Landscape-Based Geostatistics: A Case Study of the Distribution of Blue Crab in Chesapeake Bay

Short title: Landscape-based geostatistics

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SUMMARY

Geostatistical techniques have gained widespread use in ecology and environmental science. Variograms are commonly used to describe and examine spatial autocorrelation, and kriging has become the method of choice for interpolating spatially-autocorrelated variables. To date, most applications of geostatistics have defined the separation between sample points using simple Euclidean distance. In heterogeneous environments, however, certain landscape features may act as absolute or semi-permeable barriers. This effective separation may be more accurately described by a measure of distance that accounts for the presence of barriers. Here we present an approach to geostatistics based on a lowest-cost path (LCP) function, in which the cost of a path is a function of both the distance and the type of terrain crossed. The modified technique is applied to 13 years of survey data on blue crab abundance in Chesapeake Bay. Use of this landscape-based distance metric significantly changed estimates of all three variogram parameters. In this case study, although local differences in kriging predictions were apparent, the use of the landscape-based distance metric did not result in consistent improvements in kriging accuracy.

KEY WORDS: barriers, blue crab, Chesapeake Bay, distance metric, kriging, variogram.

1. INTRODUCTION

Traditionally, geostatistical approaches have specified spatial covariance based on the Euclidean distance between sampled points. Implicit in the use of Euclidean distance is the assumption that the process or feature of interest is continuously distributed between any two points. However, in many instances, the space separating two sampled points may represent a partial or complete barrier owing to biological or physical characteristics of the intervening space. Presumably, the presence of such barriers should impact the distribution of the process or feature. However, the influence of barriers in geostatistical analyses has been largely ignored.

Barriers are common in coastal or estuarine environments and in river networks. Ignoring such landscape complexity can result in inaccurate interpolation across barriers and misspecification of the spatial covariance structure (Rathbun, 1998). Previous approaches to variogram modeling and kriging using alternative non-Euclidean distance metrics explored the impact of the alternative distance metrics on model predictions (Little *et al.*, 1997; Rathbun, 1998); however, they have either not made use of efficient GIS algorithms and available habitat classification maps (Rathbun, 1998) or are difficult to apply to systems which do not approximate a linear network (e.g., Little *et al.*, 1997; Gardner *et al.*, 2003).

1.1. The Importance of Barriers in Environmental Modeling

Spatial heterogeneity is a common feature of nearly all landscapes and can have important consequences for the way organisms move and interact. One of the simplest but most important impacts of spatial heterogeneity occurs when one habitat type serves as a barrier to movement and dispersal. Barriers are important in determining biogeographic, ecological, and evolutionary patterns (Grinnell, 1914; MacArthur and Wilson, 1967; Gilpin and Hanski, 1991; Brown, 1998). The recognition of barriers, however, has been restricted generally to a few high-profile models that explicitly describe their effects (e.g. island biogeography and metapopulation dynamics). As habitat fragmentation and isolation continue to increase, barriers will be an increasingly important component of many landscapes.

Barriers are a prominent feature of the landscape of stream and estuarine systems. It has long been recognized by stream ecologists that Euclidean distance is an inappropriate metric, and distance measured along the thalweg (i.e., the center of the stream channel) is commonly used. This metric recognizes that most processes measured in a stream are continuous only within the aquatic habitat. Many estuaries are characterized by highly invaginated shorelines where converging tributaries are separated by narrow peninsulas of land. Conditions on opposite sides of a peninsula can show much greater variation than their geographic proximity suggests. In some cases, because of differences in the geology or land use of their watersheds, adjacent tributaries show remarkable differences in their chemical and biological characteristics (Pringle and Triska, 1991). Not surprisingly then, the first attempts to incorporate the effects of barriers into geostatistical modeling occurred in estuaries (Little *et al.*, 1997; Rathbun, 1998).

1.2. Geostatistics and Ecological Landscapes

Heterogeneous landscapes can impose patterns that violate the assumptions of geostatistics (Cressie, 1993). For example, the strongest assumptions of the geostatistical model, those of second order stationarity (spatial constancy of the mean and variance) and isotropy (directional constancy of the variogram), are likely to be violated in the presence of any ecologically important gradients in the landscape. In a simple example, a resource gradient in a meadow may result in a trend in mean plant density along the gradient (violation of the constant mean assumption). Spatial autocorrelation is likely to be stronger and extend further when measured perpendicular to the resource gradient (i.e. at similar resource levels), and consequently the variograms will exhibit anisotropy. This effect is often seen in data from coastal systems in which autocorrelation extends further when measured parallel to the shoreline, i.e. along rather than across depth contours. While such landscape characteristics can lead to violation of the assumptions of geostatistical methods, they often represent useful information about the underlying processes being studied. For example, in a study of snow thickness on various types of sea ice, anisotropy in variograms of snow depth highlighted the important role of prevailing wind direction in determining spatial patterns of snow distribution (Iacozza and Barber, 1999). Checking for and correcting such landscape-induced violations of the assumptions have become integral steps in geostatistical modeling through the introduction of easily applied corrections such as detrending, variogram models that incorporate geometric anisotropy, and universal kriging.

However, efficient and easily implemented solutions to landscape barriers have not been available, and so their impacts have been largely ignored. A commonly-used approach to interpolation in the presence of barriers, which is implemented in many GIS programs, is to simply reject points that are separated by a barrier. This approach effectively divides the prediction area into many convex regions in which only points contained within a given region are used for prediction. In complex landscapes with many barriers, this approach limits the number of points used for prediction in some areas, and therefore greater sample sizes are needed to achieve the same degree of accuracy.

While a simple test for the presence of influential barriers is not available, we can define conditions under which they may be important. Barriers are likely to have a substantial impact on geostatistical interpolation only when the following two general conditions apply:

1) The extent of the survey and the prediction areas are larger than the scale at which barriers intervene. For example, peninsulas may be effective barriers to the dispersal of marine organisms among adjacent bays, yet they would have little impact on predictions if the survey and the prediction area were limited to a single bay.

2) The range of spatial autocorrelation is greater than the scale at which barriers intervene. In an estuary, we would expect little impact if the Euclidean distance between sample or prediction points in adjacent tributaries was greater than the range parameter from the variogram. This is because points separated by a distance greater than the range are essentially uncorrelated and receive very little weight when predictions are made.

Visual inspection of the sample and prediction points on a map of the underlying landscape can determine quickly whether the first condition applies. It is more difficult, however, to determine *a priori* whether the range is greater than the scale at which barriers intervene since barriers may influence the empirical variogram and consequently affect the estimate of the range.

Here we present an approach to incorporate the effects of barriers in geostatistical analyses. This approach makes use of common GIS algorithms for calculating distances that are weighted based on the "cost" of the habitat type through which a given path passes. As an example, we apply the technique to data on the spatial distribution of blue crab (*Callinectes sapidus*) in Chesapeake Bay.

2. METHOD

2.1. Landscape-based distance metrics

What are appropriate alternatives to Euclidean distance when barriers exist and the spatial scale of the modeling effort and the range of spatial autocorrelation make them relevant? Sampson and Guttorp (1992) suggest an empirical non-parametric approach to determining the appropriate distance metric in cases where a time series of observations for each sample site is available. Such a data rich environment, however, is likely to be the exception in environmental applications. In his work, Rathbun (1998) divided the study region into a series of adjacent convex polygons based on a digitized shoreline of the estuary. This approach split the estuary into increasingly smaller polygons until the shortest through water distance between all sample points was achieved. Little *et al*.

(1997) recognized the suitability of a GIS as an efficient environment for conducting this type of spatial calculation. They defined a network of line segments connecting points in an estuary. Variations of this linear network approach have been used to model water temperatures (Gardner *et al.*, 2003) and fish abundance (Torgersen *et al.*, 2004; Ganio *et al.*, 2005) in stream networks. While computationally efficient for narrow regions where movement is only possible along one dimension, this approach is difficult to apply in the more open portions of an estuary where distance both along and across the principal axis of the estuary must be considered.

Here we develop a distance metric that is equally applicable to both linear networks and open areas and accounts for the presence of barriers in terrestrial or aquatic landscapes. The distances are calculated using the cost-weighted distance function common to many GIS programs. This raster function calculates the lowest-cost distance from a cell to any other cell in a digitized map. Cost is defined by a function that represents the relative ease of movement through the associated habitat type. Diagonal movements are allowed, and their cost is estimated from the length of the diagonal rather than the cell size. The total cost of a given path is the sum of the individual cost cells encountered along that path multiplied by the cell size. For each point in the survey data set, a distance raster map is produced that represents the lowest-cost distance from the cell to any sample point. This distance raster is sampled at each of the other sample and prediction locations and the corresponding values are stored in a table of distances. We note that when the landscape is defined in terms of absolute barriers, the binary case, passable habitat is given a cost of 1 while barrier habitat is given an infinite cost (e.g. a “no data” value). However, the approach need not assign costs in this binary manner and is generally expandable to any cost function.

Krivoruchko and Gribov (2002) applied a technique similar to the one developed here for calculating a lowest-cost path (LCP) distance and used it to model air quality in California. They used a digital elevation model (DEM) to define a cost map representing the relative impedance of the environment to the spread of air pollution. Regions with steep changes in elevation were given a higher cost than flat land in order to account for the preferential spread of air masses along rather than across elevation contours. Interpolation was conducted using the inverse distance weighted method. Visual inspection of interpolated maps based on Euclidean distance and those produced using the landscape-based distance support the use of the latter technique. Importantly, however, Krivorucko and Gribov (2002) did not present any quantitative comparisons of the prediction accuracy of alternative distance metrics or the effects of the distance metric on variograms.

2.2. Validity of the covariance matrix

A currently unresolved problem with using a landscape-based distance metric for kriging is assuring the validity of the covariance matrix (Rathbun, 1998). There is no guarantee that the covariance function, C(x), for a given combination of variogram model and non-Euclidean distance metric will be non-negative definite. That is:

$$\sum_{i=1}^{m}\sum_{j=1}^{m} a_i a_j C(\mathbf{s}_i - \mathbf{s}_j) \geq 0$$

where s_i and a_i represents all finite collections of spatial location $\{s_i: i = 1,\ldots,m\}$ and real numbers $\{a_i: i = 1,\ldots,m\}$ (Cressie, 1993). While criteria for consistently valid combinations of variogram model and distance metric are yet to be determined, candidate covariance functions can be tested and rejected if they fail to meet the non-negative definiteness criterion. We note that although all of the covariance matrices in this analysis met this criterion, there is no guarantee that this would hold true for the set of all possible sample locations, or for other applications. Importantly, the variograms, spatial autocorrelation statistics, and deterministic interpolation methods are not affected by this problem.

Krivoruchko and Gribov (2002) suggest a moving average approach to estimating the covariance model that is not subject to the same criterion of non-negative definiteness, and Løland and Høst (2003) use multidimensional scaling to create a Euclidean approximation of the water distance. The latter approach remaps sample locations into a new Euclidean space with the result that spatial covariance models based on distances in the new Euclidean space are guaranteed to be valid for most common variogram forms. While computationally efficient, the Løland and Høst (2003) approach represents an approximation of the water distance and the effect of this approximation on variogram model fitting and kriging prediction accuracy has not been examined.

3. APPLICATION

We tested our landscape-based approach using data from the winter dredge survey (WDS) of blue crab in Chesapeake Bay. The survey is conducted yearly by the Maryland

Department of Natural Resources and the Virginia Institute of Marine Science. These data have been used to quantify crab abundance (Zhang and Ault, 1995), fishery exploitation (Sharov *et al*., 2003), and crab distribution (Jensen and Miller, 2005) in Chesapeake Bay.

Like many estuaries, the Chesapeake Bay has several tributaries separated by long, narrow peninsulas of land that present a barrier to the distribution of many aquatic variables at a scale that makes them potentially influential for baywide modeling efforts. The tributaries differ widely in the land-use characteristics of their watersheds with some, such as the Potomac River, draining large urban areas, and others, such as the Susquehanna River and many eastern shore tributaries, draining primarily agricultural land. Thus, sample points in adjacent Chesapeake Bay tributaries, although quite close in Euclidean distance, can differ substantially in their chemical and biological characteristics (Dauer *et al*., 2000).

Preliminary variogram analysis using Euclidean distance showed that blue crab catches exhibit distinct spatial autocorrelation at a range (i.e., 24-55 km) greater than the Euclidean distance separating some sample points in adjacent tributaries. This finding indicates that Euclidean distance-based kriging techniques may rely on samples from adjacent tributaries, and that a landscape-based approach may increase prediction accuracy.

3.1. Data

WDS data from 1990 to 2002 were analyzed individually by year. Full details of the survey design and application are provided in Vølstad *et al*. (2000) and Sharov *et al*. (2003). Briefly, the survey was conducted during the winter dormant period (December to

April) and consisted of a one-minute tow of a 1.83 m wide crab dredge at each station. Stations were chosen randomly each year within geographic strata. From 1993 – present, 1255 – 1599 stations were sampled annually within three strata. During the period 1990 – 1992, there were more strata and generally fewer (867 – 1395) samples. Figure 1 shows a typical distribution of sample locations and illustrates the shoreline complexity of the Chesapeake Bay and its tributaries.

Depletion experiments (Zhang *et al.*, 1993; Vølstad, 2000) were conducted yearly to determine catchability coefficients that could be used to transform survey catches into estimates of absolute abundance based on the fraction of blue crabs caught in a single tow. The variable studied here is the density of blue crabs per 1000 m^2, calculated by dividing the absolute abundance estimate by the dredge area swept.

Sample coordinates were based on the starting location of each tow, and the tow distance was calculated from the start and end coordinates determined by Loran-C (early years) or a differential global positioning system (DGPS). Tows shorter than 15 m and longer than 500 m (1.4% of the total data) were not used in this analysis. All coordinates were projected to Universal Transverse Mercator (UTM) zone 18 before analysis. Annual density estimates were detrended to meet the geostatistical assumption of stationarity. Variogram analysis, kriging, and cross validation were conducted on the residuals. For detrending, a second order two-dimensional polynomial of spatial trend with interactions was fit to the data for each year. The model was simplified using backward elimination with a significance level of $a = 0.01$. This relatively stringent significance level cut-off was used to avoid overfitting the trend.

3.2. Incorporation of landscape-based distance into geostatistical algorithims

The detrended residuals were used to calculate empirical variograms for both Euclidean and landscape-based distance metrics. Euclidean distances were calculated using standard algorithms programmed within Matlab (The Mathworks, Cambridge, MA). Intersample LCP distances for every pair of sample locations were calculated using square cells (250 m on a side) and a cost-distance algorithm programmed in the Visual Basic macro language within ArcView v8.3 (ESRI, Redlands, CA) where LCP distance was calculated along the path that minimized the distance function:

$$\sum_j \left(C_{ij} \cdot X_j \right)$$

where C_{ij} is the cost coefficient of the i^{th} habitat type in the j^{th} cell (here $C_{ij} = 1$ for cells in the water and is effectively infinite for cells on land) and X_j is the distance across the j^{th} individual cell. X_j is equal to the cell width for cells that are crossed in the north-south or east-west direction or $\sqrt{(2 \cdot width^2)}$ for cells that are crossed diagonally.

Robust variograms were calculated according to Cressie (1993), based on distances from the Euclidean and landscape-based distance matrices. A 250 m bin size was used to calculate the empirical variogram to a distance of 40 km. Exponential and Gaussian variogram models were fit to the empirical variograms using nonlinear least squares. The best fitting variogram model, i.e. the model with the lowest mean squared error, was used for kriging and variogram comparison. The estimated variogram parameters for the Euclidean and landscape-based distance metrics were compared using signed rank tests where each year represents one observation.

Following variogram selection, kriging was conducted using ordinary kriging algorithms (Journel and Huijbregts, 1978) modified to use Euclidean and landscape-based distances from a user-defined distance matrix and a neighborhood of the 10 nearest points. Matlab functions used in this analysis and a dynamic link library for calculating LCP distances in ArcView v8.3 are available at: http://hjort.cbl.umces.edu/crabs/LCPkrige.html

Blue crab density at the center of each 1 km grid cell was predicted by adding the kriged prediction to the trend. Prediction accuracy for both Euclidean and landscape-based methods was assessed using the prediction error sum of squares (PRESS) statistic divided by n-1 sample points to allow comparison across years. The PRESS statistic is a cross-validation measure calculated by leaving one observation out of the data set and using the remaining points to predict the value at that site (Draper and Smith 1981). The PRESS statistic is given by the sum of the squared differences between the predicted and observed values. Predicted abundances were then mapped for visual comparison.

Differences between the two distance metrics are likely to be accentuated as distances between neighboring sample points increase (see condition 1 above). Within a given landscape, increased distance between sample points increases the likelihood that a barrier will intervene at some point along the straight line connecting any two points. Increasing the average distance between pairs of sample points without changing the underlying spatial structure was achieved by taking a random subsample of the data. The potential impact of increased intersample distance was examined by taking 50 random subsamples of 200 sample points drawn from the entire study area and calculating the average difference in PRESS.

Similarly, differences between the Euclidean and LCP based kriging predictions are likely to be greater in regions of the Bay where more barriers are present (see condition 1 above). In the mainstem of the Bay, few barriers exist, and the Euclidean and LCP distances are likely to be similar. However, between adjacent tributaries and in areas of the Bay with islands and complex shorelines, the Euclidean and LCP distances, and consequently the kriging predictions, are more likely to show differences. To examine these potential regional differences, predictions were made and the PRESS was compared for a subset of the data from Tangier Sound (see Figure 1.), a region with many islands and inlets. This region typically contained from 104 to 259 sample sites per year. A random subsample analysis was also conducted for the Tangier Sound region. For each year of the survey, 50 random subsamples of 50 points each were drawn from the Tangier Sound region and the PRESS was compared as described above.

4. RESULTS

Spatial trends in blue crab abundance in Chesapeake Bay were found in all years. In most cases, the underlying trend in crab density (D) was described by a model of the form:

$$D = b_0 + b_1 E + b_2 N + b_{12} E \times N + e$$

where *E* refers to the easting value and *N* the northing value. In two cases, additional terms were found to be significant: the trend model for 1998 included an E^2 term also, and that for 2000 included an E^2 and an N^2 term.

Gaussian variogram models were chosen for all years, except 1990 and 1992, for which an exponential model provided a better fit (Table 1). In several cases, the exponential model provided a marginally better fit, but was rejected because it resulted in unrealistic variogram parameters (e.g. negative nugget or unrealistically large range). In all years, choice of variogram model was the same for both distance metrics.

Comparison of the variograms calculated under a Euclidean distance metric with those from the LCP distance metric revealed systematic differences in the variogram parameter estimates. Inter-sample distances calculated using the LCP algorithm were on average 11-17 km (14-23%) greater than the equivalent Euclidean distances (Table 2). The estimated variogram parameters, nugget, sill, and range, were smaller on average for the LCP distance variograms (Table 1, Figure 2). Compared to the Euclidean distance variograms, the LCP distance variograms had a smaller nugget in eight out of the ten years compared, with an average difference of 236 (signed-rank test, $p = 0.049$); a smaller sill in nine out of ten years, with an average difference of 1,038 (signed-rank test, $p = 0.049$); and a smaller range in eight out of ten years, with an average difference of 3.32 km (signed-rank test, $p = 0.049$). The effect of this pattern of differences was to reduce the inter-station variability at any given distance. Representative variograms are shown for 1996 (Figure 3a), a year of relatively small (0.01%) difference in prediction accuracy and for 2001 (Figure 3b), the year of greatest difference (3.46%) in prediction accuracy. The variograms for 2001 were an example of a case where the exponential variogram provided a somewhat better fit than the Gaussian model, but was rejected because it resulted in an unrealistically high estimate of the range. In both years, the estimated nugget, partial sill, and range were smaller for the LCP distance metric.

Despite this difference in the distances and in the variogram parameter estimates, the PRESS statistic comparison showed little difference in prediction accuracy between the two distance metrics (Table 2). The LCP algorithm did not always result in a lower PRESS than the Euclidean approach. Of the 13 years of survey data tested, only 7 showed greater prediction accuracy when LCP distance was used. Absolute difference in PRESS ranged from 0.01 – 3.46% with a mean increase in PRESS of 0.2% when LCP distance was used.

Results of the PRESS comparisons were similar for the Tangier Sound subset and both random subsamples, scenarios in which we expected the LCP algorithm to be at an advantage (Table 3). The direction of the difference in PRESS was not consistent. Seven out of 13 years for Tangier Sound had greater prediction accuracy when LCP distance was used. In Tangier Sound, the difference in PRESS ranged from 0.15 –7.29% with a mean increase in PRESS of 0.94% when LCP distance is used. When smaller randomly-selected subsets of the data were analyzed, 4 out of 13 years for both the baywide and Tangier Sound random subsamples had greater prediction accuracy when LCP distance was used. For the baywide random subsamples, the difference in PRESS ranged from 0.07 – 1.47% with a mean increase in PRESS of 0.25% when LCP distance is used. Similarly, the

Tangier Sound random subsample showed an average increase in PRESS of 1.35% for the LCP metric.

Consistent with the small differences in PRESS, maps of predicted blue crab density show broadly similar patterns. Baywide patterns of blue crab distribution appear similar between the two methods in both 1996 (Figure 4) and 2001 (Figure 5). Small scale differences are apparent, however, especially in the unsampled upper reaches of some tributaries. In the upper Potomac River, for example, the Euclidean-based map for 1996 (Figure 4a) shows high predicted density because the nearest samples (by Euclidean distance) are high values in the adjacent Patuxent River. The LCP-based maps for the same year (Figure 4b) predict low abundance in the upper Potomac River based on the nearest samples downstream.

5. DISCUSSION

Differences in prediction accuracy were expected to result from the impact of the landscape-based distance metric at two distinct stages of the geostatistical modeling process: variogram estimation and kriging. Use of an LCP distance metric changed estimates of the underlying spatial structure as summarized in the variogram. Estimates of all three variogram parameter estimates were significantly lower under the landscape-based distance metric, indicating lower variation and a shorter estimated distance of spatial autocorrelation (range). In our kriging analysis, predictions at a point were based on a weighted sum of the 10 nearest neighboring points. The landscape-based distance metric also changed the sample points (and their weights) employed in kriging, reducing the importance of points separated by barriers from the prediction site. We note, that if all observations points were used in prediction, only the weights would have changed. Differences in variogram estimates and kriging neighbors and their associated weights, however, did not yield a consistent effect on the accuracy of the kriging predictions. No consistent improvements in kriging accuracy were seen even when the analysis was restricted to areas of the Bay with many barriers (the Tangier Sound analysis) or when distances among points were increased (the random subsample analyses).

Given the impact of the alternative distance metric on the variogram, why did we not see similar impacts on prediction accuracy and the prediction maps? Although many factors interact to influence prediction accuracy, the unique shape of Chesapeake Bay may have played a role in reducing the increase in accuracy that was expected from the LCP distance metric. Many of the Bay tributaries, particularly on the west side, run parallel to one another. Because of this parallel orientation, the nearest point in an adjacent tributary is often at approximately the same distance from the tributary mouth (Figure 6). Such a point, while in a different tributary, may well show similar blue crab density because of its similar location relative to the tributary mouth. In fact, distance from the Bay mouth is a useful predictor of female blue crab density (Jensen *et al*., 2005) because it is correlated with many biologically relevant variables. In this case, predictions using points in adjacent tributaries may actually be more accurate.

Chemical and biological differences among adjacent tributaries - factors which might favor a landscape-based distance metric – are perhaps less important in the Chesapeake Bay where similar tributaries tend to be clustered geographically. For example, the adjacent Potomac and Patuxent Rivers on the western shore both drain large urban areas (Washington DC and the Baltimore-Washington corridor). The watersheds of most eastern shore tributaries all contain flat, rich, agricultural land with relatively little urban development. Such similarities among adjacent tributaries may also influence the relative performance of different distance metrics.

Inter-annual differences were apparent in the relative prediction accuracy of the Euclidean and LCP metrics. Two geographic areas (the entire Bay and Tangier Sound) and random subsets of each area were analyzed, and in no case were the results consistent among all 13 years of data. Neither were the results consistent within a year. For example, in 1990, the LCP metric showed a slight advantage over the Euclidean metric for the Baywide data and the Tangier Sound subset, but a slight disadvantage for both of the random subsamples. Interannual differences in blue crab distribution patterns have been observed and the population has experienced a substantial decline over the study period (Jensen and Miller, 2005). Nevertheless, the small differences in prediction accuracy and the inconsistency both among and within years offer no guidelines regarding the conditions under which an LCP metric would be preferred for kriging.

We are not the first to attempt landscape distance based prediction in estuaries, and the results of other approaches to kriging with a landscape-based distance metric have been equally equivocal. Both Little *et al*. (1997) and Rathbun (1998) found improvements in the prediction of some variables but not others. Little *et al.* (1997) found improvements in prediction accuracy (on the order of 10-30% reduction in PRESS) for only four out of eight variables when they applied a linear network-based distance metric. For the other four variables, use of the network-based distance metric actually increased the PRESS by 5-10%. Rathbun (1998) found slight improvements in cross-validation accuracy using a water distance metric for predicting dissolved oxygen but slightly worse accuracy when predicting salinity. Although variogram parameter estimates differed between the two distance metrics in the Rathbun (1998) study with the water distance metric resulting in higher variance and a longer range, no systematic comparisons were possible in that study since only one sample was analyzed.

Two recent studies in stream systems (Torgersen *et al*., 2004; Gardner *et al*., 2003) apply geostatistical tools based on the distance between sample sites along a stream network. Torgersen *et al*. used a network-based distance metric to quantify spatial structure in cutthroat trout abundance in an Oregon stream system. Although the distance metric they used provided clear variogram patterns, no explicit comparison was made with a Euclidean distance metric. Gardner *et al*. found improvements (lower prediction standard errors and predictions that better met expectations) in the prediction of stream temperature when a network-based metric was used, but did not report cross-validation statistics. Variogram parameter estimates were also found to change in this study with the network-based metric resulting in smaller nugget but longer range.

The effect of alternative distance metrics on variogram parameter estimates is difficult to predict since opposing influences may interact. For example, increasing the distance between points is likely to result in a longer estimated range, as seen in the Rathbun (1998) and Gardner *et al*. (2003) studies. Since a landscape-based metric reduces the influence of points separated by a barrier, which are expected to differ more than their

Euclidean separation would suggest, it also seems likely to reduce the sill parameter (as seen in this study), a measure of overall variability. However, when variograms do not show a clear inflection point at the sill, the range and the sill parameters are highly correlated; i.e. a variogram model with higher or lower values of both the sill and range may also provide an adequate fit to the data. This correlation makes the overall effect of the distance metric unpredictable since increases in the range of spatial autocorrelation may be masked by the effect of a decrease in the sill.

While we present the simple binary (passable or barrier) case in our example, the LCP approach can incorporate varying degrees of impedance to the continuity of the process or population under study. For example, one type of habitat may represent an insurmountable barrier while another may only slow the spread of the process. Parameters used to define the degree of impedance or ‘cost’ of different landscape types could come from many sources depending on the type of variable studied. For mobile organisms, costs could be based on studies of animal movement, although the extent to which different habitat types present a barrier to movement may not be static (Thomas *et al.*, 2001). For temporary barriers the cost might simply be the inverse of the fraction of time that the barrier is passable. For spatial modeling of chemical contaminants, cost parameters might come from laboratory experiments of diffusion and transport in different media.

Landscape ecologists have long recognized that Euclidean distance is rarely the most appropriate metric when considering the ecological relatedness among points in a landscape (Forman and Godron, 1986). When flows between points are of interest “time-distance”, i.e. the quickest route, may be preferable. However, time-distance requires detailed knowledge of how an organism or contaminant disperses through various habitat types. Time-distance has an added complication in that it may be asymmetric, where the time-distance from A to B is not necessarily the same as that from B to A. This is likely to be the case in stream systems, hilly terrain, and other environments that impose directionality on movement. Nevertheless, the idea that the distance metric should reflect the relative ease/speed of moving along a particular path remains valid.

The LCP approach to variogram estimation and kriging presented here represents an easily incorporated modification to commonly used geostatistical techniques. The benefits of using this approach depend on the study environment (e.g. scale and extent of barriers), the spatial distribution of the variable being studied, and the study objectives (e.g. variogram estimation, mapping, or quantitative prediction). Although the expected increases in prediction accuracy did not materialize in this study, the relatively unique configuration of parallel tributaries within the Bay may have been partly responsible. This approach, however, is a general one and can be applied to other locations or data sets for which greater differences in accuracy may be found. The potential also exists for the LCP distance metric to be incorporated into other types of spatial analyses such as home range estimation, habitat modeling, and deterministic interpolation methods.

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Figure Captions

Figure 1. Sample locations for the 1998 (i.e., winter 1997-1998) winter dredge survey of blue crab in Chesapeake Bay. The rectangle represents the region used for the Tangier Sound subset.

Figure 2. Comparison of the nugget (a), sill (b), and range (c) parameters from variograms based on Euclidean and Lowest Cost Path (LCP) distance metrics. The black line represents equality.

Figure 3. Euclidean and Lowest Cost Path (LCP) distance based variograms for 1996 (a) and 2001 (b).

Figure 4. Map of predicted 1996 blue crab density (individuals per $1000m^2$ classified by quintile) based on a Euclidean distance metric (a) and an LCP distance metric (b). Note: negative values are a result of the two stage (detrending then kriging residuals) approach.

Figure 5. Map of predicted 2001 blue crab density (individuals per $1000m^2$ classified by quintile) based on a Euclidean distance metric (a) and an LCP distance metric (b). Note: negative values are a result of the two-stage (detrending then kriging residuals) approach.

Figure 6. Map of Lowest Cost Path (LCP) distance (km) from the Bay mouth (represented by the black circle).

Table 1. Summary of variogram model parameters. Numbers in italics denote parameters that were fit by eye and were not used in variogram comparisons.

Year	Sample size	Distance Metric	Variogram Model	Nugget	Partial Sill	Range(km)
1990	863	Euclidean	Exponential	18,173	22,455	54
		LCP	Exponential	16,448	25,042	55
1991	964	Euclidean	Gaussian	9,736	30,484	55
		LCP	Gaussian	*8,000*	*12,000*	*30*
1992	1392	Euclidean	Exponential	792	1,408	25
		LCP	Exponential	763	997	16
1993	1253	Euclidean	Gaussian	6,963	20,254	50
		LCP	Gaussian	*6,000*	*6,000*	*35*
1994	1427	Euclidean	Gaussian	7,108	885	35
		LCP	Gaussian	*7,000*	*900*	*30*
1995	1598	Euclidean	Gaussian	1,324	10,165	49
		LCP	Gaussian	1,178	5,436	41
1996	1580	Euclidean	Gaussian	3,877	11,461	34
		LCP	Gaussian	3,444	7,453	28
1997	1587	Euclidean	Gaussian	2,848	6,075	29
		LCP	Gaussian	2,860	4,446	29
1998	1573	Euclidean	Gaussian	1,160	1,580	33
		LCP	Gaussian	1,195	1,222	38
1999	1519	Euclidean	Gaussian	581	2,042	33
		LCP	Gaussian	564	1,181	27
2000	1511	Euclidean	Gaussian	592	1,220	24
		LCP	Gaussian	587	1,075	23
2001	1556	Euclidean	Gaussian	281	1,114	25
		LCP	Gaussian	263	830	22
2002	1530	Euclidean	Gaussian	416	1,409	35
		LCP	Gaussian	377	867	30

Table 2. Baywide. Prediction Error Sum of Squares (PRESS) for kriging predictions based on Euclidean and Lowest-Cost Path (LCP) distance metrics, the percent difference in PRESS between the two metrics (positive numbers indicate greater prediction accuracy for the LCP metric), the average increase in intersample distance for the LCP metric, and the mean percent difference over 13 years.

Year	Euclidean PRESS ($*10^3$)	LCP PRESS ($*10^3$)	Percent Difference	Average Absolute Increase in Intersample Distance (km)	Average Percent Increase in Intersample Distance
1990	65.64	65.09	0.84	16.84	23.12
1991	61.08	61.53	-0.73	12.13	15.27
1992	6.46	6.49	-0.47	12.77	16.53
1993	38.00	38.21	-0.54	14.60	20.11
1994	29.57	29.48	0.28	16.19	21.10
1995	19.80	19.63	0.87	14.13	18.99
1996	50.00	49.99	0.01	12.87	16.83
1997	16.12	16.19	-0.41	11.10	14.52
1998	9.58	9.68	-1.04	11.86	15.65
1999	10.23	10.14	0.95	11.87	15.44
2000	5.24	5.23	0.11	11.34	14.50
2001	4.49	4.65	-3.46	11.06	14.09
2002	6.10	6.04	0.94	11.68	15.30
		mean:	-0.20	12.96	17.03

Table 3. Tangier Sound and Baywide random subsample. Prediction Error Sum of Squares (PRESS) for kriging predictions based on Euclidean and Lowest-Cost Path (LCP) distance metrics, the percent difference in PRESS between the two metrics (positive numbers indicate greater prediction accuracy for the LCP metric), and the mean percent difference over 13 years. Only the mean percent difference in PRESS is given for the random subsamples.

Year	Tangier Euclidean PRESS ($*10^3$)	Tangier LCP PRESS ($*10^3$)	Tangier Percent Difference	Baywide Random Subsample Percent Difference	Tangier Random Subsample Percent Difference
1990	31.60	31.28	1.02	-0.36	-0.30
1991	5.78	5.91	-2.22	0.55	-0.93
1992	1.30	1.31	-0.92	-0.74	-0.04
1993	0.30	0.33	-8.45	-0.84	-9.18
1994	10.93	10.89	0.38	0.67	0.34
1995	3.55	3.41	3.98	-0.05	-3.62
1996	5.38	5.33	0.87	-1.29	0.42
1997	1.72	1.70	0.70	0.07	-0.78
1998	1.29	1.29	0.15	-0.86	0.56
1999	0.51	0.51	1.15	1.47	0.76
2000	1.22	1.23	-1.15	-0.86	-1.31
2001	0.80	0.86	-7.29	-0.46	-2.62
2002	0.44	0.44	-0.41	-0.58	-0.83
		mean:	-0.94	-0.25	-1.35

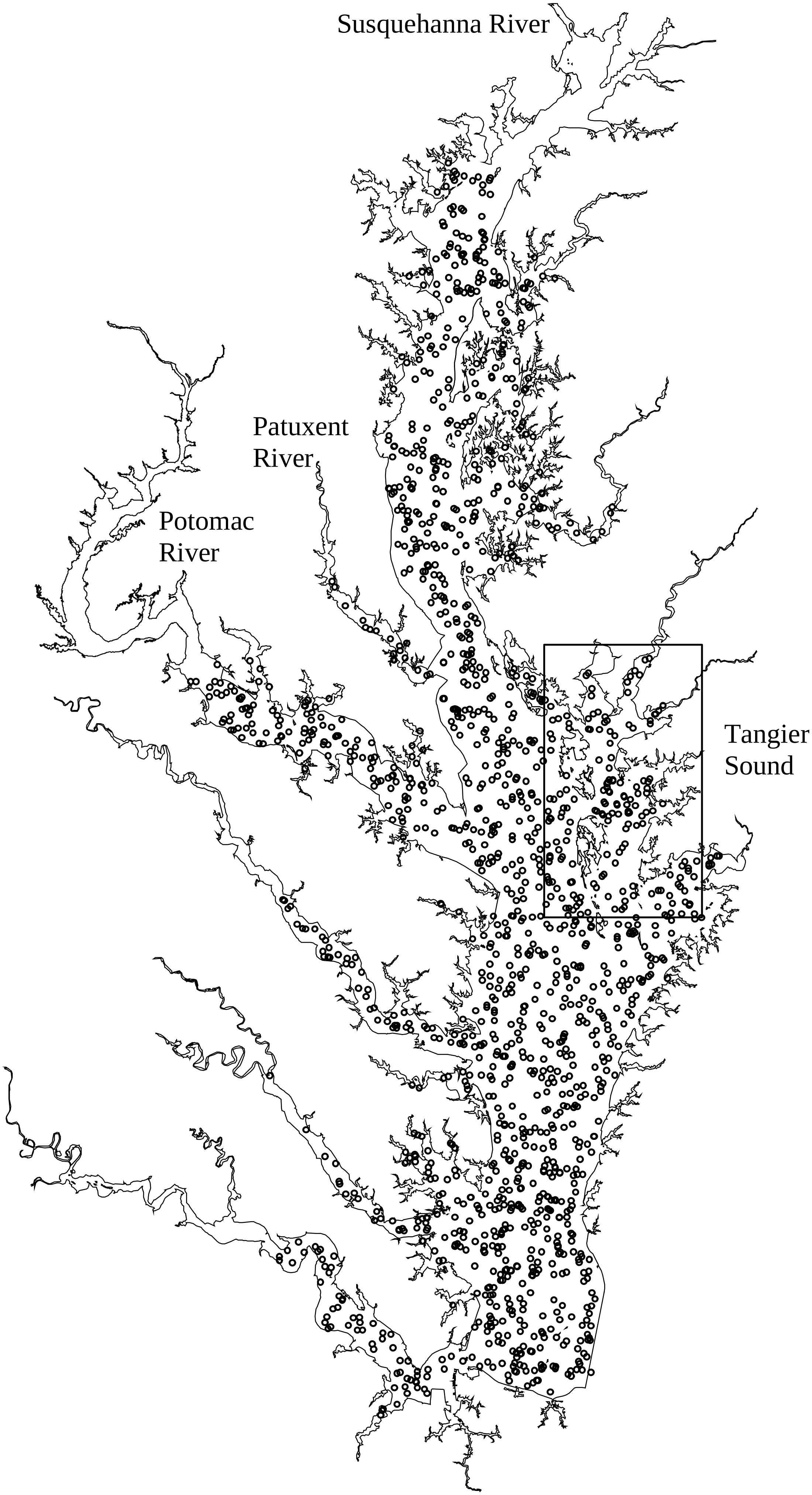
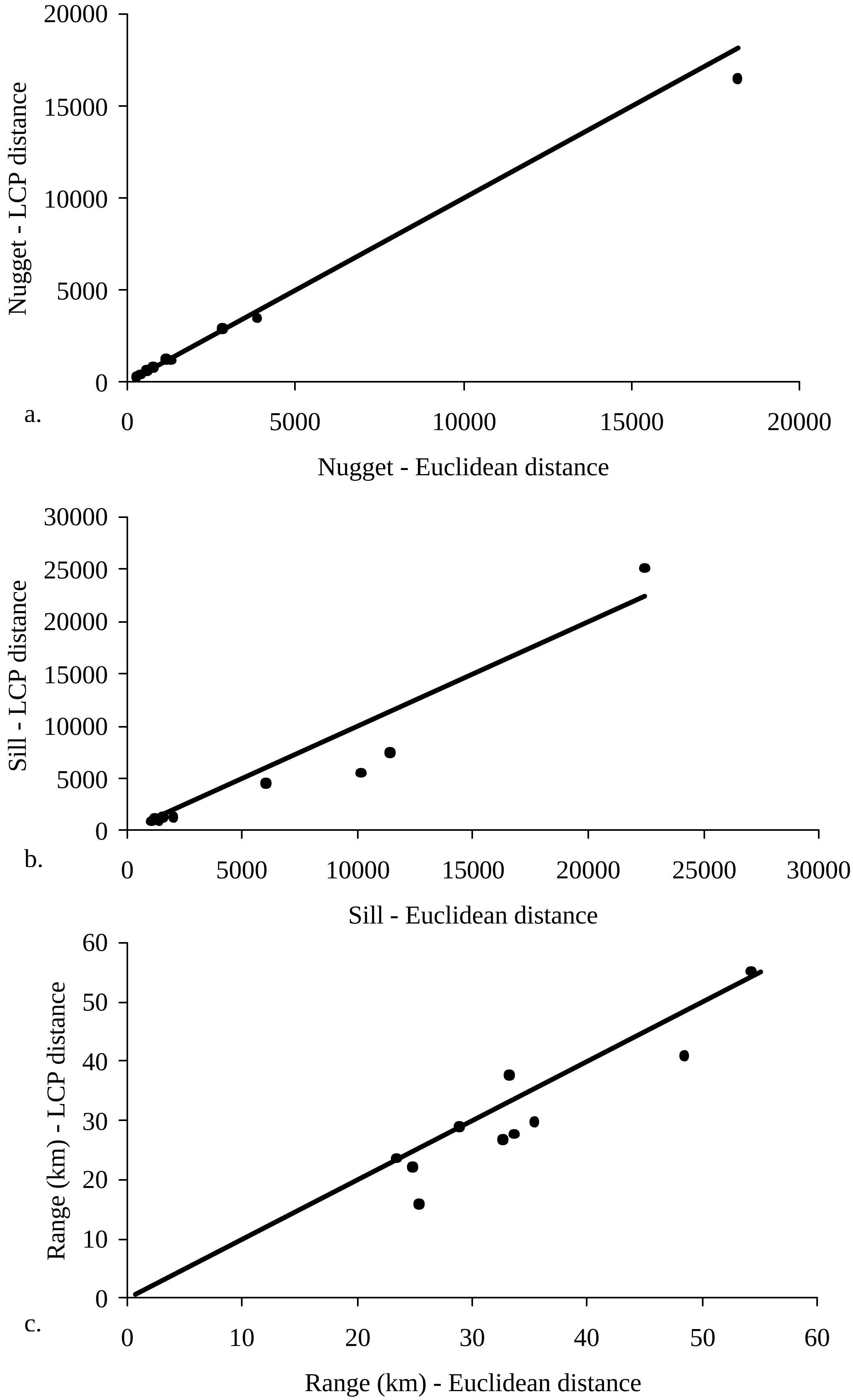
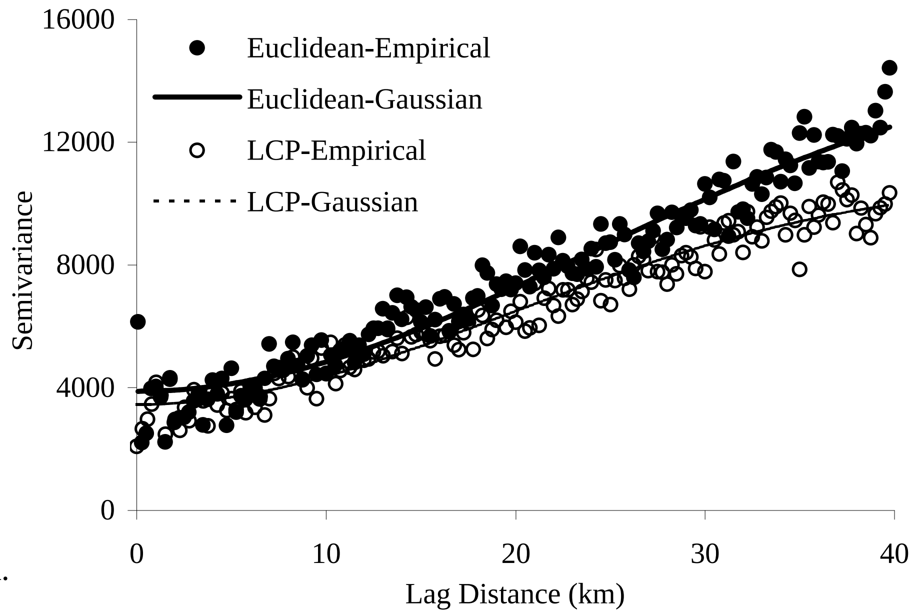

Susquehanna River
Patuxent
River
Potomac
River
Tangier
Sound

Figure 1.



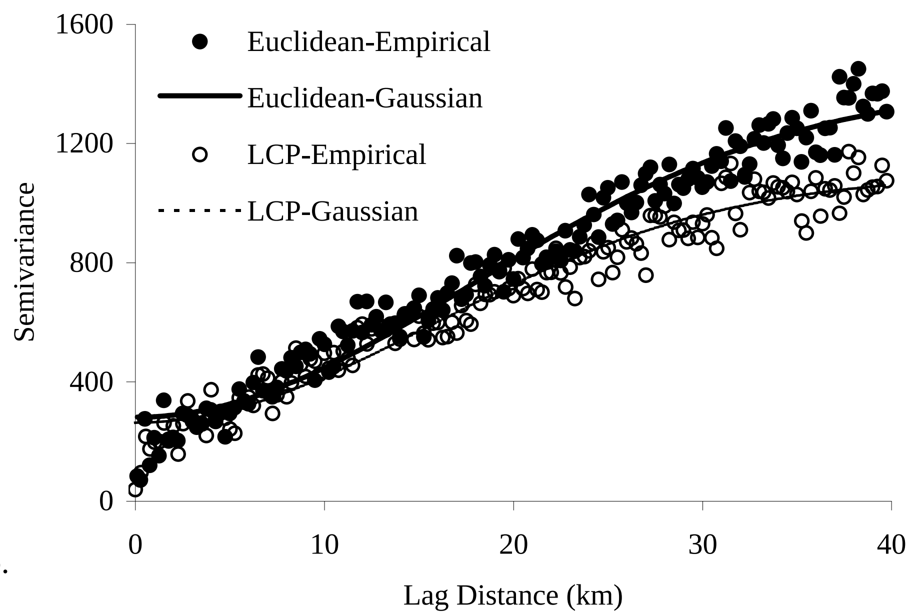
Nugget - LCP distance
20000
15000
10000
5000
0
a.
0
5000
10000
15000
20000
Nugget - Euclidean distance
Sill - LCP distance
30000
25000
20000
15000
10000
5000
0
b.
0
5000
10000
15000
20000
25000
30000
Sill - Euclidean distance
Range (km) - LCP distance
60
50
40
30
20
10
0
c.
0
10
20
30
40
50
60
Range (km) - Euclidean distance

Figure 2.



16000
12000
8000
4000
0
Semivariance
Euclidean-Empirical
Euclidean-Gaussian
LCP-Empirical
LCP-Gaussian
0
10
20
30
40
Lag Distance (km)

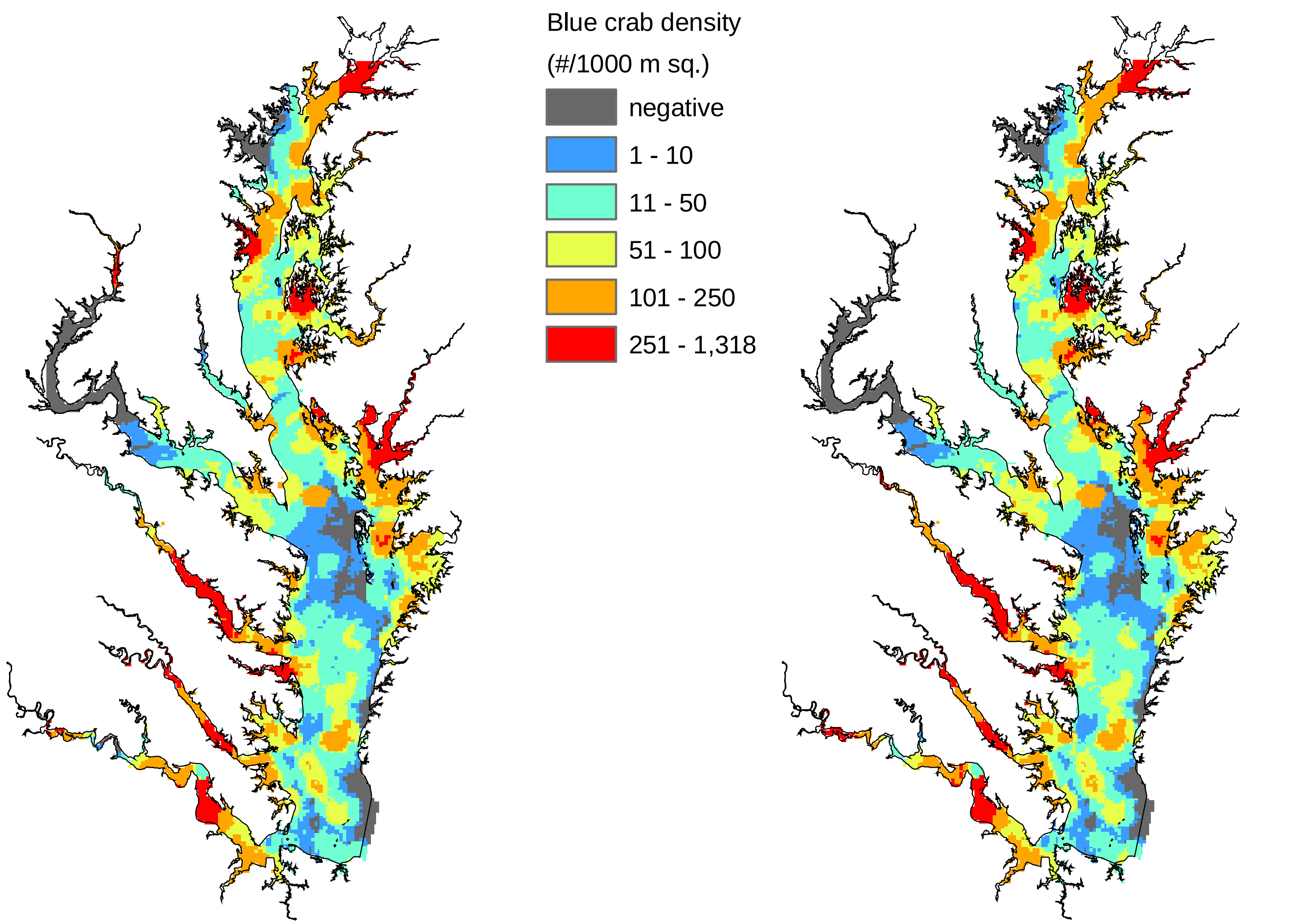
a.



1600
1200
800
400
0
Semivariance
Euclidean-Empirical
Euclidean-Gaussian
LCP-Empirical
LCP-Gaussian
0
10
20
30
40
Lag Distance (km)

b.

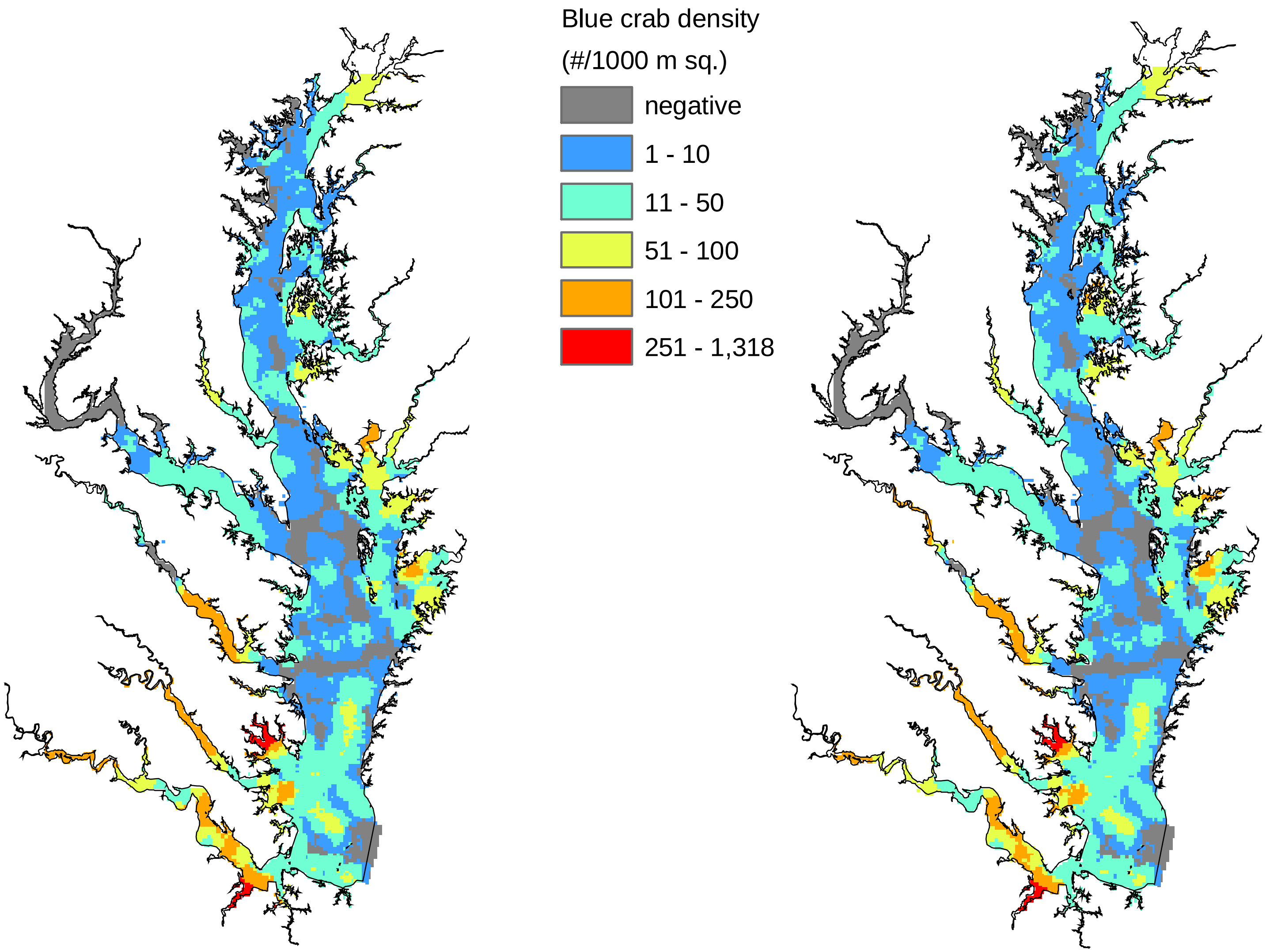
Figure 3.



a. Euclidean distance metric

b. LCP distance metric

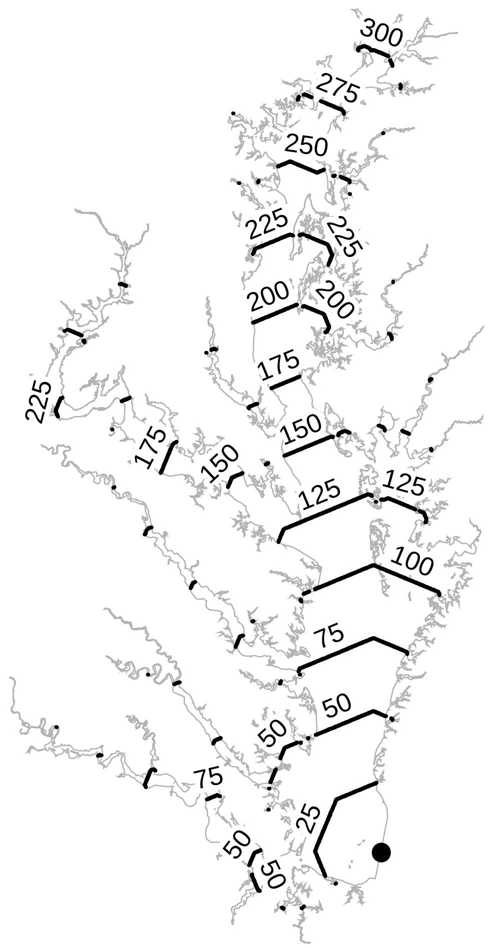
Figure 4.



a. Euclidean distance metric

b. LCP distance metric

Figure 5.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50
50

Figure 6.