Assessment of grass/shrub habitat fragmentation in the Whitewater Watershed using GIS and Spatial Linear Regression to model Sensitive Species Population Densities.

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Abstract

Fragmentation analysis of the Whitewater watershed, in southeast Minnessota, revealed 4 structural measures of grass-shrub habitat that were significant predictors of sensitive species population densities. Models were developed using simple linear regression and further refined to incorporate spatial autocorrelation using a Moran's test. Significant variables were divided into a five class ordinal model based on Jenks Optimization Method. Ordinal values were summed to determine an overall measure of subwatershed restoration potential. Results suggest that grass-shrub habitat should be restored in 0.6 ac patches equally dispersed about the landscape to optimize sensitive species densities.

Introduction

Geographic Information System (GIS) technology is becoming an important tool for holistic watershed management. A GIS can show what, where and even how restoration efforts should be focused. A GIS increases efficiency by giving land managers tools to answer difficult land management questions. This efficiency results in quicker implementation of management plans that can be based on quantifiable data.

Holistic watershed management is an adaptive ecosystem-based approach to resource management. It focuses on improving the health of the ecosystem as measured by the diversity of species the system supports. This approach is best carried out by those who have an interest in the system. Ideally it is a group of concerned citizens who form watershed partnerships to set goals, identify needs, pool resources and team with state and federal agencies for technical assistance. This is the concept behind the Whitewater Watershed Partnership (WWP).

The WWP was formed to improve management throughout the Whitewater watershed. The WWP has identified habitat fragmentation, flooding, sedimentation and nutrient loading as threats to biodiversity in the watershed. This project in cooperation with the WWP attempts to answer what, where and how restoration efforts should be focused to enhance biodiversity in the Whitewater watershed based on GIS and statistical analysis.

The objectives of this study are twofold. First, determine if habitat structure and sensitive species presence can be modeled in the Whitewater watershed. Second, locate high potential restoration areas at the subwatershed scale.

Study Area

The Whitewater watershed extends from near Rochester, Minnesota to the Weaver Bottoms, near the town of Weaver, where it eventually joins the Mississippi River (Figure 1). The characteristics of the Whitewater watershed are typical of the Driftless region (Hawkins 1998). Sometimes called the Blufflands region, the Driftless region is a zone of habitat transition from Eastern Deciduous Forest to Western Cornbelt which was historically tall grass prairie (Omerinik 1987, 1995). The 83,000 ha that are the Whitewater watershed change distinctly from the headwaters to the outlet. The gently sloping headwaters of the watershed, once tall grass prairie, are heavily utilized by agricultural practices ranging from family dairy farms to industrial cash crop operations.

Approximately midway through the watershed the topography changes dramatically. Steep bluff hillsides are mostly forested by mast producing hardwoods and the connectivity of the forest is occasionally broken by limestone outcroppings. The bases of these bluffs mark the start of the lower portion of the watershed. A low gradient and an expansive flood plain also characterize the lower watershed.

The habitat of the lower watershed is a matrix of wetland, prairie and forest with some intermixing on agricultural lands. Because this watershed is located in an area of transition it has habitat characteristics of both the Driftless and the Western Cornbelt regions. It has been reasoned that more complex habitats offer a greater number of potential niches and therefore should support a greater variety of species (MacArthur et al. 1962). In the Whitewater watershed, this increase in habitat equates to an increase in species as evidenced in the Natural Heritage and Nongame Research Program (NHP) sensitive species data. According to NHP data, the Whitewater watershed contains at least six species listed on Minnesota's endangered species list. Another nine species found in the watershed are considered threatened.

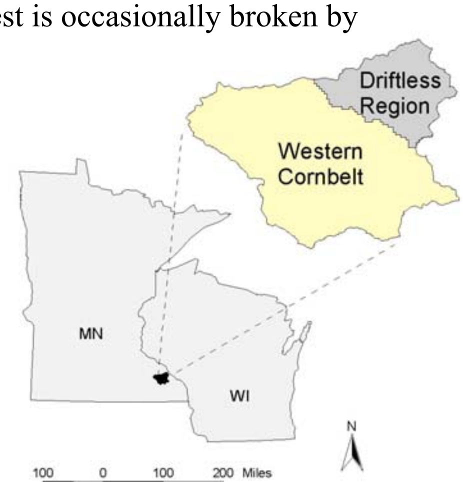

Figure 1. Location of study area

Assembly of GIS

The first step in this project was building a GIS for the Whitewater Watershed. Some data sets, like watershed boundaries, already existed and only needed to be converted into a common coordinate system. This project used Universal Transverse Mercator (UTM) Zone 15; North American Datum 1983 (NAD83). Other data sets, such as sub-watershed boundaries, were delineated on 1:24,000 scale United States Geologic Survey (USGS) topographic maps and hand digitized using ArcInfo software (ESRI 1992 c). Digital elevation model (DEM) data were obtained from USGS and converted from Spatial Data Transfer System (SDTS) format to ESRI grid coverage format. These grids were ultimately mosaiced into one data layer. Additional data sets were provided by the Natural Resource Conservation Service (NRCS), the Minnesota Department of Natural Resources (MNDNR), Environmental Protection Agency (EPA), and Minnesota Department of Transportation (MNDOT).

The final GIS was extensive and consisted of the following:

- land cover/land use
- ownership
- hydrography
- elevation
- wetland
- feed lots
- stream monitoring stations
- transportation
- political boundaries
- protected areas
- NHP sensitive species point data.

The analysis herein described does not use all of the GIS data developed for the WWP but I believe it is important to inform others that most of the data is available from the current Whitewater watershed GIS coordinator (John Cole– Whitewater WMA Rt.-2 Box 333 Altura MN 55910).

Methods

The land cover data for this study was derived via aerial photo interpretation and available at a scale of approximately 1:5,000. The available ecoregion data was much coarser and was available at an approximate scale of 1:100,000. Scale differences meant that analysis at the ecoregion level would not field much information. Instead I focused analysis at the subwatershed scale. Comparison by subwatersheds offered a repeatable analysis frame with somewhat static physical boundaries for future work in the Whitewater watershed.

Sensitive species data

The fundamental assumption of ecosystem management is that health of an ecosystem can be measured by the diversity of the organisms found using that ecosystem. While accepted in theory it is very difficult to measure in nature. Rather than attempting to quantify every organism from bacteria to mammals within an ecosystem, a more common practice among land managers is to look for indicator species. Indicator species are defined as a plant or animal species related to a particular kind of environment. Its presence indicates that specific habitat conditions are also present (USDA 2000). Indicator species are generally sensitive to certain environmental factors. In practice sensitive species are generally indicators of anthropogenic disturbances like land use changes and pollution.

For this analysis, I make the broad assumption that the plant and animal species contained in the NHP sensitive species database can be used as indicators of ecosystem health within the Whitewater watershed. I use the overall abundance of sensitive species observations rather than diversity of species as an indicator of subwatershed health. These assumptions were made because sensitive species have low populations and this methodology based on NHP sensitive species observations, allows quantitative analysis.

Sensitive species data development

A key data set used in this analysis is the database of sensitive species site locations compiled by the NHP. It contains 137 observations for animal species and 248 observations for plant species throughout the entire watershed. NHP point data are not available for public use, and I have summarized data by subwatershed for display and quantitative analysis.

The NHP data set has many shortcomings, the most significant being the data only depict locations for which species are present. This experimental design creates issues of bias such as search effort, travel patterns and site accessibility which all effect the randomness associated with these data. It is important to know which locations were studied and what was found at those locations. For locations with no data we can only wonder if species exist. Knowledge of sampling locations combined with presence-absence data would be far more helpful in determining biologic explanations for species locations. Many experimental designs such as a random block sampling provide more informative and less bias data. With the NHP data set an analyst has little alternative but to summarize observations by area and create a density. Analysis by density essentially averages out small biological variations by assuming that observations are randomly scattered within subwatersheds.

Sensitive species density data are not normally distributed for the entire watershed. After experimenting with square root, exponential and logarithmic transformations, a log transformation was found to eliminate the most skew in these density data. The original sensitive species density data and log-

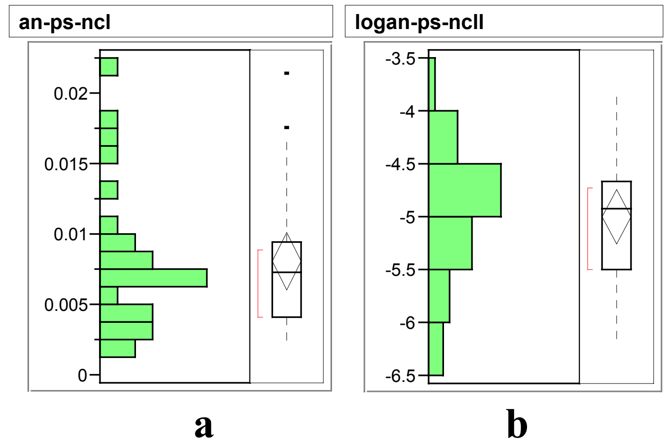

Figure 2. Distribution of population density data with (a) and without (b) log treatment applied. Headings an-ps-ncl and logan-ps-ncl represent the database attribute names for the untreated and log treated summation of plant and animal observations divided by class area.

treated density data distributions can be seen in Figure 2.

Building the GIS

Fragstats software was used to analyze 1996 land cover data (McGarigal and Marks 1994). Fragstats allows quantitative comparisons of the patch, class and landscape structural makeup of subwatersheds. Structure is the spatial relationships among the distinctive ecosystems or "elements" present—more specifically, the distribution of energy, materials and species in relation to the sizes, shapes, numbers, kinds and configurations of the ecosystems (Foreman and Godron 1986). Fragstats offers a quantifiable way to compare subwatershed structure within the Whitewater watershed. My analysis utilized the raster version of Fragstats because it offers the most versatility in processing and analysis.

Fragstats required several modifications to the land cover input data. I used ESRI ArcInfo software

(ESRI 1992 c) to prepare the GIS data for Fragstats analysis as follows.

The first processing step was to simplify land cover data to seven classes. This simplification was done because Fragstats could not process the complexity of 17 classes.

Simplification was done using ArcInfo and look up tables to collapse the 1996 land cover data into seven classes. The ArcInfo “eliminate” command was used to remove sliver polygons that were less 0.5 ac in size. The keepedge option was used to preserve coverage boundary polygons.

Proper calculation of edge indices requires data for an area larger than the evaluation unit. For the WWP work I “clipped” the landcover data to a distance of 500 meters beyond the actual watershed boundary. I then used the ArcInfo “union” command to combine land cover data with my subwatershed data layer. This created a landcover dataset that contained attributes from my subwatershed data set for subsequent data processing and analysis. This concluded the hands-on portion of data development.

A macro was developed using ESRI Arc Macro Language (AML) (ESRI 1992 a) that looped through a series of data processing steps for each of the 50 subwatersheds. The AML repeated the “buffer” and “eliminate” operations explained above and performed a series of attribute operations to calculate background data to negative values. The final processing operation was conversion of landcover data from a vector to raster format. I used a 5 m cell size to maximize data resolution. Background values were calculated to negative values and no data values were calculated to a –99 value as required by Fragstats software (McGarigal and Marks 1994).

Processing

The raster version of Fragstats needs several parameters at run time. A distance of 50 m was established for core area determination for two reasons. First, this value was often encountered in literature. Second, the 50 m value ensured that any core area in the landscape would be slightly larger than the 0.5 ac minimum patch size of my land cover data.

The edge weighting option was not used because this analysis focuses on surface strata. I chose to export landscape, class and patch level statistics to ensure scale relevant data for analysis. The resulting files were assembled into a database. Spatial data analysis used ERSI ArcView software (ESRI 1992 b). Statistical analysis used JMP software (JMP 2000). Geostatistical processing used SPlus software (SPlus 1998).

Exploratory data analysis

Each run of Fragstats produced data for approximately 50 landscape level metrics. The class level Fragstats generates a set of 40 metrics for each landcover class found in each subwatershed. Patch level data were available but not used in this project. Analysis of patch level data could be of aid to Whitewater watershed restoration planners.

Data exploration focused on determining which Fragstat variables had the greatest influence on sensitive species population densities. The majority of the literature I obtained focused analysis at the landscape level and I began there. Using log transformed sensitive species population density values as the independant variable, I used linear regression modeling for all continuous valued landscape and class level Fragstats metrics in the database. I used JMP software (JMP 2000) for simple linear regression modeling.

Spatial Autocorrelation

Classic statistical methods are based on the fundamental assumption the data are randomly and normally distributed. This assumption rarely holds true in nature. The classic bell curve of data distribution is often skewed as we see in Figure 2a. Spatial autocorrelation is commonly used to explain non-normal distribution in spatial data.

Spatial autocorrelation can broadly be defined as a property of mapped data that exhibit a pattern (Upton and Fingelton 1985). A qualitative assessment spatial autocorrelation can be quickly determined by visual inspection of mapped data.

Quantitative determination of spatial autocorrelation influence is more complex. Spatial statistical methods are built on the fundamental assumption that data which are close in physical distance are more similar than those data which are more distant.

Several statistical packages now interface with GIS to aid in analysis of spatial autocorrelation. For this project I used SPlus Spatial Statistics Extension (Splus 1998) in conjunction with ArcView 3.2 (ESRI 1996 b) GIS software.

Visual analysis of the WWP Fragstat indices found patterns of data values indicating potential presence of spatial autocorrelation. Quantitative analysis of autocorrelation influence was explored by using a contiguous neighbor matrix as a weighting function for a Moran's test (Moran 1948). A Moran’s test has the null hypothesis of no spatial autocorrelation (Equation 1). Upton and Fingleton (1985) suggest that it is sometimes easier to understand spatial autocorrelation by understanding where it does not exist.

Incorporation of spatial influence in a regression model can improve the predictive powers of that model. If spatial autocorrelation is found to be present in a dataset it can be accounted for in a spatial linear regression model (SLM). A SLM accounts for unexplained variance in the non-spatial model by incorporating the information present in the Moran’s test during regression.

Equation 1.

Moran’s I

$$I = \frac{n}{\sum_{i=1}^{i=n}\sum_{j=1}^{j=n} W_{ij}} \bullet \frac{\sum_{i=1}^{i=n}\sum_{j=1}^{j=n} W_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{i=n}\left(x_i - \bar{x}\right)^2}$$

Where:

W_{ij} is neighbor matrix
n is total number of polygons.
i current polygon
j is neighbor polygon

Spatial Ranking of Watersheds:

The final goal of this project was to determine where to focus restoration efforts in the watershed. To answer the question I used ArcView’s natural breaks data classification to create an ordinal score per evaluation unit for each WWP Fragstat variable that was found

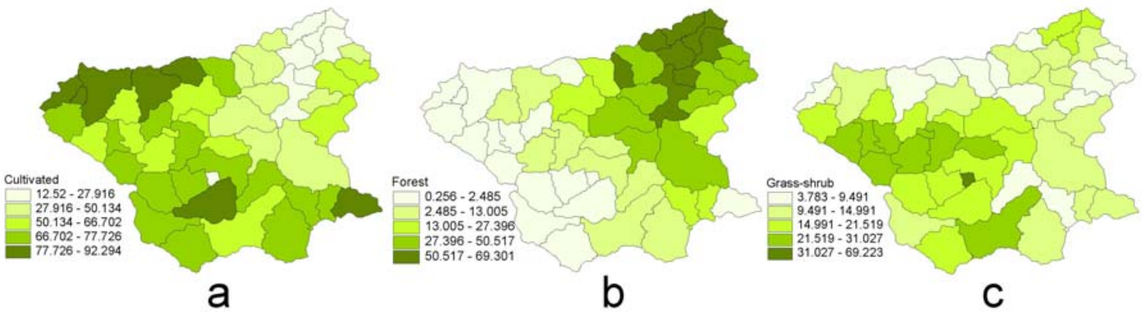

Figure 3. Class percentage of subwatershed.

to be significant predictors of NHP sensitive species population densities. The natural breaks classification system is based on Jenk's Optimization Method which uses statistical standards of deviation to group data (Jenks 1971). I broke each metric into five classes. Negatively correlated variables were inversely ranked. The final model had four variables with a possible subwatershed sum ordinal value of 20. Higher values were more conducive to sensitive species population density. Finally, a composite score was calculated for each subwatershed by summing all the ordinal scores for each metric. These data were then displayed using ArcView software.

Results

Analysis of Fragstat metrics at the landscape level proved to be fruitless. After much trial and error I decided that any landscape level analysis would need to be qualitative rather than quantitative. Linear regression models were generally powerless to predict sensitive species densities at the subwatershed scale in the Whitewater watershed. I believe that landscape level analysis of landcover data using Fragstat metrics is not appropriate because of issues of scale. A subwatershed is not a large enough evaluation unit to observe landscape level change. I found Fragstats class level metrics to be more meaningful in the determination of sensitive species populations.

I examined class level metrics next. Class heterogeneity from subwatershed to subwatershed was troublesome. Although the original landcover data had 17 classes, cultivated, forest and grass-shrub habitat types encompassed more than 70% of the Whitewater watershed after simplification. As depicted in Figure 3, forest, cultivated land, and grass-shrub could be found in all 50 subwatersheds.

Figure 4. Subwatersheds with NHP data.

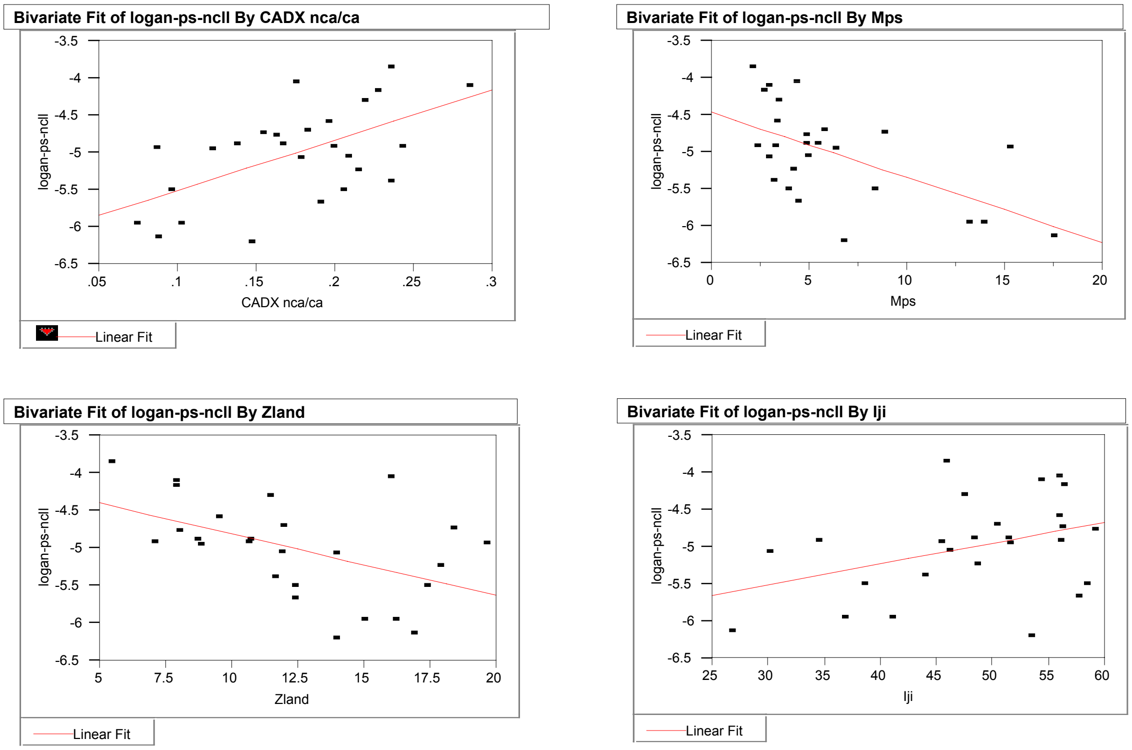

Figure 5. Linear regression plots

Grass-shrub habitat containing NHP data were restricted to the 26 adjacent subwatersheds located in the lower portions of the Whitewater watershed (Figure 3c). The spatial distribution of NHP data observed on grass-shrub habitat (Figure 4) was very similar to the morphologic extent of the Driftless Region as depicted in Figure 1. This relationship warranted further exploration.

I tested each Fragstat metric for significance in predicting sensitive species population density using simple linear regression. These tests were performed on all class level data pooled and grouped by land cover type. The strongest linear relationships for sensitive species population density were found among the grass-shrub class Fragstat metrics. Because NHP observed on grass-shrub habitat were only found in 26 subwatersheds, I created a new dataset that contained only variables for these subwatersheds.

Simple linear regression with data from this subset of watersheds found four class level Fragstat metrics that were indicitative of sensitive species population density. Linear regression scatter plots can be seen in Figure 5. Fragstat variables were as follows (McGarigal and Marks 1994):

- A modified core area density (CADX)
- Class area as a percentage of the landscape (Zland)
- Mean patch size (MPS)
- Interspersion juxtaposition index (IJI)

Model A Table 1 – Found a positive relationship between the log transformed sensitive species population density and the core area density (CADX) of a subwatershed. The CADX variable is a slight modification from the standard CAD class variable found in Fragstats literature. Core area density is the number of core patches divided by

Table 1. Linear regression models

	Model	β_0	y_o	r^2	t	*p*	n
	Log(an-ps-ncll) ~ CADX	6.76	-6.19	0.34	3.50	0.002	26
B	Log(an-ps-ncll) ~ MPS	-0.09	-4.47	0.34	-3.49	0.002	26
C	Log(an-ps-ncll) ~ ZLAND	-0.08	-3.99	0.25	2.82	0.010	26
D	Log(an-ps-ncll) ~ IJI	0.03	-6.37	0.16	2.12	0.050	26

100 ha. (McGarigal and Marks 1994). The CADX variable is the number of core patches divided by the total class area of the subwatershed. I found this metric to be more representative value for core area density in subwatersheds that varied in size.

Model B Table 1 – Found a negative relationship between the log transformed sensitive species population density and a subwatershed's mean patch size (MPS).

Model C Table 1 – Found a negative relationship between the log treated sensitive species population density and the percentage of a landscape composed of grass-shrub habitat (ZLAND).

Model D Table 1 - Found a positive relationship between the log transformed sensitive species population density and the interspersion and juxtaposition index (IJI). The IJI metric is a measure of class dispersion in an evaluation unit. Higher values represent more even spatial interspersion of similar class patches. The interspersion index is a relative index that represents the observed level of interspersion as a percentage of the maximum possible given the total number of patch types (McGarigal and Marks 1994).

Spatial autocorrelation

Visual analysis of GIS mapping of subwatershed values of class variables showed some spatial clustering. This visual evidence of spatial autocorrelation warranted investigation. The modeled variables were tested for spatial autocorrelation using a first order adjacent edge matrix and Moran's test. Results in Table 2 show a significant spatial autocorrelation influence exists

Table 2. Moran's test results for regression variables.

Variable	Correlation	*p*
CADX	0.320	0.006
MPS	0.335	0.007
ZLAND	0.139	0.073
IJI	0.053	0.231

for core area density (CADX) and mean patch size (MPS). Moran's test has a null hypothesis of no spatial autocorrelation. Statistically interpreted, there is a 99% probability that spatial autocorrelation exists in the subwatershed values for CADX and MPS Fragstat metrics. Class percentage of the landscape (ZLAND) and interspersion juxtaposition index (IJI) have a 93% and 77% probability of having a spatial autocorrelation influence, respectively.

The Moran's test results in Table 2 suggest a spatial autocorrelation presence exists for the variables used to develop the linear regression models in Table 1. Since spatial autocorrelation was found to exist in our model variables investigation of aspatial linear

Table 3. Results for residual Moran's test.

Variable	Correlation	*p*
$(CADX_R)^2$	0.322	0.001
$(MPS_R)^2$	0.242	0.003
$(ZLAND_R)^2$	0.205	0.001
$(IJI_R)^2$	0.190	0.011

regression model residuals was warranted. Residuals from each model were extracted and mapped (Figure 6). Visual analysis of mapped residuals reveals some presence of spatial autocorrelation for each model variable. A Moran's test was performed on these residuals to quantify the spatial autocorrelation influence on the proposed model residuals from Figure 1. Residual values were squared to ensure positive values for the residual Moran's I testing. The results of the residual Moran's I test are provided in Table 3.

A quick glace down Table 3 reveals that the Moran's I test determined almost 100% probability that spatial autocorrelation was present in the squared residual values for models A, B and C from Table 1. The interspersion juxtapostition index (IJI) model residuals were found to have a 99% probability that spatial autocorrelation was present.

Since spatial autocorrelation was found to be present in these data, I decided to develop a new set of models using spatial linear regression (SLR). SLR simply removes the influence of spatial autocorrelation from the linear regression model. Table 4 shows the spatial linear regression models. All four SLR models show significant power in determining sensitive species densities in the Whitewater watershed. The *p* values ranged from 0.01 to 0.04. Stated another way, there is at least a 96% chance that the relationships stated in each model are not due to random chance.

Model H was found to be the strongest predictor of sensitive species densities with an $r^2 = 0.96$. Model F was found to be the weakest with a $r^2 = 0.74$. Comparisons between the linear regression Table 1 and spatial linear regression models in Table 4 can be made. For example, 58% of the variability for Model A was due to spatial autocorrelation. This value was determined by subtracting the Model E r^2 value (0.92) from the Model A r^2 value (0.34).

Analysis

Spatial Model

For analysis purposes I will only discuss the models found in Table 4 because they are progressions of the Table 1 models. These models did not always turn out as I expected but generally there is a biological explanation for the model. These models are only as good as the data they are based on. In addition, I issue the standard warning that these models are only valid for the range of data values for which they were created.

Table 4. Spatial regressive models.

	Spatial Regressive Models	β_1	y_0	r^2	t	p	**n**
	Moran.Log(an-ps-ncll) * Moran.CADX	6.72	-6.18	0.92	3.54	0.002	26
F	Moran.Log(an-ps-ncll) * Moran.MPS	-0.09	-4.49	0.74	-4.00	0.001	26
G	Moran.Log(an-ps-ncll) * Moran.ZLAND	-0.08	-3.97	0.90	-2.82	0.010	26
H	Moran.Log(an-ps-ncll) * Moran.IJI	0.03	-6.42	0.96	2.18	0.040	26

Extrapolations of these models are not recommended.

Model E suggests that the greater the number of grass-shrub core habitat patches (CADX) within a subwatershed, the greater the density of sensitive species observed in that subwatershed. The CADX Fragstat metric is very useful in determining fragmentation in a landscape (McGarigal and Marks 1994). Extremely fragmented landscapes can have a high patch density but will generally have a much lower core area density value because many small patches lack a core area. In this analysis a grass-shrub patch had to be at least 2,500 m^2 to contain a core area. Grass-shrub core areas are statistically important for sensitive species densities in the Whitewater watershed, however the 2,500 m^2 patch size appears to be a threshold for patch size according to Model G.

Model G suggests the greater the percentage of grass-shrub habitat in a subwatershed the lower the number of sensitive species in that subwatershed. This model is alarming. How can density of grass-shrub core patches be an important positive predictor of sensitive species population density and the percentage of grass-shrub habitat in a watershed be a negative predictor of sensitive species population density? I do not know if I can fully answer this but the data are statistically significant and interesting.

If Model G is truly linear, then extrapolation would dictate that sensitive species densities would be at their highest values when no grass-shrub habitat existed in a subwatershed. Although we cannot test this, it seems unlikely because of the 26 subwatersheds that contain NHP data only 2 subwatersheds lack sensitive species observations occurring on grass-shrub habitat. These values suggest that a relationship exists between presence of grass-shrub habitat and sensitive species populations.

Experimentation with various non-linear models revealed nothing to improve Model G. Visual analysis of the scatter plot for Model C, Figure 5, reveals a sharp decline in sensitive species population density when grass-shrub habitat is between 11% and 18% of the landscape. The WWP data offer no opportunities of determining if this is a random effect or an actual threshold response from sensitive species to the percentage of grass-shrub habitat in the landscape. Because the WWP study is so general, I suspect the former explanation, but more data from a wider

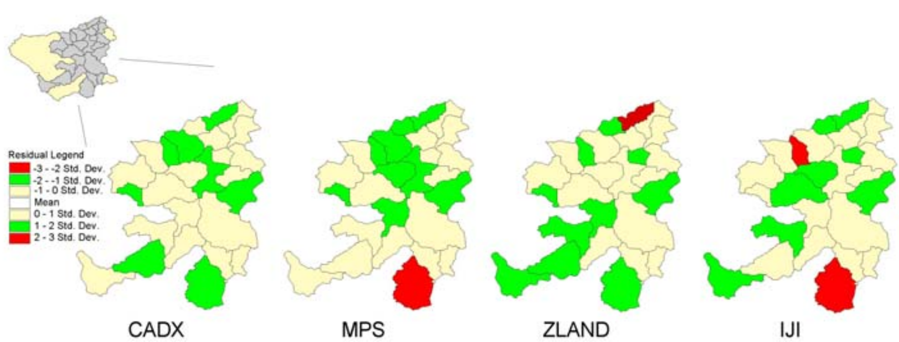

Figure 6. Spatial mapping of residuals from simple linear regression models.

array of grass-shrub habitat compositions would certainly be needed for a conclusion to be reached. This leaves me with little alternative but to conclude that this model can only be linear for the range of values for which we have grass-shrub percentage of the landscape data.

Model F suggests that the larger the average grass-shrub patch size, (MPS) the lower the subwatershed sensitive species population densities. Again, this model seems to be counterintuitive, but I believe it to be valid for the range of data collected. Like Model G, I struggle to find a reasonable explanation for the negative correlation of MPS with sensitive species density. I believe the answer is a fundamental rule of ecology. Much as literature has stated for years, more complex habitats have greater species densities. I believe Leopold (1933) is credited for first noting that wildlife diversity is greater in more diverse landscapes. His observations have been more eloquently stated: "*The relationship between vegetation structure and animal community organization has received extensive empirical examination. It has been reasoned that more complex habitats offer a greater number of potential niches and therefore should support a greater variety of species*" (MacArthur et al. 1962). Following MacArthur, larger MPS equates to less complex landscape. Take two theoretical subwatersheds with a fixed amount of grass-shrub habitat. Arrange one with a few large patches and the other with many small patches. The subwatershed with a greater number of patches offers more habitat complexity and therefore should contain a greater variety of species. It should be observed that this example also explains Model E. Model E suggests the greater the number of grass-shrub core habitat patches within a subwatershed the greater the density of sensitive species observed in that subwatershed.

The final model in Table 4 is H. Model H suggests the more evenly dispersed grass-shrub patches are within a subwatershed the higher the density of sensitive species populations within that subwatershed. I find this model interesting because the effects of habitat fragmentation are very species specific.

Early wildlife management was based on the theory that increased edge habitat increased species diversity (Leopold 1933). More recently it has been noted that increased edge habitat is detrimental to many species (Kroodsma 1982; Sanders, Hobbs and Margules 1991). However, most fragmentation studies are landscape level studies designed to study forest fragmentation. According to Model H, even dispersion of grass-shrub patches equates high sensitive species density. Leopold and MacArthur can explain Model H in that even dispersion of grass-shrub habitat translates to greater diversity of habitat. It could be further argued that even dispersion of grass-shrub habitat offers important connectivity to forest habitat. Many ecologists observe a positive relationship between vertical habitat complexity and species diversity (MacArthur and MacArthur 1961; Recher 1969). Vertical habitat can be considered the number of strata within a habitat. While forest offers more vertical complexity than grass-shrub habitat, the later offers more vertical complexity than cultivated land. Visual analysis of Figure 3 shows that cultivated land is less prevalent in the subwatersheds that contain grass-shrub

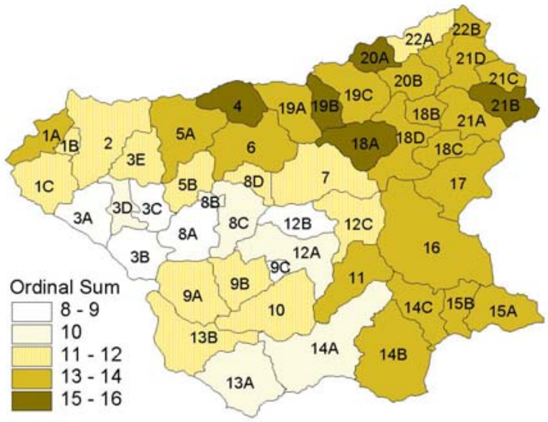

Figure 7. Sum Ordinal model.

habitat. I conclude that Model H makes biological sense and provides statistical evidence to support GIS modeling of Whitewater subwatershed restoration efforts in an attempt to spatially place restoration areas uniformly about the landscape.

Ordinal Model

Analysis of the sum ordinal model in Figure 7 reveals that subwatersheds 4, 18A, 19B and 21B have the best mix of grass-shrub habitat according to our models. Subwatersheds 3A, 3B, 3C, 8A, 9C and 12B are the most in need of restoration. All of these subwatersheds have a high percentage of grass-shrub habitat. Restoration of grass shrub habitat would further decrease the Ordinal Model sum values. According to the models in Table 4, MPS and ZLAND are negatively correlated with sensitive species density. Therefore a high ordinal ranking translates to a low Fragstat metric value. Identification of subwatersheds suitable for restoration through introduction of grass-shrub habitat must start by identifying which subwatersheds have the lowest percentage of grass-shrub composition resulting in high ZLAND ordinal score. Visual analysis of the Figure 8. plots shows many high scoringsubwatersheds. A GIS query for high ZLAND ordinal score and low sum ordinal score results in three high potential restoration candidates. Subwatersheds 1B, 2 and 13B are the best candidates.

Further analysis of the Ordinal Model can refine restoration focus. Subwatersheds 1B, 2, and 13B all received a MPS ordinal value of 4. All 3 of these subwatersheds have moderately low MPS fragstat values in comparison

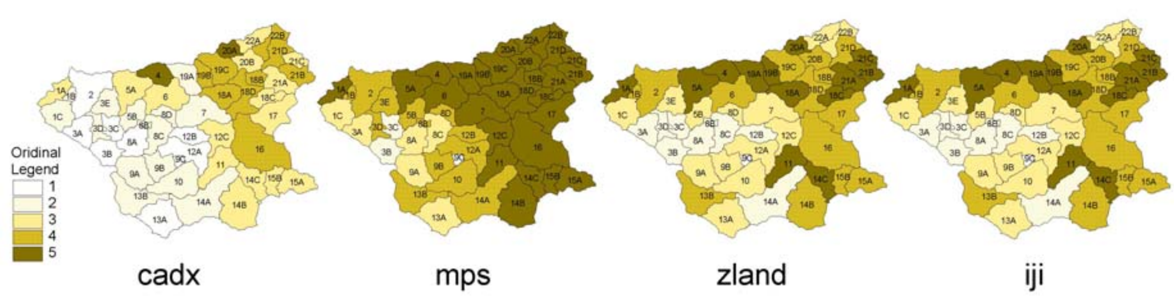

Figure 8. Spatial displays of ordinal values.

with other subwatersheds in the Whitewater. These 3 subwatersheds have very little potential for restoration by manipulation of grass-shrub habitat patch size.

Analysis of the CADX variable is more interesting. Subwatersheds 1B, 2, and 13B had ordinal CADX values of 2, 1 and 2. These subwatersheds, subwatershed 13B in particular, have good potential for restoration by increasing the grass-shrub core area density in accordance with the models listed in Table 4.

Analysis of the IJI variable is also interesting. Subwatersheds 1B, 2 and 13B had ordinal IJI values of 2, 3 and 2. Subwatersheds 1B and 13B would benefit from more even spatial distribution of grass-shrub habitat patches in accordance with the models listed in Table 4.

To summarize, subwatersheds 1B and 2 are very similar and restoration efforts for these 2 subwatersheds should be focused on increasing core area density and interspersion of both new and existing grass-shrub habitat. According to the proposed sensitive species models subwatershed 2 has less restoration potential than subwatersheds 1B and 2. Restoration efforts for subwatershed 2 should be focused toward increasing core area density of both new and existing grass-shrub habitat.

For all three subwatersheds suitability would be enhanced by increased habitat complexity. Introduction of other habitats like forest would increase habitat complexity but, as discussed earlier, this type of restoration would be costly. Forest restoration would take generations to enhance habitat and the cost is prohibitive. I conclude that restoration for these subwatersheds should be focused on introducing small, 0.6 acre, grass-shrub patches uniformly across the landscape.

Conclusion

I believe these four models suggest that rehabilitation efforts in the Whitewater watershed should follow some general guidelines. First, grass-shrub habitat should be introduced in subwatersheds where it is currently limited.

Grass-shrub habitat was found to be the most important habitat for predicting sensitive species populations in the Whitewater watershed. Grass-shrub habitat can be restored. Plantings become established in months as opposed to generations needed to restore forests. Finally, federal NRCS programs like the Conservation Reserve Program (CRP), buffer strip initiative, and Wetland Reserve Program (WRP) are established to provide assistance and monies for grass-shrub restoration efforts.

These models suggest that more is not always better. Models indicate that an even distribution of 0.6 ac (2500 m^2) grass-shrub core areas offers the best possible habitat to enhance sensitive species density in the Whitewater watershed. This WWP project used GIS to locate high potential restoration locations at the subwatershed scale. One finding of this project is that uniform spatial positioning of grass-shrub habitat is important in predicting sensitive species populations. Future work in the Whitewater watershed should focus restoration planning at the patch level. GIS is an important tool in locating these patches for site specific restoration efforts.

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