (3 cm), 10 (6 cm), and 20 (12 cm) of actual site values.

TABLE 5.—Root mean square errors of substrate interpolations by the ordinary kriging (OK), inverse distance weighted (IDW), universal kriging (UK), natural neighbor (NN) and spline (SP) methods. Based on actual values, the study site had a substrate dispersion rate of 0.039. The estimated dispersion rates produced by UK and NN were the closest to that of the study site.

	Available data	
Interpolation method	2.50%	5.00%
OK	0.002	0.016
IDW	0.022	0.028
UK	0.025	0.040
NN	0.030	0.036
SP	0.072	0.143

threshold. The trend curve indicated that more than 90% of all predictions were within 12 cm of actual depth for all NN interpolations, including those made by the 2.5% model.

Discussion

Interpolation methods using small amounts of field data produced accurate maps of stream habitat variables. With minimal-data interpolation methods, we created accurate maps of stream habitat using data from as little as 5% of the available study area (Figures 1, 2). The NN interpolation method worked better than the others because it can effectively deal with large and clustered (autocorrelated) data sets. Spatial autocorrelation is a well-documented issue for geospatial studies (Henebry and Merchant 2002; Liebhold and Gurevitch 2002) and contributes to predictability and accuracy in ecological mapping and prediction methods (Klute et al. 2002; Rotenberry et al. 2002), including habitat interpolation methods (Robertson 1987). This is particularly true in stream habitats in which proximate areas are more similar than distant areas, such as with the common stream characteristics of substrate and depth (Leopold and Maddock 1953; Knighton 1998; Powell 1998; Ferguson 2003).

The prediction of silt in our study is representative of NN interpolation's performance with respect to the key point selection process. Silt was the least common substrate type in the stream reach, representing only 1.25% of the actual area of the site. This is a negligible amount that may be missed entirely by macrohabitat-scale measurements alone. The key point selection system allowed for the proper placement of silt on predictive maps by NN interpolation (Figures 1, 2). This shows that NN interpolation may overestimate sparsely occurring substrate and underestimate the most prevalent substrate while maintaining overall site integrity.

As shown by the trend analysis, a larger number of initial data points will increase the accuracy of the interpolated data. However, the majority of the gains in accuracy were achieved by using 5% of the area of the site instead of 2.5%. Further research should examine in more detail the threshold scale that relates sample size with accuracy (Host et al. 1995; Winkler and Fang 1997) and the related cost–benefit function. Importantly, this relationship is expected to differ with habitat complexity. Interpolation of stream habitat within homogeneous pools would probably require a smaller initial sample size than interpolation of riffle habitats. At a larger scale, interpolation of habitat for stream sections with a high pool : riffle ratio would probably require a smaller sample size than one with a complex, high-gradient profile (Kiem and Skauset 2002).

This study was conducted on a low-order, low-gradient system, and additional studies are needed for larger and higher-gradient systems. The potential versatility of the method that we used lies as much in the point selection process as in NN interpolation. The

TABLE 6.—Percentages of substrate type predicted by the inverse distance weighted (IDW), natural neighbor (NN), ordinary kriging (OK), spline (SP), and universal kriging (UK) methods using 2.5% and 5.0% of the data available, along with the actual percentages.

Interpolation method (% data)	Land	Silt	Sand	Gravel	Cobble	Boulder
IDW (2.5)	3	14	29	30	23	2
IDW (5.0)	5	18	22	19	32	4
NN (2.5)	15	12	23	21	22	4
NN (5.0)	17	5	18	13	25	20
NN (2.5)	16	12	23	22	23	4
NN (5.0)	17	5	19	13	26	20
OK (2.5)	0	3	44	41	12	0
OK (5.0)	0	1	15	43	38	4
SP (2.5)	22	16	14	11	12	25
SP (5.0)	20	8	14	14	20	23
UK (2.5)	7	15	31	27	20	0
UK (5.0)	13	6	18	25	33	5
Actual	***20***	***2***	***21***	***7***	***27***	***23***

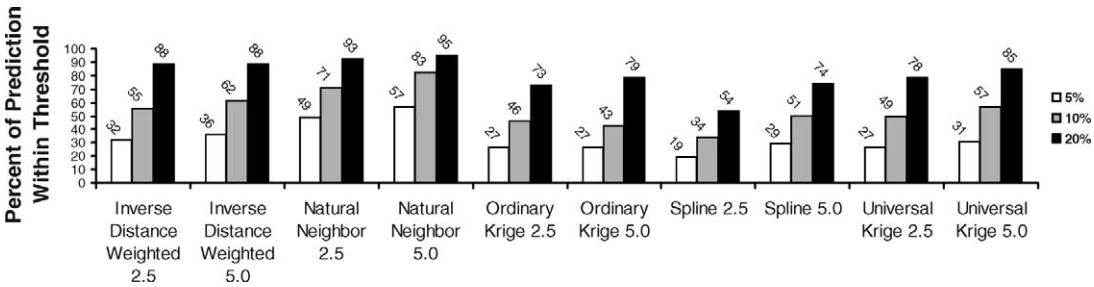

FIGURE 5.—Accuracy of the depths interpolated from data for 2.5% and 5.0% of the area of the study site at Aaron's Creek based on threshold values of 5, 10, and 20% (corresponding to interpolations within 3, 6, and 12 cm, respectively, of the actual values) by the inverse distance weighted (IDW), natural neighbor (NN), ordinary kriging (OK), spline (SP), and universal kriging (UK) methods. For example, NN interpolations based on data from 5.0% of the total area had a 10% threshold value of 83%, meaning that 83% of all points were within 6 cm of the actual values.

method is designed to deal with habitat patches and deposition pattern. The point selection process may require adjustment in the number of points for acceptable accuracy in high-gradient or highly heterogeneous streams.

As stated in the introduction, the assessment of habitat is immensely important to the management and conservation of fish (Thayer et al. 1996; Noss et al. 1997; Orth and White 1999; Kohler and Hubert 1999). Further, the technology to convert habitat data into accurate and practical maps is increasingly important to aquatic species management (Meaden and Do Chi 1996; Smith and Greenhawk 1998; Manson and Todd 2000; Kostylev et al. 2001; Fisher and Rahel 2004). Our findings show that accurate habitat assessments can be based on interpolation from as little as 5% of the total habitat area, which should markedly decrease the costs associated with such assessments.

One possible extension of habitat interpolation methods is the use of interpolated maps to predict species occurrence (Rubec et al. 1998; Scott et al. 2001). Although we focused on depth and substrate, stream maps could also include other habitat attributes, such as water chemistry, velocity, and food sources, which together would allow the prediction of species occurrence based on species' habitat requirements. This use of interpolated maps will benefit ecosystem and rare-species management, particularly when habitat loss or habitat specificity is an important management concern.

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References

Armstrong, M. P. 2000. Geography and computational science. Annals of the Association of American Geographers 90:146–156.

Atkinson, P. M. 1996. Optimal sampling strategies for raster-based geographical information systems. Global Ecology and Biogeography Letters 5:271–280.

Bain, M. B., T. C. Hughes, and K. K. Arend. 1999. Trends in methods for assessing freshwater habitats. Fisheries 24(4):16–21.

Bain, M. B., and N. J. Stevenson, editors. 1999. Aquatic habitat assessment: common methods. American Fisheries Society, Bethesda, Maryland.

Brenden, T. O., R. D. Clark, A. R. Cooper, P. W. Seelbach, L. Wang, S. S. Aichele, E. G. Bissel, and J. S. Stewart. 2006. A GIS framework for collecting, managing, and analyzing multiscale landscape variables across large regions for river conservation and management. Pages 49–74 *in* R. M. Hughes, L. Wang, and P. W. Seelbach, editors. Landscape influences on stream habitats and biological assemblages. American Fisheries Society, Symposium 48, Bethesda, Maryland.

Bunte, K., and S. R. Abt. 2001. Sampling surface and subsurface particle-size distributions in wadable gravel- and cobble-bed streams for analyses in sediment transport, hydraulics, and streambed monitoring. U.S. Forest Service General Technical Report RMRS-GTR-74.

Childs, C. 2004. Interpolating surfaces in ArcGIS Spatial Analyst. ArcUser(July–September):32–34.

Demers, M. N. 2005. Fundamentals of geographic information systems, 3rd edition. Wiley, New York.

Ferguson, R. I. 2003. Emergence of abrupt gravel–sand transitions along rivers through sorting processes. Geology 31:159–162.

Fisher, W. L., and F. J. Rahel, editors. 2004. Geographic information systems in fisheries. American Fisheries Society, Bethesda, Maryland.

Frissell, C. A., W. J. Liss, C. E. Warren, and M. D. Hurley. 1986. A hierarchical framework for stream habitat

classification: viewing streams in a watershed context. Environmental Management 10(2):199–214.

Greenberg, L. A. 1991. Habitat use and feeding behavior of thirteen species of benthic stream fishes. Environmental Biology of Fishes 31:389–401.

Henebry, G. M., and J. W. Merchant. 2002. Geospatial data in time: limits and prospects for protecting species occurrences. Pages 291–302 *in* J. M. Scott, P. J. Heglund, and M. L. Morrison, editors. Predicting species occurrences: issues of accuracy and scale. Island Press, Washington, D.C.

Host, G., H. Omre, and P. Switzer. 1995. Spatial interpolation errors for monitoring data. Journal of the American Statistical Association 90:853–861.

Kiem, R. F., and A. E. Skauset. 2002. Physical aquatic habitat errors associated with measurement and estimation of residual pool volumes. North American Journal of Fisheries Management 22:145–150.

Klute, D. S., M. J. Lovallo, and W. M. Tzilkowski. 2002. Autologistic regression modeling of American woodcock habitat use with spatially dependent data. Pages 335–343 *in* J. M. Scott, P. J. Heglund, and M. L. Morrison, editors. Predicting species occurrences: issues of accuracy and scale. Island Press, Washington, D. C.

Knighton, D. 1998. Fluvial forms and processes: a new perspective. Oxford University Press, Oxford, UK.

Kohler, C. C., and W. A. Hubert, editors. 1999. Inland fisheries management in North America. American Fisheries Society, Bethesda, Maryland.

Komar, P. D., and P. A. Carling. 1991. Grain sorting in gravel-bed streams and the choices of particle sizes for flow-competence evaluations. Sedimentology 38:489–502.

Kostylev, V. E., B. J. Todd, G. J. B. Fader, R. C. Courtney, G. D. M. Cameron, and R. A. Pickrill. 2001. Benthic habitat mapping on the Scotian Shelf based on multibeam bathymetry, surficial geology, and sea floor photographs. Marine Ecology Progress Series 219:121–137.

Leopold, L. B., and T. Maddock. 1953. The hydraulic geometry of stream channels and some physiographic implications. U.S. Geological Survey Professional Paper 252.

Liebhold, A. M., and J. Gurevitch. 2002. Integrating the statistical analysis of spatial data in ecology. Ecography 25:553–557.

Manson, G., and B. J. Todd. 2000. Revolution in the Nova Scotia scallop fishery: seabed maps turn hunting into harvesting. Fishing News International 39:20–22.

McPherson, J. M., W. Jetz, and D. J. Rogers. 2006. Using coarse-grained occurrence data to predict species distributions at finer spatial resolutions: possibilities and limitations. Ecological Modeling 192:499–522.

Meaden, G. J., and T. Do Chi. 1996. Geographical information systems: applications to marine fisheries. FAO (Food and Agriculture Organization of the United Nations) Fisheries Technical Paper 356.

Murphy, B. R., and D. W. Willis, editors. 1999. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.

Noss, R. F., M. O'Connel, and D. D. Murphy. 1997. The science of conservation planning: habitat conservation under the Endangered Species Act. Island Press, Washington, D.C.

Orth, D. J., and R. J. White. 1999. Stream habitat management. Pages 249–284 *in* C. C. Kohler and W. A. Hubert, editors. Inland fisheries management in North America. American Fisheries Society, Bethesda, Maryland.

Powell, D. M. 1998. Patterns and processes of sediment sorting in gravel-bed rivers. Progress in Physical Geography 22:1–32.

Purkait, B. 2002. Patterns of grain-size distribution in some point bars of the Usri River, India. India Journal of Sedimentary Research 72:367–375.

Rastetter, E. B., A. W. King, B. J. Cosby, G. M. Hornberger, R. V. O'Neill, and J. E. Hobbie. 1992. Aggregating fine-scale ecological knowledge to model coarse-scale attributes of ecosystems. Ecological Applications 2:55–70.

Robertson, G. P. 1987. Geostatistics in ecology: interpolating with known variance. Ecology 68:744–748.

Rotenberry, J. T., S. T. Knick, and J. E. Dunn. 2002. A minimalist approach to mapping species' habitat: Pearson's planes of closest fit. Pages 281–290 *in* J. M. Scott, P. J. Heglund, and M. L. Morrison, editors. Predicting species occurrences: issues of accuracy and scale. Island Press, Washington, D. C.

Rubec, P. J., M. S. Coyne, R. H. McMichael, and M. E. Monaco. 1998. Spatial methods being developed in Florida to determine essential fish habitat. Fisheries 23(7):21–25.

Scott, J. M., J. Heglund, and M. L. Morrison, editors. 2001. Predicting species occurrences: issues of accuracy and scale. Island Press, Washington, D.C.

Simonson, T. D. 1993. Correspondence and relative precision of stream habitat features estimated at two spatial scales. Journal of Freshwater Ecology 8:363–373.

Smith, G. F., and K. N. Greenhawk. 1998. Shellfish benthic habitat assessment in the Chesapeake Bay: progress toward integrated technologies for mapping and analysis. Journal of Shellfish Research 17:1433–1437.

Smith, G. H., and R. I. Ferguson. 1995. The gravel–sand transition along river channels. Journal of Sedimentary Research A 65:423–430.

Thayer, G. W., J. P. Thomas, and K. V. Koski. 1996. The habitat research plan of the National Marine Fisheries Service. Fisheries 21(5):6–10.

Welsh, S. A., and S. A. Perry. 1998a. Habitat partitioning in a community of darters in the Elk River, West Virginia. Environmental Biology of Fishes 51:411–419.

Welsh, S. A., and S. A. Perry. 1998b. Influence of spatial scale on estimates of substrate use by benthic darters. North American Journal of Fisheries Management 18:954–959.

Winkler, P., and K. T. Fang. 1997. Application of threshold-accepting to the evaluation of the discrepancy of a set of points. SIAM Journal on Numerical Analysis 34:2028–2042.

Yang, C. T. 1971. Formation of riffles and pools. Water Resources Research 7:1567–1574.

Yang, C. T. 1996. Sediment transport: theory and practice. McGraw-Hill, New York.