EXPLORING LANDSCAPE FORM AND UPLAND FOREST FRAGMENTATION ON AQUATIC CONDITION IN SUSQUEHANNA RIVER BASIN HEADWATERS

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1. INTRODUCTION

Metabolization of natural habitat for human need has resulted in fragmented landscapes that are increasingly vulnerable to anthropogenic disturbances (Leu et al., 2008). With overconsumption of natural resources, it has been commonly accepted that human impacts are not limited to a single area and their associated disturbances have far reaching consequences; albeit, affecting multiple ecosystems far from the location of initial encounter (Turner et al., 2001). As all land surfaces are contained within a watershed, it follows that anthropogenic impacts on upland environments will eventually affect the aquatic ecosystems in streams and other bodies of water (Paul and Meyer, 2001). Thus, terrestrial waters are often the ecosystems most impacted by stressors associated with landscape change (Foley et al., 2005; Novotny et al., 2005; Liu et al., 2007; Milly et al., 2008).

Previous studies between landscape and freshwater resources have typically correlated changes in ecological condition with simple aggregates of urbanization (e.g., percent urban) (Alberti et al., 2007). This paradigm has been reaffirmed since Klien’s (1979) seminal work with dozens of regional investigations on how land cover composition relates to aquatic integrity (Morley and Karr, 2002; Alberti et al., 2007, Shandas and Alberti, 2009). With that said, these relationships are typically non-linear (Novotny et al., 2005), and by no means can account for all the variability in aquatic ecosystems. Recent studies have implied the importance of incorporating configuration metrics into landscape-aquatic condition research (e.g., Alberti et al., 2007; Shandas and Alberti, 2009). These findings provide much needed information to planners, natural resource managers, and landscape design specialists that cannot be addressed with simple aggregates of land cover (Alberti et al., 2007). However, few landscape studies have fully addressed the needs of spatial data (e.g., spatial autocorrelation) in species-environment spatial analysis (King et al., 2005; Wagner and Fortin, 2005).

This research aims to develop a vector based “watershed landscape” spatial investigation between landscape form and upland forest fragmentation measures, and an indicator of aquatic ecological condition. Using multivariate statistical methods two null hypotheses are tested: (1) no significant relationship exists between landscape form and forest fragmentation variables, and a measure of instream ecological integrity; and (2) spatial multivariate statistical techniques and linear discriminant analysis do not support and improve ordinary least square (OLS) methods. Using a benthic index of biotic integrity (B-IBI), as our measure of aquatic ecological condition, this research examines landscape form and upland forest fragmentation in the headwater of the Susquehanna River basin. Specifically, OLS, exploratory spatial data analysis (ESDA), geographically weighted regression (GWR), and classical discriminate analysis were employed in the ensuing analysis.
2. METHOD

2.1 STUDY AREA

We have focused our empirical study between landscape form and upland forest patterns, and a B-IBI within the headwaters of the Susquehanna River basin (Figure 1). Specifically, 29 Hydrologic Unit Code (HUC-10) watersheds were utilized for landscape assessment. Average catchment area of the 29 watersheds is 435 km², and the total area of the study region is 12,605 km². Several characteristics of our study area make it ideal for this research. Study area elevation ranges from 250 to 730 meters above sea level, and geology is consistent with all 29 watersheds completely within the Alleghany Plateau. It is characterized by a temperate-continental climate and has average annual precipitation of 39 inches (past 30 years). This area of Central New York has a rich landscape change and settlement history with incorporations reaching back to the late 1700’s. In the Northeast US, many forested areas have decreased in size and become increasingly fragmented due to human development (White et al., 2010). As of 2006, the dominant land cover for the study area was forest (56%), followed by agricultural lands (30%), and then urban (5%); wetlands and rangeland occupy roughly four percent of the 29 HUC-10 landscapes (percentages obtained from this analysis).

![Location and Relative Index Scores of 52 B-IBI Sample Sites Within 29 Corresponding HUC-10 Watershed Landscapes](image)

The Susquehanna River watershed drains more than 71,200 km² of land area; its source comes from Otsego Lake in New York and flows over 714 km to the Chesapeake Bay at Havre de Grace, Maryland, where it contributes over half of the freshwater inflow to the Bay (Hoffman, 2008). More than 80 percent of the basin’s 1,400 plus municipalities are prone to flooding (SRBC, 2007a), and many of the communities along the Susquehanna had their second worst flood (2006) and worst flood (2011) of their history. The Susquehanna River is
now recognized as one of the nation’s most flood-prone watersheds and experiences flood-related damages greater than $150 million in costs each year (SRBC, 2007b).

Major causes of aquatic impairment for the Susquehanna River are linked to poor land use practices. Specifically, deficiency in stream integrity is linked to elevated metals and sulfate concentrations and depressed pH due to abandoned mine drainage (Huffman, 2008). Other land use related impairments include sediment and nutrient enrichment due to habitat alteration, loss of riparian habitat, channelization, and agricultural and urban runoff, as well as some limited impacts from sewage treatment plants (Huffman, 2008). Land use effects and flooding events that occur within the Susquehanna River basin have historically degraded the ecological condition of the Chesapeake Bay, and it can be presumed that these conditions will continue to degrade as flooding events increase in occurrence and magnitude.

2.2 CHESSIE B-IBI AND SAMPLE POINT SELECTION

Access and management of water resources is now considered a prerequisite for human development (Gleick, 2003). To support this, many nations throughout the world have adopted laws to protect or improve the integrity of hydrologic systems (Karr, 2006). A recurring theme throughout these regulations is to restore and maintain the biological integrity of their respected waters. Monitoring programs for assessing human impacts on aquatic and water quality have existed for decades. Specifically, indicators of aquatic integrity have gained popularity for quantifying the impact of human activities on the biota and are in practice on six of the seven continents throughout the world (Roset et al., 2007). A variety of measuring techniques has been applied to aquatic organisms as indicators of biological integrity; however, the Index of Biotic Integrity (IBI) (Karr, 1981) has developed into the applied method of choice. IBI has been welcomed as a robust method for investigating landscape-aquatic interactions (Karr and Yoder, 2004; Novotny et al., 2005), and has been found to help diagnose causes of ecological impacts and suggest appropriate management actions (Karr and Chu, 1999).

A localized benthic index of biological integrity (known commonly as the Chessie B-IBI), provided by the Chesapeake Bay Program (CBP), was utilized to analyze the effects of landscape change in our study area landscapes. The CBP B-IBI is a compilation of 23 federal and state macro-invertebrate monitoring programs across the watersheds of the Chesapeake Bay into one common rubric. Datasets had to comply with the US Environmental Protection Agency (EPA) Rapid Bioassesment Protocols (RBP). In our study area, the New York State Department of Environmental Conservation (NYSDEC) is responsible for compliance of the Chessie multi-metric index. To create the final B-IBI, 42 out of 127 recommended metrics were chosen, which were divided into 5 types of measurements: species tolerance, species richness, species habit, feeding guild, and species composition (see Buchanan et al., 2011 for details). For our study, replicates samples were chosen for most landscapes in locations downstream and in high stream confluence (Figure 1). 52 B-IBI samples were utilized from different seasons and different years (20 points from 7/3/2003-10/2/2003 and 32 points from 7/17/2006 -8/7/2008), which reduced error from spatial autocorrelation of biotic processes (e.g., species interactions), spatial dependence from abiotic processes (e.g., deterministic structures such as canopy cover), and temporal variability. A detailed example of upland landscape complexity and corresponding replicate B-IBI sample sites is provided in Figure 2.

2.3 LANDSCAPE FORM AND FOREST FRAGMENTATION DATA

Power metrics consist of additive natural or built landscape features. Topographic form and catchment area are fundamental to understanding landscape-aquatic interaction, thus mean degree slope and area were calculated for all HUC-10 watershed landscapes. Degree slope was calculated from a common 30m resolution digital elevation model (DEM) provided by the USGS. Total number of remediation sites was summarized for each of the 29 landscapes; those sites consist of brownfields, superfund sites or voluntary cleanup programs. Total number of mines or quarries consists of above ground or underground, active or inactive
mining sites. More than half of the mining sites in the study area were inactive and reclaimed unconsolidated material surface mines, with the majority of active sites being unconsolidated material surface mines. Total number of road-river intersections consists of any bridge, road, or culvert that interacts with a waterway. River (2004) and road (2012) data were provided by the NYSDEC.

**FIGURE 2**
EXAMPLE OF UPLAND LANDSCAPE COMPLEXITY AND B-IBI SITE SELECTION

*Land cover (composition) and forest patterns (configuration)* were quantified using landscape ecology metrics developed for quantifying the spatial arrangement of land cover and land use (Turner *et al.*, 2001; McGarigal *et al.*, 2002). Land cover data were acquired through the National Land Cover Database (NLCD) (USGS 2011). We reclassified the 2006 NLCD land cover data for New York state into seven applicable classes based on Anderson *et al.* (1976) level one land use and land cover classification system. FRAGSTATS version 3.4 (McGarigal *et al.*, 2002), free and publicly accessible software, was used for computing composition and forest pattern metrics for each landscape. The reclassified land cover data was preserved at 30m resolution. Five major land cover variables and 72 landscape forest class metrics were computed for each of the 29 HUC-10 watershed landscapes used in the following statistical analysis. As there is no causal ordering in space as there is in time, and there remains no minimum set of landscape metrics for capturing the majority of landscape structure (Wagner and Fortin, 2005), forest class metrics were calculated and then statistically reduced into a highly relevant subset. Please see McGarigal *et al.* (2002) for landscape composition and forest class configuration metric details.

Principal Components Analysis (PCA) and Robust Pearson correlations were used to reduce the set of landscape forest class and form metrics. Forest class metrics with strongest loadings that exhibited different patterns of orthogonal axes were selected. All remaining landscape variables were then reduced further by Robust Pearson correlations, to remove metrics that exhibited a high degree of multicollinearity ($r > 0.75$). Eighteen independent explanatory landscape variables remained to be used in the forthcoming stepwise regression
To meet the assumptions of normality for all variables required during parametric tests, we used two types of transformation: negative arcsine (proportion data) and log10 (length/score data). The remaining landscape form variables were standardized using a z-transformation to set all parameters to a mean of 0 and variance of 1. Other software packages implemented in this analysis were: SYSTAT 12 and JMP version 10 (SAS Institute, 2012).

### TABLE 1
SELECTED LANDSCAPE METRICS AND THEIR OLS/GWR BIVARIATE RELATIONSHIP WITH B-IBI

<table>
<thead>
<tr>
<th>Power metrics</th>
<th>Composition metrics</th>
<th>Forest class configuration metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Watershed area /***</td>
<td>% Urban/Built-up /***</td>
<td>FRAC_AM /***</td>
</tr>
<tr>
<td>Mean degree slope /***</td>
<td>% Agricultural /***</td>
<td>NLSI /**</td>
</tr>
<tr>
<td>Total # road-river intersections**/***</td>
<td>% Rangeland**/***</td>
<td>CLUMPY /***</td>
</tr>
<tr>
<td>Total # remediation sites /**</td>
<td>% Wetland /***</td>
<td>SHAPE_MN*/***</td>
</tr>
<tr>
<td>Total # Mine/Quarry /***</td>
<td>PRD /***</td>
<td>CORE.CV /***</td>
</tr>
<tr>
<td></td>
<td>SHDI /***</td>
<td>ENN.MN*/***</td>
</tr>
</tbody>
</table>

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

### 2.4 DATA ANALYSIS

The first law of geography states that things that are near are more similar (autocorrelated) than things that are farther apart (Tobler, 1970; Fortin and Dale, 2005). In spatial environmental studies it is imperative to take into account spatial autocorrelation. Spatial autocorrelation is the lack of independence between pairs of observation at given distances in time and space and is commonly found in environmental data (Legendre, 1993). In order to evaluate the spatial patterns of B-IBI and independent landscape variables, an ESDA was conducted. For this study a common ESDA technique, spatial autocorrelation index global Moran’s I-test, was applied. Spatial autocorrelation index scores vary from each other; however, positive scores indicate similar values are spatially clustered and negative scores indicate unlike values are spatially clustered (Wong and Lee, 2005). ESDA is frequently used in studies of geographical ecology and macroecology (Lichstein et al., 2002; Wagner and Fortin, 2005; Dormann et al., 2007; Rangel et al., 2010), and can be particularly useful when testing spatial autocorrelation in environmental systems. ESRI’s ArcMap 10 Spatial Statistics toolbox was employed to assess the level of spatial autocorrelation of variables used in this study.

Spatial autocorrelation is problematic for classical statistical tests (e.g., ANOVA, OLS regression) because it violates the assumption of independently distributed errors (Lichstein et al., 2002); furthermore, the standard errors are usually undervalued when positive autocorrelation is present increasing the potential for type I error rates (falsely rejecting the null hypothesis of no effect) (Dormann et al., 2007). Furthermore, spatial autocorrelation can cause a shift in regression coefficients depending on whether spatially explicit or non-spatial modeling is used (Bini et al., 2009). Spatial autocorrelation may be particularly problematic in regional-scale studies because landscape form (e.g., land cover) is typically not uniformed over space and often correspond with the underlying foundation (e.g., geology, soils) of its landscape. In landscape scale research this phenomenon is occasionally acknowledged and rarely addressed quantitatively (King et al., 2005). Lennon (2000) called attention to the problems associated with autocorrelation in ecological research ‘red herrings’ and argued that virtually all geographic analyses had to be redone by taking into account spatial autocorrelation.

### TABLE 1
SELECTED LANDSCAPE METRICS AND THEIR OLS/GWR BIVARIATE RELATIONSHIP WITH B-IBI

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</table>

*Significant at 10%. **Significant at 5%. ***Significant at 1%.
Traditional multivariate regression techniques (i.e., OLS) have been commonly applied in landscape-aquatic condition research; however, these methods are problematic because they assume spatial stationarity in the relationships between variables under study (Legendre, 1993; Foody, 2003). Autocorrelation, the lack of independence between pairs of observations at a given distance in time or space, is found commonly in environmental data (Legendre, 1993). A failure to account for spatial autocorrelation prevents an in-depth interpretation of almost all ecological studies over space (Boots, 2002; Jetz et al., 2004). GWR, a refinement to traditional regression methods, utilizes a distance decay weighted philosophy that explicitly deals with the spatial non-stationarity of empirical relationships (Fotheringham, 2004). GWR assesses local influences, allowing for a spatial shift in parameters and a more appropriate model fit (Wang et al., 2005). Therefore, GWR models are not designed for extrapolation beyond the region in which they were established (Foody, 2003), and remain stochastic and cannot assure accuracy (Shaker et al., 2009).

Independent landscape form and forest fragmentation variables were reduced to those that significantly correlated with B-IBI using a multivariate statistical technique. This exploratory analysis for model development used a forward stepwise regression method (P-value = 0.05 to remove). A multivariate landscape form and forest fragmentation model explaining B-IBI was created to test our hypotheses. Spatial Analysis in Macroecology (SAM) version 4, software specifically developed to address spatial data needs found naturally in macroecological and biodiversity data (Rangel et al., 2010), was then used to calculate and interpret the multivariate GWR model. In multivariate regression techniques, the dominant practice is to rank the standard partial regression coefficients (Sokal and Rohlf, 1995) or associated t-values of coefficients of explanatory variables (Tognelli and Kelt, 2004) under the assumption that higher coefficients represent stronger “effects” on the dependent variable (Bini et al., 2009). To measure the impact of multicollinearity we estimated the variance inflation factor (VIF). VIF > 10 indicates definite problems of multicollinearity; VIF > 2.5 indicates potential areas of concern.

As suggested by Shaker et al. (2009), classical discriminant analysis was added to this study to help validate the multivariate landscape model. The purpose of discriminant analysis is to find and/or test a linear equation (discriminant function) to separate two or more groups of objects with respect to several variables simultaneously (Klecka, 1980). In this study, we adopted the five category rating scale of non-Coastal Plain B-IBI established by Buchanan et al. (2011). That narrative condition rating system grouped B-IBI scores into the following categories: excellent (≥ 67%), good (50 - <67%), fair (30% - <50%), poor (17% - <30%), and very poor (<17%). A challenge lies when investigating and comparing discriminant models with low to moderate correlations, relating to which model is the most discriminant model. Wilks’ lambda is frequently used to test differences between the means of identified groups for a combination of dependent variables selected for a discriminant model (Klecka, 1980). Because Wilks’ lambda is a type of inverse measure, significance levels near zero denote high discrimination between groups. Generally, if the Wilks’ lambda significance level is less than 0.05, then this represents sufficient discriminatory power.

3. RESULTS

3.1 EXPLORATORY SPATIAL DATA ANALYSIS

Taking all 52 B-IBI sample locations into account, Global Moran’s I analysis revealed very low spatial autocorrelation in both the dependent and independent variables (Table 2). Only one variable utilized in model development displayed a degree of spatial autocorrelation. Global Moran’s I index reported a score of 0.28, z-score = 2.39 for mean Euclidean nearest-neighbor distance (ENN_MN), thus signifying that there is less than 5% likelihood that this spatial pattern could be the result of random chance.
3.2 MULTIVARIATE SPATIAL ANALYSES

Results of the stepwise exploratory analysis eliminated 14 of the remaining 18 independent landscape variables. The remaining four variables combined to make a multivariate landscape form and forest fragmentation model for explaining B-IBI. The model consists of one power metric, one composition metric, and two forest class configuration metrics (Table 3A). The one power metric was: total number of road-river intersections (ROAD-RIVER INTERSECTION). The one land cover composition metric was: percent urban/built-up land (PERCENT URBAN/BUILT-UP). The two forest class configuration metrics were: clumpiness index (CLUMPY) and mean Euclidean nearest-neighbor distance (ENN_MN). As VIF magnitudes in Table 2 are between 1.0 and 1.6, the collinearity problem among our independent variables is virtually nonexistent.

Based on OLS methodology, the four aforementioned landscape metrics combined to explain 33 percent of the variation in B-IBI scores ($R^2 = 0.33, P < 0.001$), across Susquehanna headwater landscapes (Table 3B). Based on the OLS model, the strongest positive influence of an individual landscape metric predicting B-IBI was clumpiness index (CLUMPY, std. coeff. = 0.44, $P = 0.005$, Table 3A). Based on the OLS model, the strongest negative influence of an individual landscape metric predicting B-IBI was mean Euclidean nearest-neighbor distance (ENN_MN, std. coeff. = -0.39, $P = 0.006$, Table 3A).

Landscape-aquatic relationships are inherently spatial, thus GWR methodology proved to be an enhancement over OLS (Table 3B). With the GWR model, the four landscape metrics combined to explain 51 percent of the variation in B-IBI scores ($R^2 = 0.51, P = 0.002$), across Susquehanna headwater landscapes (Table 3C, Figure 3A). Investigating spatial autocorrelation of the landscape multivariate model further, autocorrelation has been minimized from GWR methodology based on normal distribution of model residuals (Figure 3B) and correlogram of Moran’s I model residuals (Figure 3C).

The results from the classical discriminant analysis revealed that the four landscape metrics combined to explain 68 percent of the variation in five groups of aquatic ecological condition ($Rc^2 = 0.68, P = 0.000$), across Susquehanna headwater landscapes. Wilks’ lambda significance test revealed that the landscape model represented sufficient discriminatory power (Wilks’ -$\lambda = 0.004$).

4. CONCLUSION

Our analysis revealed that aquatic ecological condition is affected by a complexity of landscape variables simultaneously across watersheds in the headwaters of the Susquehanna River basin. Thus, the first null hypothesis can be rejected because statistically significant relationships were found between 52 B-IBI sample points, and landscape form and upland forest fragmentation measures within 29 watersheds. The second null hypothesis stated that
spatial multivariate statistical techniques and linear discriminant analysis do not support and improve OLS methods. GWR and linear discriminant analysis improved model Coefficient of Determination by explaining 18 and 35 percent more of B-IBI variation, respectively. With these combined results, the second null hypothesis is also rejected. Much work remains for applied geographers to improve understanding of coupled landscape-aquatic ecosystems.

TABLE 3
RESULTS OF STEPWISE MULTIPLE REGRESSION FOR B-IBI AS A FUNCTION OF LANDSCAPE FORM AND FOREST FRAGMENTATION. (A) FINAL REGRESSION MODEL SHOWING STANDARDIZED COEFFICIENTS; (B) ANALYSIS OF VARIANCE; AND (C) OVERALL SIGNIFICANCE

A. Standardized regression model

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS Coeff.</th>
<th>Std. Error</th>
<th>Std. Beta Coeff.</th>
<th>t-Ratio</th>
<th>P-value</th>
</tr>
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<tbody>
<tr>
<td>CONSTANT</td>
<td>38.4</td>
<td>3.52</td>
<td>0.00</td>
<td>10.91</td>
<td>&lt;0.001</td>
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<tr>
<td>ROAD-RIVER INTERSECTION</td>
<td>10.33</td>
<td>3.59</td>
<td>0.35</td>
<td>2.88</td>
<td>0.006</td>
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<tr>
<td>PERCENT URBAN/BUILT-UP</td>
<td>-9.79</td>
<td>3.96</td>
<td>-0.33</td>
<td>-2.48</td>
<td>0.017</td>
</tr>
<tr>
<td>CLUMPY</td>
<td>13</td>
<td>4.42</td>
<td>0.44</td>
<td>2.94</td>
<td>0.005</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>-11.64</td>
<td>4.07</td>
<td>-0.39</td>
<td>-2.861</td>
<td>0.006</td>
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</tbody>
</table>

B. Analysis of variance (ANOVA)

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<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>Mean Sq.</th>
<th>F-Ratio</th>
<th>P-value</th>
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<tbody>
<tr>
<td>Regression</td>
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<td>4</td>
<td>3648.33</td>
<td>5.67</td>
<td>&lt;0.001</td>
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<td>Residuals</td>
<td>30258.34</td>
<td>47</td>
<td>643.79</td>
<td></td>
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<tr>
<td>GWR Residuals</td>
<td>21842.01</td>
<td>37.8</td>
<td>577.8</td>
<td>1.58</td>
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<tr>
<td>GWR Improvement</td>
<td>8416.33</td>
<td>9.2</td>
<td>65.99</td>
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</table>

C. Diagnostics statistics

<table>
<thead>
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<th>Dependent Variable</th>
<th>B-IBI</th>
</tr>
</thead>
<tbody>
<tr>
<td>N:</td>
<td>52</td>
</tr>
<tr>
<td>Correlation Coefficient: R (OLS)</td>
<td>0.57</td>
</tr>
<tr>
<td>Coefficient of Determination: R-Square (OLS)</td>
<td>0.33</td>
</tr>
<tr>
<td>Std. Error of Estimates (OLS)</td>
<td>25.37</td>
</tr>
<tr>
<td>Correlation Coefficient: R (GWR)</td>
<td>0.72</td>
</tr>
<tr>
<td>Coefficient of Determination: R-Square (GWR)</td>
<td>0.51</td>
</tr>
<tr>
<td>F-ratio (GWR)</td>
<td>3.03</td>
</tr>
<tr>
<td>P-value (GWR)</td>
<td>0.002</td>
</tr>
</tbody>
</table>
FIGURE 3
(A) ACTUAL VERSUS PREDICTED PLOT OF B-IBI SCORE FROM GWR MODEL; (B) FREQUENCY DISTRIBUTION DISPLAYING GWR MODEL RESIDUALS; AND (C) SPATIAL CORRELOGRAM OF B-IBI SCORE, ESTIMATED B-IBI SCORE, AND GWR MODEL RESIDUALS

5. REFERENCES


McGarigal, K., S.A. Cushman, M.C. Neel, and E. Ene. 2002. *FRAGSTATS: spatial pattern analysis program for categorical maps*. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: http://www.umass.edu/landeco/research/fragstats/fragstats.


