Application of GIS and Land Use Models - Artificial Neural Network based Land Transformation Model for Future Land Use Forecast and Effects of Urbanization within the Vermillion River Watershed

Olaniyi Oyebode
Department of Resource Analysis, Saint Mary's University of Minnesota, Minneapolis, MN 55404

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Abstract

The Vermillion River Watershed is an important natural and economic resource for Dakota County, Minnesota due to its scenic beauty, water quality, and recreational opportunities. As the county continues to develop, the watershed is also undergoing rapid urbanization as a result of land use changes. Land use changes result from complex interactions of many factors including policy, management, economics, culture, human behavior, and the environment (Pedlowski, et al, 1993). Understanding land use change is critical since these anthropogenic processes can have broad impacts on the environment. This project illustrates how combining a geographic information system (GIS) and artificial neural networks (ANNs) can aid the understanding of land use change and the effects of watershed urbanization on stream flow characteristics. Historic land use maps and other spatial data layers (drivers) along with ANNs and stream gauge records to assess stream flow changes. During the period of 1990 – 2000, urban land use increased from 9% to 13% within the vermillion watershed. Assuming all driving factors remain the same, the urban land use will be 26% by year 2010. Between the period of 2000 and 2006, median and minimum daily discharges, total volume runoff and flood magnitude in the Vermillion River north creek subwatershed increased moderately.

Introduction

Study Area

Vermillion River Watershed occupies the central part of Dakota County located in the southern part of the Saint Paul and Minneapolis metropolitan area of Minnesota as shown in Figure 1. This watershed is home to five cities as well as several townships spread throughout thousands of acres of farmland. It is an important and major tributary to the Mississippi River.

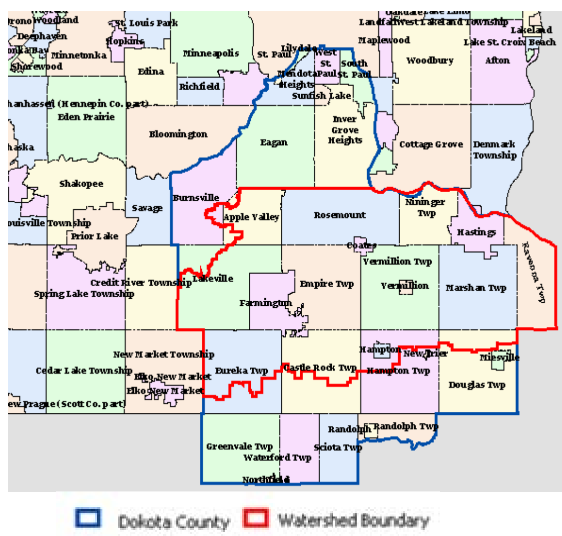

Figure 1. Vermillion study area.

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Vermillion River Watershed

The Vermillion River watershed is one of the largest watersheds in the Twin Cities (Minneapolis/Saint Paul) metropolitan area. The river begins in the southeastern part of Scott County, and flows through the central part of Dakota County to the city of Hastings. Previous research conducted on the Vermillion River in the early 18th century indicated that this area was a vast coverage of prairie, oak trees, and other timbers coupled with a network of clean flowing rivers and streams (Riggs, 2002).

During this period, people who made their homes along the Vermillion River and its surrounding area appreciated the area's fertile soils and its natural native to small streams, creeks, lakes, and spring ponds; additionally, farmers grew various crops such as wheat, corn, oats, barley, and potatoes along the Vermillion River (Riggs, 2002).

Population figures from previous research shows that there is a tremendous change around the Vermillion River. In 1900, more than half of Dakota County's population lived in rural areas. Twenty years later, the population figure dropped to less than 40 percent (Riggs, 2002). World War II also has significant effects on farming activities and the communities in this study area. Previous research indicated that in the early 1940s, the U.S. government acquired more than 11,000 acres of land in the city of Rosemount to build Gopher Ordnances powder plant (Riggs, 2002).

After the war, some of the communities near the Vermillion River lost additional farmland as Twin Cities resident moved farther south. Farms gave way to residential and commercial development. In 1960, Dakota County's population was 78,303; by 1998, the population was 339,256. By 2020, the Twin Cities Metropolitan Council projects that Dakota County's population will exceed 456,000 (Riggs, 2002).

Generally, it was inferred that over 150 years, the areas near Vermillion River have tremendous changes from prairie, oak trees, and forests to farmland and towns. Farmland, however, still dominates much of the area, with increasing urban landscapes that is made up of streets, highways, and bridges. As land use/land cover near the Vermillion River changes, so too has the river.

Because of drastic changes in land use as a result of urbanization, there is a greater need to forecast future land use based on past historic land use data so that stakeholders, engineers, and planners can better understand what planning efforts should be made as development continues in the area (Figure 2).

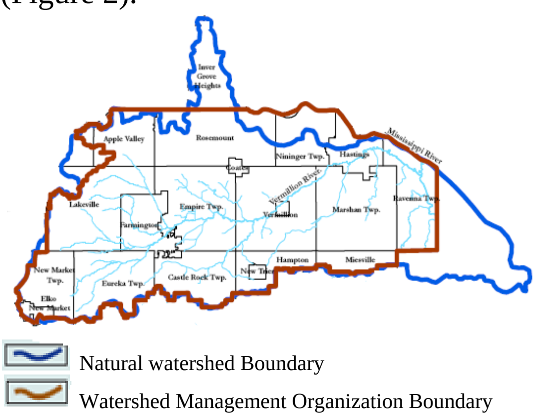

Figure 2. Management boundaries within Vermillion River watershed.

The process of land use planning adopted the use of the Land Transformation Model (LTM), which couples geographic information systems

(GIS) with artificial neural networks (ANNs) to forecast land use changes.

GIS and LTM

The value of the LTM regression-type model is that the relative contribution of different variables for predicting a given land use change is easily obtained. Because of the spatial nature of many of the input variables, integration with GIS is essential. GIS will be used to manage and analyze spatially explicit data associated with the model. For example, GIS will be used in building input variables for the model, identifying spatial pattern in data (Openshaw and Clarke, 1996) and quantifying observed and/or predicted temporal changes in spatial pattern (de Koning et al., 1999).

The Land Transformation Model, based on Artificial Neural Networks (ANN) was designed to emulate the functionality of biological neurons in order to achieve a higher parallel processing potential for digital data. ANNs are a branch of information science that is classified as “machine learning algorithms.” There are many different types of ANNs. The multi layer perception (MLP) neural net described by Rumelhart et al. (1986) is one of the most widely used ANNs, which will be adopted for this research. MLP consists of three different layers: input, hidden, and output. The MLP allows a computer to develop the best possible fit between input vectors.

ANNs are used to learn the pattern of development in the area and test the predictive capacity of the model. The LTM follows four steps:

1. Processing of data to create spatial layers of predictor variables; inputs are generated from a series of spatial layers that are stored and managed within GIS. These base layers represent land use (such as agriculture parcels and urban areas) or features in the landscape (e.g. roads, rivers, lakes). Grid cells are coded to represent predictors as binary (presence =1 or absence = 0).
2. Applying spatial rules that relate predictor variables to land use transitions for each location in the area; there are four classes of transition rules in ANN: (1) neighborhoods; (2) patch size; (3) site specific characteristics; and (4) distance from the location of a predictor cell. The choice of rules depends on the individual involved and the study area. Neighborhood effects are based on the premise that the composition of surrounding cells has an effect on the tendency of a central cell to transition to another use. Patch sizes relate the variable values of all cells within a defined patch (e.g. parcel) to the likelihood of land use transition. Site-specific characteristics are values assigned to a cell based on characteristics specific to each grid cell. The distance spatial transition rule relates the effect of the Euclidean distance between each cell and the closest predictor variable. Certain locations are coded so that they do not undergo transitions; this is necessary for areas within the study area where development is prohibited, such as parks and water. These cells are coded with a “0” if a transition cannot occur; all other locations are assigned a

"1." All such layers are then multiplied together to generate one single layer of "exclusionary zones."

3. Integrating predictor variables; there are three different types of integration methods: multi-criteria evaluation (MCE), ANNs and logistic regression (LR). In this research, all input grids were integrated using ANN, the cell size was set to 100 x 100 m and the analysis window to a fixed base layer – Vermillion River watershed boundary.
4. Temporally indexing; this is the amount of land that is expected to transition to urban over a given time period. This was determined using a "principle index driver" (PID). This involved calculating the amount of area that underwent transition to urban use based on analysis of historical land use data. Future projections will be made for each 10 year time step by assuming that the same number of cells will transition to urban in each 10-year period as in the observed 10-year period.

Methods

Data Sources

The land use database was obtained through MetroGIS Datafinder, which is a site for discovering geospatial data pertaining to the seven counties in Minneapolis-St. Paul Metropolitan Area. The 1990 land use layer consisted of a rectified 1990 air photo, mylars showing 1980 and 1984 land use delineations (scale of 1:9600), and county parcel data with assessors attributes indicating various land use type information; furthermore, a 2000 land use layer was developed from 2000 digital orthophoto quarter quads (0.6 meter resolution). This layer was delineated from 1997 land use and county parcel data with assessor attributes indicating various land use type information. These land use layers were classified using the Anderson land use/land cover classification system (Anderson et al., 1976).

This system was aggregated to 6 super classes – urban (residential, industrial & commercial), agriculture/forest, highways, shrub/undeveloped, water and parks/recreations. Other spatial layers such as county roads, highways, rivers, lakes and parks were obtained from Dakota County. Annual discharge statistics were derived from daily mean discharge records ($ft^3 S^{-1}$) for the Vermillion River Watershed north creek gauge, which was obtained from the Dakota County Soil and water Conservation District (SWCD).

GIS-Based Predictor Variables

Forecasting models predict the future values of a series using two sources of information: the past values of the series and the values of other time series variables. Other variables used to predict a series are called predictor variables (SAS/ETS User's Guide, 1999). A predictor variable is a variable used in regression to predict another variable. It is sometimes referred to as an independent variable if it is manipulated rather than just measured.

Five predictor variables and the exclusion zones were calculated and stored as separate Arc/Info grids using the GIS interface; the method of calculating them is summarized below and illustrated in figures 3a-f:

Transportation: The distance from each cell in the region to the nearest highway and county roads was calculated and stored. These two grids represent the potential accessibility of a location for new development. These features serve to improve the access of the site to larger urban areas.

Landscape features: The distance from lakes and rivers was also calculated. Cooper et al. (1997) has found that landscape topography is an influential factor contributing toward residential use

Urban services: The urban distance variable was the minimum distance of each cell to the nearest urban cell from the 1990 historical land use, and was calculated and stored as a separate grids. It was assumed that the cost of connecting to current urban services decreases with distance from urban areas.

Exclusionary Zones: The exclusion zone for this research work was composed of the following GIS layers: areas that were urban in 1990 (existing urban areas); locations of open water; locations of parks within Vermillion River watershed were restricted as being areas of non-development.

In Figures 4a-f, the distance refers to the Euclidean distance, which is the straight line distance to the spatial layers of predictor variables from the mask layer (the boundary polygon of the study area). The legend areas of “high” approach distances ranging between 33,430.7 and 8,285.5 feet while the areas of “low” approach distances of 0.0 feet.

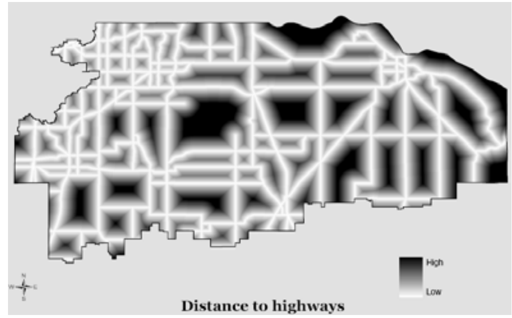

Figure 3a. Distance to major highways.

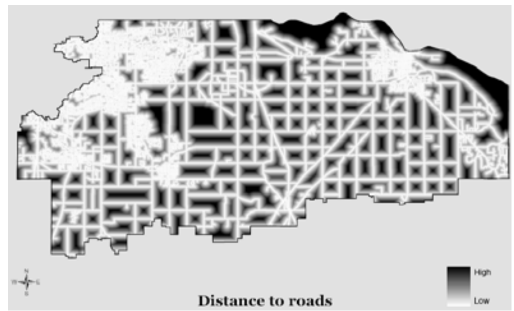

Figure 3b. Distance to roads.

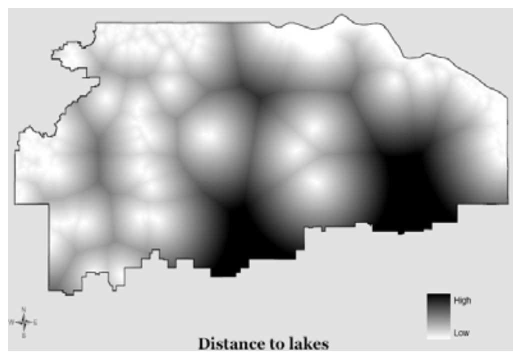

Figure 3c. Distance from lakes.

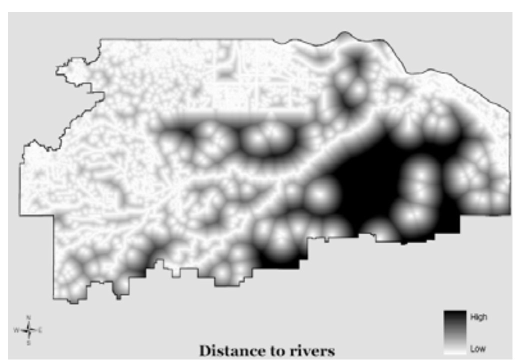

Figure 3d. Distance from rivers.

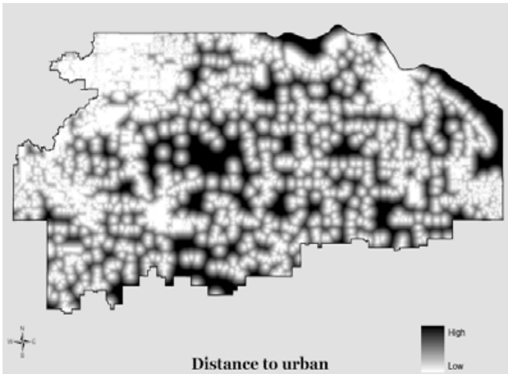

Figure 3e. Distance to urban areas.

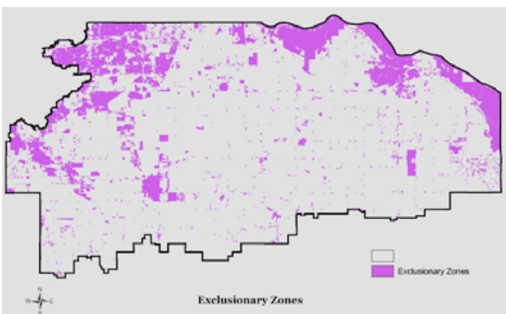

Figure 3f. Exclusionary Zones within the study area. These areas are restricted and are not to be impacted by development.

Procedures

Analysis involved the following sequence:

1. Gather all available data including roads, rivers, lakes, highways, county boundary, Vermillion River watershed boundary, parks/open spaces and historical land use data for 1990 and 2000.

2. Re-project all required data on the fly into the Dakota County geographic coordinate systems MN Dakota Lambert Conformal Conic - (UTM NAD83).

3. Use Spatial Analyst to calculate the straight-line distance from each cell in the study area to the nearest spatial features such as roads, lake, rivers, highways and urban for the year 1990; the outputs are refered to as predictor variables or drivers.

4. The land use data from 1990 and 2000 were converted from features to raster; the following layers were then reclassified: urban = 1 and the remaining data (agriculture/forest, parks, undeveloped, highways and water) = 0; they are named as “landusebase” and “landusefinal” respectively.

5. The output layers in step 3 above were converted to ASCII files by selecting the raster to ASCII option of Conversion Tools in ArcToolbox as observed in Figure 4.

Figure 4. Raster to ASCII process.

All the generated outputs were stored in the same folder that contain all the LTM executables files.

6. Each of the two outputs, landusebase and landusefinal from step 4, were reclassified to restrict certain portions of the datasets from the analysis. This restricted data was not included in the analysis. In this research, such cells were reclassified as 4, while the rest of the data was assigned a value of 0. In these datasets, urban, water, parks/open spaces areas, and no data in 1990 were excluded as areas that will not be allowed to be urbanized in the future. The output was named RE_LU_1990. Since ANN ‘learns’ from land use from 1990 to 2000, landusefinal water, parks, and no data were reclassified as 4, while urban (to avoid being re-urbanized) and the rest of the data were assigned a value of 0, and it was named RE_LU_2000. The

two output layers above – RE_LU_1990 and RE_LU_2000, contained values which were added in spatial analyst. The calculation output was then reclassified again. The output grid contained cell values of 4 and 8 and were reclassified as 4 while cell values of 0 were assigned a value of 0. The final output was then converted to an ASCII file with the aforementioned ASCII conversion model. The ASCII file generated in tabular format was used as input for the neural network application.

Implementing the LTM

The LTM was used to project patterns of urban land development in the year 2000 using ANNs trained on the actual changes between 1990 and 2000 for Vermillion River watershed. In order to develop a network with adequate predictive capacity, it was necessary to train and test the ANN with different input data. Training involved presenting input values and adjusting the weights applied at each node according to the learning algorithm. Testing presented a separate data set to the trained network independently to calculate the error rate. The neural network was designed to have a flexible number of inputs depending on the number of predictor variables presented to it. All input grids, which existed in Arc/Info Grid formats, were then normalized to a range of 0.0 to 1.0 and converted into ASCII representation called a "pattern file," which is the required format for ANNs. The neural network trained on the input and output data for 10,000 cycles, after which no significant difference in mean square error between the modeled output and presented data was observed. The testing exercise that followed used the driving variable input from all cells (except those located in the exclusionary zone) in the study area but with the output value removed. The network file generated from the training exercise was used to estimate output values for all of the cells. The output was estimated as values from 0.0 (not likely to change) to 1.0 (likely to change); the output file created from this test exercise was called a "result" file as shown in Figure 5.

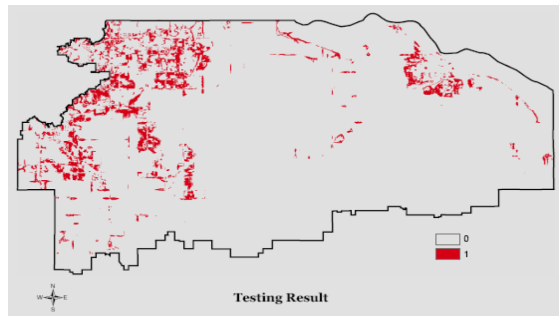

Figure 5. Test results derived from ANNs and LTM. Values of 1 indicated likelihood for land to change; values of 0 indicated land areas not likely to change.

GIS was used to determine that 51,179 cells (or 12.0202 acres) transitioned into urban areas in Vermillion River watershed during the 10 year period from 1990 – 2000. Thus, 51,179 cells were selected from the result file that had the greatest likelihood values; these cells were classified as 'new urban' as these areas experienced new urban development.

Testing was completed by comparing those cells that were observed to transition (mutation changing) based on the data (Figure 6). Testing showed the cells with highest likelihood of transition. The following metric was used to assess the performance of the model:

$$\frac{\text{No. of cells predicted to change}}{\text{No. of cells that transitioned (i.e. 51,179)}}$$

Urban Growth

Percentage of urbanization that occurred between year 1990 and 2000 was calculated via GIS. Urban areas were summed in acreages for years 1990 and 2000 and then divided by the total acreages value of the entire study area, then multiplied by 100 to convert to a percentage.

$$\text{Urban \%} = n / T * 100$$

Where n = number of urban acres for that year, and T = number of the acres of the entire study area.

Annual Hydrologic Statistics

For the stream gauge data collection period (2000 – 2006), maximum, median, and minimum annual discharges were calculated as well as the total annual runoff volume and total annual precipitation. Annual discharge statistics were derived from daily mean flow records ($ft^3\,S^{-1}$). Maximum and minimum annual discharges are the single daily mean maximum and minimum discharge values ($ft^3\,S^{-1}$) for each water year, respectively. Median annual discharges are daily mean discharge values with equal number of higher discharge values above it and lower discharge values below it for each water year. Annual runoff was estimated by averaging the mean daily discharge for each day of the year and converting this annualized mean daily discharge into a total annual flow volume (ft^3 per year). Annual discharge statistics and total runoff volume was plotted on a logarithmic scale. Temporal hydrologic trends were estimated with the linear regression model:

$$\log (D) = a + bY$$

Where D is discharge, Y the year, a is the y-intercept, and b is the regression coefficient. To assess hydrologic changes in response to increasing urbanization, regression analyses used only hydrologic summary statistics from 2000 to 2006. The regression analyses are not intended to be used for predicting future discharge values but rather are used as an aid in identifying trends in discharge over the period of records for stream gauging. The back-transformed regression coefficient (B)

$$B = 10^b - 1$$

This coefficient provides an estimate of the percent increase in discharge per year, over the period considered in the regression analysis.

Annual precipitation was estimated for each year by summing daily rainfall totals for the entire year. Days reported with “trace” amounts of rainfall were treated as zeros in this calculation. Annual summary statistics were plotted on logarithmic scales.

Flood Frequencies

To estimate the frequency of flood flow, that is, a 1-in-N-year (where N = number of years) flood event, the recurrence intervals of the peak annual stream discharge during the period of the record were determined. To determine the reoccurrence intervals, annual peak stream discharges during the period of 2000 – 2006 were ranked from highest to lowest, that is; the highest discharge receives a rank of 1 while the lowest is 5. Reoccurrence intervals were calculated for the period of 2000 – 2006.

$$P = \text{Rank/No of observations} + 1$$
$$P = m / (n+1)$$

Where p is the probability, n is the number of discharges ranked, and m is the rank of each discharge.

$$T = 1/P$$

Flood recurrence interval (T) is the reciprocal of flood probability (P) (White and Greer 2004). Discharge values and reoccurrence intervals were then plotted for evaluation.

Results

Land Transformation Model

The LTM was used to forecast the year 2000 and a change detection of differences between the observed and predicted. These are shown in (Figure 6). The results from the LTM simulation for Vermillion River watershed are provided in Figure 7(a-c). Recall that land use data used for the training and testing of the neural network were from 1990 and 2000 historic land use data. Urbanization that was experienced between the period of 1990 to 2000 were used to then project the next locations that were expected to transition to urban areas (considering the restricted exclusionary zone). Time progressions of 2010 and 2020 were then mapped using GIS.

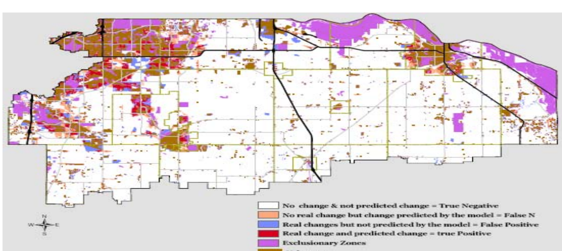

Figure 6. An overlay of model predictions and observed changes in Vermillion River watershed (Red cells are the new urban areas from 1990 to 2000).

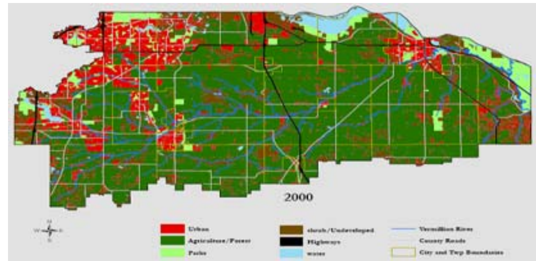

Figure 7a. Land use 2000; Urban area in year 2000 is represented in red.

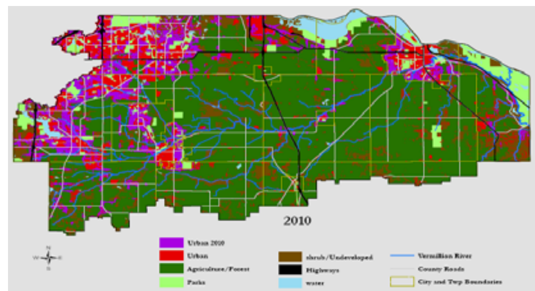

Figure 7b. Urban land use projection for 2010; Forecasted urban growth for year 2010 is represented in purple.

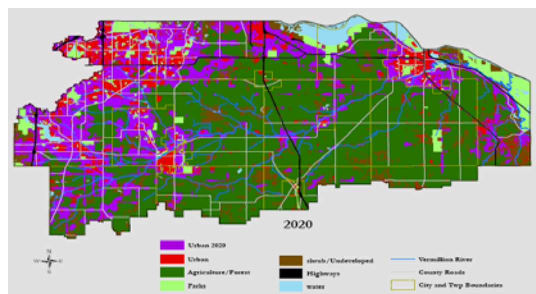

Figure 7c. Urban land use projection for 2020;. Forecasted urban growth for year 2020 is represented in purple.

During the model development, these maps were used as visualization tools to discern the types of spatial error patterns that might suggest missing driving variables. A 46% percent correct match of targets and observed urban change was obtained in the final model simulation presented in Figure 7 (correctly modeled targets are represented in red; locations not correct are represented in blue).

Based on changes between the years of 1990 and 2000, LTM predicted a doubling of urban areas. Thus, if urbanization was occurring at the same rate as it did between 1990 and 2000 (10 year interval) and with the same influences (pressures, incentives, drivers, etc) figures 8b and 8c could be the possible scenario for urban expansion in 2010 and 2020.

These projections illustrate how the ANN could be trained on relationships between urbanization and all of the predictor variables that occurred in Vermillion River watershed. The amount of urban development within the Vermillion River watershed moderately increased during the period of 1990 to 2000. When expressed as percentages of the total watershed area, the amount of urbanized land increased from 9% to 13%, and that of year 2010 was projected to be 26% considering all the driving factors were the same.

Annual Discharge, Runoff Statistics, and Flood Frequencies

Annual minimum and median discharges in Vermillion River watershed increased slightly from 2000 to 2006, which may have resulted from more forest/ agricultural land being exposed to human activities during urban development (Figure 8). Annual maximum discharge provides a measure of the magnitude of the flood in a stream during a year (Konrad and Booth, 2002). The regression coefficient (b) was used to identify the trends of discharge over the period of 2000 to 2006, and the back-transformed regression was used to provide an estimated percentage increase in discharge per year over the period of 2000 to 2006 as considered in the regression analysis, while the coefficient of determination (R^2) is a statistic that gives information about the goodness of fit of a model. The higher the R^2, the more useful the model, as shown in (Table 1). The median discharge values were the highest, meaning that the regression fits more accurately than either for the maximum or minimum.

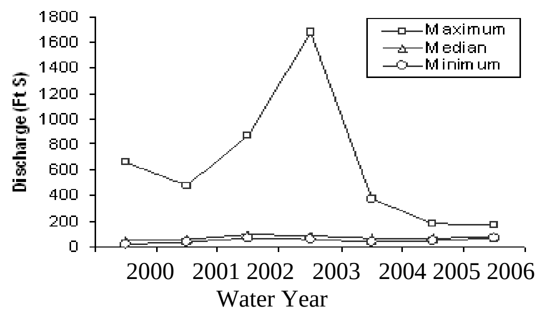

Figure 8. Annual maximum, median, and minimum discharges recorded at Vermillion River watershed north creek gauge during the period of 2000 – 2006.

Table 1. R^2 expresses the coefficient of determination; b defines the regression coefficient; B expresses the back-transformed regression coefficient.

	R^2	b	B
Maximum	23.76	0.02	0.05
Median	50.99	0.05	0.12
Minimum	49.86	0.04	0.09

The total annual runoff in the Vermillion River watershed exhibited a high degree of annual variation but showed a slight increase trend during the period of 2004 – 2006 (Figure 9).

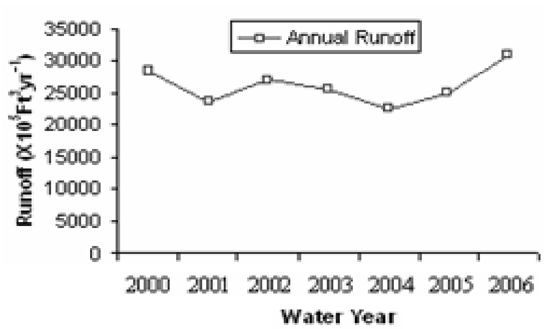

Figure 9. Annual runoff for 2000 -2006 at the Vermillion River watershed north creek gauge.

Much of the rainfall in the watershed covered with forest and pastures is absorbed into the porous soils (infiltration). This is stored as ground water, and moves back into streams through seeps and springs. Thus, in many rural areas, much of the rainfall does not enter streams all at once, which helps prevent flooding

When areas are urbanized, much of the vegetation and top soil is replaced by impervious surfaces such as roads, parking lots, and pavement. When natural land is altered, rainfall that used to be absorbed into the ground now must be collected by storm sewers that send the water runoff into local streams or water retention ponds. These streams were not "designed by nature" to handle large amounts of runoff, and thus, they can be prone to more flooding. Flood magnitude in the Vermillion River north creek has increased with increasing in urbanization in the watershed as seen in Figure 10.

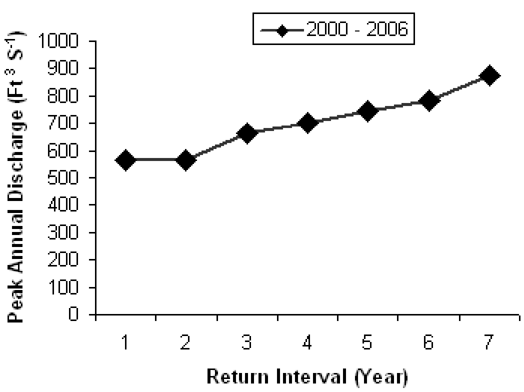

Figure 10. Flood frequency during 2000 -2006.

Impervious surfaces can have an effect on local streams, water quality, and stream flow and flooding characteristics. Although this research did not measure impervious cover, the ANNs simulation output and results increased when urbanization was forecasted, which predicts a greater increase in impervious surfaces thereby leading to the greater potential for flooding and lack of runoff infiltration.

Effects of Urbanization

Urbanization occurs as a result of land use changes, which include some of the following: deforestation, bulldozing of land for houses and subdivisions, septic tanks, and wells (Hunt and Steuer, 2001). Construction of new roads impact and divert streams. In the course of construction, there will be more storm runoff and erosion because there is less vegetation to slow water. Flooding can also occur because water-drainage patterns have changed. This increases and promotes the likelihood of greater sediment loading in streams. This increases the chance of flooding and harms the water quality of streams. In some areas, small streams are paved over (using culverts) and natural land that used to soak up runoff are replaced by roads and large areas of pavement (Figure 11). Consequently, water that used to soak into the ground now runs off into streams. The runoff can also be collected by storm sewers and sent to small streams, which can increase flood potential as well.

Figure 11. An example of impervious surfaces.

Recommendations

Recommendations are sought to learn how Dakota County and VRWJPO – Vermillion River Watershed Joint Power Organization can use this study to reduce the effect of urbanization on the study area watershed. After observing the findings, it is strongly recommended that any new development in a recharge area of the stream be required to preserve infiltration and minimize runoff. High infiltration areas in the watershed should be identified as desirable green space for parks, trails, and other recreational uses. Future development in the Vermillion River watershed should be planned to reduce runoff so as to protect the watershed by siting detention basins in high-runoff areas.

Conclusion

This paper outlines the Artificial Neural Networks based Land Transformation Model and the relationship between 6 predictor variables and urbanization. The model was performed with a relatively predictive ability (46%) at a resolution of 100m X 100m.

Several assumptions were made in order to keep the model simple. First, it was assumed that the pattern of each predictor variable remained constant beyond the year 2000. For example, the location of roads and highways are likely to change (e.g. new roads will be built) and they may respond to changes in land use. Second, spatial rules used to build the interactions between the predictor cells (set of spatial predictor variables that are used to predict the locations of changes-drivers) and potential locations for transition (historical data) are assumed to be correct and remain constant overtime. Finally, the neural network itself was assumed to remain constant over time. Thus, the relative effect of each predictor variable was assumed to be stable. This study found that the urban areas in the Vermillion River watershed increased from 13% to 19% between the periods of 1990 to 2000. With all of the predictors and other driving factors remaining the same, the urban areas for the year 2010 and 2020 was forecasted. This study also illustrated how increased urbanization of Vermillion River watershed has resulted in (1) a slight increase in annual, median, and minimum discharge; (2) an increase in flood magnitudes; and (3) geomorphic changes to stream channel. The changes were also attributed to an increased conveyance of storm runoff from greater impervious surface area. Findings of this study can be effectively utilized by resources managers, community planners, policy analysts, city and county engineers, and commissioners in Dakota County or other counties to help assist them in urban planning. The advantage of planning on a watershed basis proves most beneficial to the stream as a whole if development is concentrated, while other areas are left as open space. Another aspect of watershed planning provides an inventory of important natural resources throughout the watershed and implementing setback distances from critical resources. The findings and methods can also be generalized toward anyone that has an interest in land use planning and assessment.

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