# Investigating Land Cover and Urban Pattern Impacts on Watershed Integrity: A GWR and ANN Approach



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INVESTIGATING LAND COVER AND URBAN PATTERN IMPACTS ON WATERSHED INTEGRITY: A GWR AND ANN APPROACH

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## 1. INTRODUCTION

Numerous studies have demonstrated the importance of watershed scale research for improving aquatic and water quality over other management scales (e.g., reach, riparian zone) (Wang *et al*., 2003; King *et al*., 2005; Potter *et al*., 2005; Wang *et al*., 2006; Alberti *et al*., 2007). Starting in the mid 1970s, the watershed management paradigm changed the way aquatic ecologists look at the landscape. "In every respect, the valley rules the stream" (Hynes, 1975). "Rivers and streams serve as a continent's circulatory system, and the study of those rivers, like the study of blood, can diagnose the health not only of the rivers themselves but of their landscapes" (Sioli, 1975).

The current integrity of the planet is being stressed beyond its biological capacity, and understanding human created landscapes is more important now than ever. Changes in land cover, through the appropriation of natural landscapes to provide for human needs, has been found to be one of the most pervasive alterations to native ecosystems resulting from human activity (Foley *et al*., 2005; Liu *et al*., 2007). Landscape change influences natural systems by fragmenting landscape patches, isolating habitats, abridging ecosystem dynamics, introducing exotic species, controlling and modifying disturbances, escalating climate change, and disrupting energy flow and nutrient cycling (Picket *et al*., 2001; Alberti, 2005; Foley *et al*., 2005; Liu *et al*., 2007; Alberti, 2008; Milly *et al*., 2008). Albeit, terrestrial waters are often the ecosystems most affected by those stressors associated with landscape change (Foley *et al*., 2005; Novotny *et al*., 2005; Liu *et al*., 2007; Milly *et al*., 2008).

Access and management of water resources is now considered a prerequisite for human development of watershed management (Baron *et al*., 2002; Gleick, 2003). To support this, many nations have adopted laws to protect or improve the integrity of hydrologic systems (Karr, 2006). A reoccurring theme throughout these regulations is to restore and maintain biological integrity of their respected waters. Monitoring programs for assessing human impacts on aquatic and water quality have existed for decades. Specifically, fish indicators of biological 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 have been applied to fish as indicators of biological integrity; however, the Index of Biotic Integrity (IBI) has developed into the applied method of choice. The IBI (Karr, 1981), has been widely applied to fish assemblage data for assessing the environmental quality of aquatic habitats (Roset *et al*., 2007). Further, the Fish Index of Biotic Integrity (F-IBI) is 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).

Previous studies between landscape-aquatic relationships have typically correlated changes in ecological integrity with simple aggregates of urbanization (e.g., percent urban) (Alberti *et al*., 2007); albeit, these relationships are often found to be non-linear (Novotny *et al*., 2005), and cannot account for a large portion of the variability in aquatic ecological integrity. A preliminary investigating using data from this study supports these findings ($P$=0.0059) (Figure 1). In recent studies, research has implied the importance of incorporating configuration metrics into landscape-aquatic condition research (e.g., Alberti *et al.*, 2007; Shandas and Alberti, 2009), but few have addressed the non-linear relationships typically found between landscapes and aquatic ecosystems. In this paper, using the context of a landscape-watershed ecological condition study in Southern Wisconsin, land cover (composition) and urban patterns (configuration) relationships were explored.

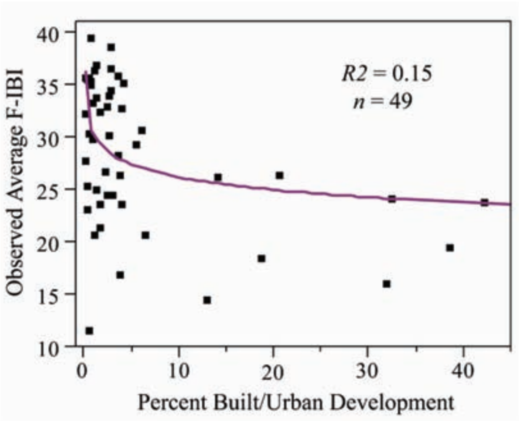


FIGURE 1
NON-LINEAR SCATTER PLOT BETWEEN WBI (AVERAGE F-IBI) AND NATURAL LOG OF PERCENT BUILT/URBAN DEVELOPMENT AT THE HUC-10 SCALE

## 2. APPROACH

For this study, it is hypothesized that urban patterns, and their associated uses, are the greatest stressors on aquatic ecological integrity in Southern Wisconsin at the watershed scale. At the watershed level, there remains uncertainty about 1) spatial and scale dependencies of ecological condition indicators and which hydrological unit scale is most appropriate for data aggregation; 2) which quantitative methods are best for investigating landscape-aquatic condition relationships; and 3) how the urban land mosaic affects hydrological ecosystems. A Watershed Biotic Integrity (WBI) score was created for two aggregation scales (subwatershed and watershed) by averaging F-IBI scores from various dated sample sites throughout a watershed. By averaging F-IBI scores to create a WBI, errors associated with spatial autocorrelation of biotic processes (e.g., dispersal or species interactions), spatial dependence from abiotic processes (e.g., deterministic structures such as canopy cover), and temporal variability are reduced. In the following, Exploratory Spatial Data Analysis (ESDA) was used to investigate watershed management scales based on spatial structure of WBI. Upon selection of the more appropriate landscape management scale, Geographically Weighted Regression (GWR), and Artificial Neural Networks (ANN) were used to examine relationships between-landscape composition and urban land configuration and- WBI as an indicator of watershed ecological condition.

### 2.1 EXPLORATORY SPATIAL DATA ANALYSIS

ESDA was performed on the spatial arrangement of the response variable (WBI) at both the subwatershed and watershed scale. ESDA is typically employed to examine the spatial patterns of areal data, such as watersheds or neighborhoods, and has been applied in many fields including crime analysis, urban systems, public health studies, and transportation planning (O'Sullivan and Unwin, 2003; Ackerman and Murray, 2004; Myint, 2008; Rybarczyk and Wu, 2009). ESDA can be classified into two groups: global and local statistics. Global spatial statistics attempt to examine the global patterns of the spatial data, while local spatial statistics highlight local variations. For this study, a common ESDA technique, global spatial autocorrelation analysis, was applied. Spatial autocorrelation is the lack of independence between pairs of observation at given distances in time and space (Legendre, 1993).

## 2.2 GEOGRAPHICALLY WEIGHTED REGRESSION

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). When investigating landscape-aquatic conditions it is essential to understand that natural systems are influenced by many different processes over space. In environmental research, spatial autocorrelation has been found to be problematic for classical statistical tests like standard least squares regression for violating the assumption of independently distributed errors for geographically referenced observations (Legendre, 1993). Further, standard errors are usually undervalued when positive autocorrelation is present and Type *I* errors may be strongly exaggerated (Legendre, 1993), especially in association with changes in spatial scale (Hawkins *et al.*, 2007). In most cases, the presence of spatial autocorrelation is seen as a significant shortcoming for hypothesis testing and prediction (Lennon, 2000; Dormann, 2007). To date, there remain few methods for dealing with non-stationarity across an entire region of study (Osborne *et al.*, 2007).

In this analysis, GWR was implemented for investigating the relationships between landscape factors and WBI. GWR is a technique, developed as a refinement to normal regression methods, to explicitly deal with spatial non-stationarity of empirical relationships (Fotheringham *et al.*, 2004). Using a Bayesian-modified linear regression technique, GWR utilizes a distance decay weighting philosophy (LeSage, 1999). The assumption with traditional statistics is that the relationship under study is spatially constant, and thus, the estimated parameters remain constant over space; however, in environmental research, most relationships vary over space. GWR assesses local influences, allowing for a spatial shift in parameters and a more appropriate fit (Wang *et al.*, 2005). Although the technique does not allow for extrapolation beyond the region in which the model was established, GWR may provide more suitable and accurate results for descriptive and predictive purposes (Foody, 2003).

## 2.3 ARTIFICIAL NEURAL NETWORKS

Many factors can influence aquatic ecosystems; many factors of which have yet to be quantified accurately. Recently, ANN has gained popularity in the natural sciences to help describe complex and non-linear relationships between environmental processes (e.g., May *et al.*, 2008; Salazar-Ruiz *et al.*, 2008; Wieland and Mirschel, 2008). ANN is a relatively new data-driven computational technique that is inspired by the neurobiology of the brain. Its methodology is designed after human and animal brain function of study, memory, reasoning, and induction (Beale and Jackson, 1998; Moore, 2000). According to Fischer and Abrahart (2000), ANN offer solutions by learning and adapting to information that is difficult to understand, incomplete, noisy, and fuzzy. ANN ability to learn and adapt is considered one of its most important characteristics (Beale and Jackson, 1998). ANN has been found to be particularly important in studies with data shortcoming (Openshaw, 1998; Fischer and Abrahart, 2000). In general, ANN operates by creating connections between processing elements (analogous to neurons in the brain). Each processing element takes many input signals, then, based on an internal weighting system, produce output signals that are sent as inputs to the other processing elements (Porwal *et al*., 2003).

The network weights are modified in a training process through a number of learning algorithms based on back propagation learning (Brown *et al*., 2003). During the learning process, it is imperative that the training and validation sets are representative of the same population. Optimally, two independent databases would be used (Lek and Gue´gan, 1999), one for training and one for validating the model (e.g., Obach *et al*., 2001). When limited data are available it might be necessary to split the available data into a training set and a validation set. A frequently used procedure is the k-fold cross-validation method (e.g, D'heygere *et al*., 2006). In this case, the dataset is equally divided into k parts and fit repeatedly k times on overlapping (k-1)/k proportions of the data. The variance of the performance results gives an indication of the robustness of the *a priori* model(s). There remains limited knowledge on the optimal k-value; therefore it is best to try out a set of combinations of k between 3 and 10. By doing so, a balance between robustness and reliability will be determined for the developed models.

A typical ANN consists of three layers: input processing elements, hidden layers, and output. The number of input processing elements (neurons) is equal to the data variables used. The number of hidden layers depends on the architecture of the network and is usually determined by trial-and-error (Samanta *et al*., 2006). In recent landscape studies, progress has been made on ANN architecture, circumventing vagueness (see Pijanowski *et al*., 2005; Lakes *et al*., 2009). ANN cannot incorporate spatial information into an analysis, so when conducting a spatial analysis it is important to couple ANN with a geographic information system (GIS). This method has been found to be a successful technique for processing and analyzing spatial information (Hosseinali and Alesheikh, 2008).

Recently, ANN has been accepted as an effective alternative tool for modeling complex and non-linear relationships in hydrological systems (e.g., Wu *et al*., 2009). Applications of ANN to various aspects of the hydrological system have provided promising results. Those studies include landslide analysis (Pavel *et al*., 2008), rainfall-runoff process (Chiang *et al*., 2007), sediment concentration estimation (Nagy *et al*., 2002), and groundwater inrush (Wu *et al*., 2009). However, applications of ANN for investigating relationships between land cover (composition) and land patterning (configuration) and aquatic ecological conditions are still limited.

## 3. STUDY AREA AND DATA

This study focuses its empirical analysis between- land cover and urban land patterns- and WBI within Southern Wisconsin, USA (Figure 2). Population growth has had a major influence on land use and land cover change, resulting in a variety of landscape patterns throughout the study area. Primarily, the mixture of landscape patterning is a result of suburban and exurban growth metabolizing and reshaping agricultural lands surrounding the two largest cities in the state: Madison and Milwaukee.

The nested study area subwatershed (HUC-12) and watersheds (HUC-10) were selected based on 427 fish sample sites, and an adjacent sampling of basins on an urban to rural to urban gradient. The fish sample sites used in this analysis are managed by the Wisconsin Department of Natural Resources (WDNR). Fish data collected over a span of four years (2001-2005) were used to calculate the F-IBI for each sample site; albeit, all F-IBI data and scores were collected and calculated by the WDNR. Due to geographical affects on speciation, the F-IBI employed is based off of John Lyons (1992) fish community research for the state of Wisconsin. Following the Wisconsin method for wadeable streams, fish samples are collected from a segment of stream with length equal to thirty-five times the mean stream width. This method is designed to, and usually does, include different habitats (Lyons, 1992). The F-IBI for Wisconsin is calculated for an individual sample from each stream segment and calibrated by comparing the observed values of each metric with values expected in comparable streams of high environmental quality (Lyons, 1992). The Wisconsin F-IBI scales between 0 and 100, with increasing scores equaling higher environmental quality. For the 427 fish sample sites used, F-IBI scores ranged from 10 (very poor) to 50 (good). As previously stated, F-IBI scores were averaged by watershed to created WBI- an overall rating of watershed ecological condition.

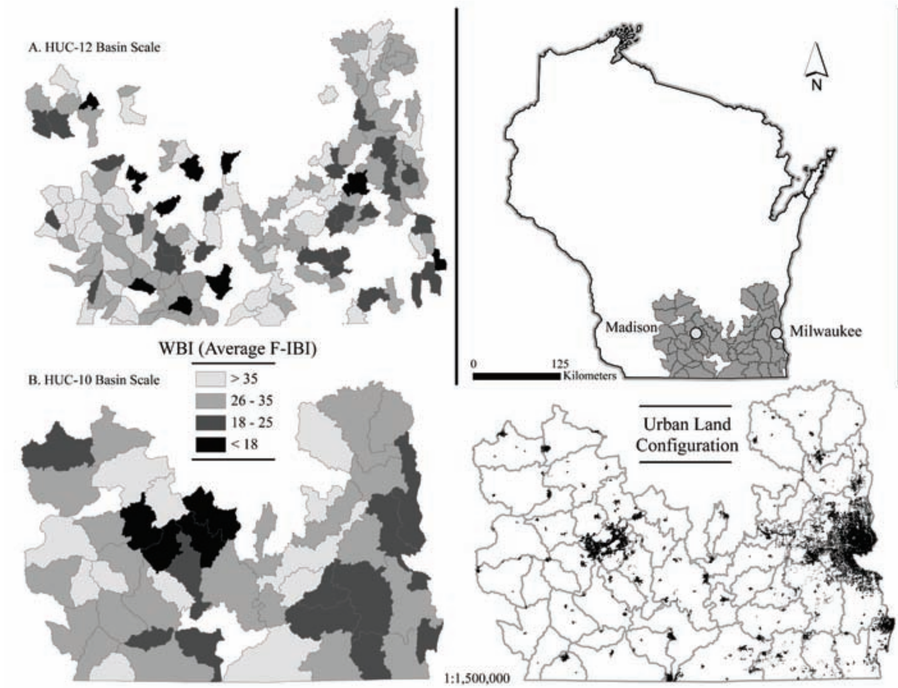


FIGURE 2
MAP OF STUDY AREA BASIN SCALES AND URBAN LAND CONFIGURATION

The study area is comprised of 136 HUC-12 subwatersheds and 49 HUC-10 watersheds with varying sizes and shapes. HUC is the acronym for Hydrologic Unit Code (HUC) and every hydrologic unit is uniquely identified through its code (2 to 12 digits) based on its scale within the hydrological system. Referred to as 5th level watersheds, the HUC-10 watersheds used in our analysis have an average size of 359 km$^2$ with a total study area of 17,600 km$^2$. The HUC-10 watersheds chosen in this analysis were published in shapefile format by the WDNR in 2002. These data were digitized by interpreting USGS 7.5-minute (1:24,000) topographic and hydrologic paper maps. Referred to as the 6th level watersheds, the HUC-12 subwatersheds used have an average size of 73 km$^2$ with a total study area of 9,934 km$^2$. The HUC-12 subwatersheds chosen in this analysis were published in shapefile format by the USDA Forest Service in 2007. These data were digitized by interpreting USGS 7.5-minute (1:24,000) topographic and hydrologic paper maps, (1:24,000) elevation Digital Raster Graphics (DRGs), and (1:24,000) digital orthophotos. The nested 136 subwatersheds and 49 watersheds should be considered as individual landscapes.

The land cover data used in this analysis was published by the WDNR in 1998 as part of a larger project for the Upper Midwest Gap Analysis Program (UMGAP) Image Processing

Protocol. The land cover data, entitled WISCLAND, is a raster representation of vegetation and land cover for the entire state of Wisconsin that was acquired from the national Multi-Resolution Land Characteristics Consortium (MRLC). The WISCLAND data was created using dual-data Landsat Thematic Mapper (TM) imagery data primarily from 1992. The original pixel size of the TM source data is 30 meters; however, excluding urban areas, patches were generalized to areas no smaller than four contiguous pixels (roughly 0.4 hectares). After processing, the data have a minimum mapping unit of 5 acres, delineating land cover features roughly 1.6 hectares in the data. WISCLAND was designed to be used between scales 1:40,000 and 1:500,000 for a wide variety of resource management and planning applications. Its land cover data is classified into a three level hierarchy modeled after Anderson *et al.* (1976) land use and land cover classification system with level one being most broad (9 classes) to level three being most detailed (30 classes). Focusing on major land cover composition and urban land patterning, and due to misclassification error being reduced at broader scales, level one was employed for this analysis.

## 4. METHOD

Before studying the landscape-ecological condition, an ideal basin scale needed to be selected. Employing ESRI's ArcMap 9.3.1 Spatial Statistics toolbox, global spatial statistic Getis-Ord General *G* was used to calculate the spatial autocorrelation of WBI across the entire study area at both the subwatershed and watershed scale. At the HUC-12 subwatershed scale, the Getis-Ord General *G* index reported 2.47 z-score standard deviation; albeit revealing that WBI has a less than 5 % chance of random spatial distribution at this basin scale. At the HUC-10 watershed scale, the Getis-Ord General *G* index reported WBI to be spatially random with a 0.71 z-score standard deviation. Due to WBI spatial dependencies at the HUC-12 subwatershed scale, the subsequent methods were conducted at the HUC-10 watershed scale.

Landscape metrics are often used in predictor analyses of ecological processes. In this analysis, major land cover (composition) and agricultural land patterning (configuration) were quantified using landscape ecology metrics developed for quantifying the spatial arrangement of land cover and land use (McGarigal and Marks, 1995; Turner *et al.*, 2001; McGarigal *et al.*, 2002). FRAGSTATS version 3.3 (McGarigal *et al.*, 2002), a free and publicly accessible software, was used for computing agricultural land pattern metrics for each watershed (see Hargis *et al.*, 1998; Leitao *et al.*, 2006). As there is no apparent causal ordering in space as there is in time, there remains no minimum set of landscape metrics for capturing the majority of landscape structure (Gustafson, 1998; Fortin *et al.*, 2003). Further, landscape metrics are highly sensitive to scale; albeit, measurement changes coming primarily from differences in data resolution and extent of study area (Turner *et al.*, 2001; Wu *et al.*, 2002). Preserving 30m resolution, four major land cover composition variables and 55 landscape urban class metrics were computed for each of the 49 watershed used in the subsequent statistical analysis.

A method is presented hereafter to assess watershed ecological condition through the combination of traditional and spatial statistics. Specifically, multivariate statistical techniques, GWR, and ANN were used to investigate relationships between 1) landscape composition and urban land configuration and 2) WBI (averaged F-IBI) at the watershed scale. The relationships between landscape disturbance factors and WBI were tested using a three-step process. To meet the assumptions of normality for all variables of parametric tests, two types of transformation were used: negative arcsine (proportion data) and log10 (length/score data). Variables comprising the final dataset were standardized using a z-transformation to set all parameters to a mean of 0 and variance of 1. Statistical software packages implemented in this analysis were SYSTAT 12, JMP version 8, and the freeware Spatial Analysis in Macroecology (SAM) version 3.1.

First, using Principle Components Analysis (PCA) and Robust Pearson correlation, urban class metrics were reduced. Metrics with strongest loadings that exhibited different patterns of orthogonal axes were selected; those metrics were then reduced further by Robust Pearson correlation to remove any metrics that exhibited a high degree of multicollinearity ($r > 0.8$). Eight urban class metrics remained to be used in the following statistical step. Second, using GWR as an exploratory tool, relationships between WBI and four major land cover composition metrics and eight remaining urban class metrics were measured. GWR was undertaken using a Bi-Square spatial weighting with optimization for minimizing corrected Akaike Information Criterion (AICc). For variable evaluation, AICc was applied as a preferred measure of model fit (see Akaike, 1978; Fotheringham *et al*., 2002). In general, the lower the AICc, the closer the approximation of the model is to reality. It should be noted that a 'serious' difference between two models is when the difference in AICc values differs by at least three (Fotheringham *et al*., 2002). Third, using k-fold cross-validation ANN, non-linear relationships were explored between urban class metrics and WBI. A 3-layer ANN model architecture of neurons- comprising of input layers, hidden layers, and one output later was selected (Figure 3). A set of *a priori* ANN models, based on the statistically significant urban class metrics, were developed. Ten cross-validation groups were selected for k-fold cross-validation for all models. As suggested by Pijanowski *et al*. (2005), the same number of hidden layers and input layers were used. Root mean squared error (RMSE) was used for measuring network performance and model comparison. Due to flexibility in ANN methods, only statistically significant urban class metrics from the GWR analysis were used in apriori ANN model development.

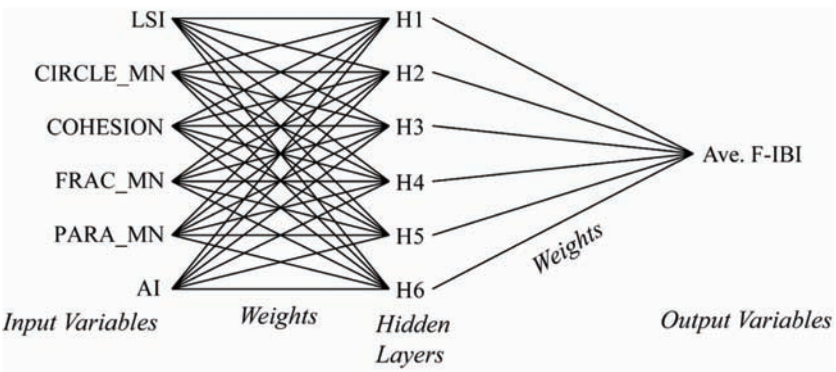


FIGURE 3
STRUCTURE OF URBAN CONFIGURATION ANN FOR PREDICTING WBI

## 5. RESULTS

### 4.1 GEOGRAPHICALLY WEIGHTED REGRESSION

GWR captured the spatial relationships between major land cover and urban pattern metrics and the indicator of watershed ecological condition, WBI (Table 1). The results of this study suggest that the urban mosaic is equally as important as landscape composition for explaining watershed ecological condition. Overall, the best land cover composition predictor of WBI was percent urban (AICc = 323.8, $R^2$ = 0.49). Landscape Shape Index (LSI), a class aggregation or urban clumpiness measure (McGarigal *et al*., 2002), was the best urban land class metric at explaining WBI (AICc = 333.25, $R^2$ = 0.43). The proportion of a watershed that is forest and wetland also proved to be statistically significant at explaining some of the variability of WBI. The urban land configuration metrics: Mean of Related Circumscribing Circle Distribution (CIRCLE_MN), Patch Cohesion Index (COHESION), Mean of Fractal Index Distribution (FRAC_MN), Mean of Perimeter-Area Ratio Distribution (PARA_MN), and Aggregation Index (AI) also proved to be statistically significant at explaining a portion of the variability of WBI. Of the six statistically significant urban class metrics, one is an urban density measure, three are urban patch shape measures, one is an urban patch connectivity measure, and one is an urban contagion/interspersion measure (McGarigal *et al*., 2002). The composition metric percent agricultural was only marginally significant ($P$-value = 0.055). The urban land configuration metrics Range of Contiguity Index Distribution (CONTIG_RA) and Standard Deviation of Related Circumscribing Circle Distribution (CIRCLE_SD) were found to be not statistically significant at explaining watershed ecological condition ($P$-value = 0.293 and 0.423, respectively).

TABLE 1
GWR BIVARIATE RESULTS BETWEEN WBI AND LANDSCAPE PREDICTORS

| GWR Rank | Predictor | AICc | $R$ Square | DF | F | $P$-value |
|---|---|---|---|---|---|---|
| 1 | % Urban | 323.8 | 0.49 | 39.82 | 4.52 | <0.001 |
| 2 | LSI | 333.25 | 0.43 | 39.19 | 3.33 | 0.002 |
| 3 | % Forest | 330.45 | 0.4 | 40.21 | 3.45 | 0.002 |
| 4 | CIRCLE_MN | 333.79 | 0.4 | 39.89 | 3.25 | 0.004 |
| 5 | % Wetland | 331.25 | 0.39 | 40.32 | 3.41 | 0.002 |
| 6 | COHESION | 333.57 | 0.38 | 40.54 | 3.28 | 0.004 |
| 7 | FRAC_MN | 334.38 | 0.38 | 39.66 | 2.85 | 0.008 |
| 8 | PARA_MN | 337.93 | 0.34 | 39.54 | 2.37 | 0.02 |
| 9 | AI | 338.39 | 0.29 | 40.13 | 2.08 | 0.031 |
| 10 | % Agland | 335.12 | 0.15 | 44.04 | 1.98 | 0.055 |
| 11 | CONTIG_RA | 334.52 | 0.05 | 45.75 | 1.09 | 0.293 |
| 12 | CIRCLE_SD | 334.98 | 0.04 | 45.92 | 0.82 | 0.423 |

## 4.2 ARTIFICIAL NEURAL NETWORKS

Highly significant non-linear relationships were found between urban land configuration metrics and the indicator of watershed ecological condition (Table 2). The results of the apriori ANN models vary between $R^2$ (adjusted) = 0.97, $P<0.0001$ for model 1 and $R^2$ (adjusted) = 0.22, $P<0.0004$ for model 5. Observed versus predicted WBI (average F-IBI) is shown for the best overall urban configuration ANN model (Figure 4).

TABLE 2
APRIORI ANN MODEL RESULTS BETWEEN WBI AND URBAN LAND COFIGURATION METRICS

| Model Rank | Independent Variables | Number of Hidden Nodes | $R$ Square Adjusted | $P$-value | RMSE |
|---|---|---|---|---|---|
| 1 | LSI, CIRCLE_MN, COHESION, FRAC_MN, PARA_MN, and AI | 6 | 0.97 | <0.0001 | 0.9852 |
| 2 | LSI, CIRCLE_MN, COHESION, FRAC_MN, and PARA_MN | 5 | 0.93 | <0.0001 | 1.8261 |
| 3 | LSI, CIRCLE_MN, COHESION, and FRAC_MN | 4 | 0.76 | <0.0001 | 3.3803 |
| 4 | LSI, CIRCLE_MN, and COHESION | 3 | 0.51 | <0.0001 | 4.8493 |
| 5 | LSI, and CIRCLE_MN | 2 | 0.22 | 0.0004 | 6.1012 |

5. DISCUSSION AND CONCLUSION

In recent landscape studies, configuration of land cover/land use has proven to be highly related to aquatic conditions (Alberti *et al*., 2007; Shandas and Alberti, 2009). Although studies like these provide detailed information for use at the landscape scale, they rarely acknowledge and address the needs of spatial data. Lennon (2000) called attention to these problems in ecological research and argued that virtually all geographic analyses had to be redone by taking into account spatial autocorrelation. Furthermore, to date, few studies have tried to model non-linear relationships between landscape predictors and indicators of aquatic condition. By investigating the non-linear relationships between urban patterns and ecological conditions, knowledge related to specific thresholds of effects can be gained. The response profile for model 1 provides insight on how urban patterns combine to relate to watershed ecological condition (Figure 5).

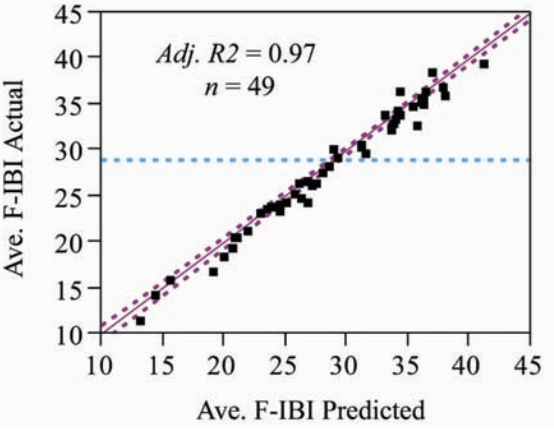


FIGURE 4
ACTUAL VERSUS PREDICTED PLOT FROM FIRST RANKED ANN MODEL

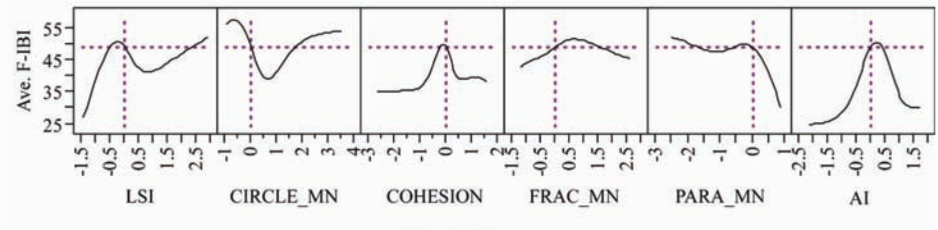


FIGURE 5
RESPONSE PROFILE OF FIRST RANKED ANN MODEL

In conclusion, this study provides an exploration of problematic phenomenon related to landscape-aquatic condition research. Specifically, spatial and scale dependencies of ecological condition indicators and quantitative methods that address non-linear needs were investigated. ESDA provided a prerequisite addendum for investigating spatial dependencies of when using ecological condition indicators. Further, by combining GWR and ANN an improved methodology for investigating non-linear relationships between landscape predictors and ecological condition was revealed. Knowledge from studies like these help determine processes that need to be modified or maintained to ensure the future of global systems.

## 6. ACKNOWLEDGEMENTS

Project supported by the US EPA/NSF/USDA STAR Watershed Program Grant No. R83-0885-010 to Northeastern University and the University of Wisconsin-Milwaukee. The findings and conclusions within are those of the author and not of the funding agencies.

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