Forecasting and assessing the impact of urban sprawl in coastal watersheds along eastern Lake Michigan

RUNNING TITLE: Urban Sprawl along Lake Michigan

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ABSTRACT

The Land Transformation Model (LTM), which as been developed to forecast urban use changes in a grid-based geographic information system, was used to explore the consequences of future urban changes to the years 2020 and 2040 using non urban sprawl and urban sprawl trends. The model was executed over a large area containing nine of the major coastal watersheds of eastern Lake Michigan. We found that the Black-Macatawa and Lower Grand watersheds will experience the most urban change in the next twenty to forty years. These changes will likely impact the hydrologic

budget, may reduced the amount of nitrogen exported to these watersheds, result in a significant loss of prime agricultural land and reduce the amount of forest cover along the streams in many of these watersheds. The results of this work have significant implications to the Lake Michigan Lake Area Management Plan (LaMP) that was recently developed by the United States Environmental Protection Agency.

Keywords

Land use change, urban sprawl, ecological assessment, prime farmland, riparian zones, coastal watersheds, Lake Michigan

INTRODUCTION

The Land Transformation Model (Pijanowski *et al.* 1997, Pijanowski *et al.* 2000, Pijanowski *et al.* 2002) has been developed to simulate land use change in a variety of locations around the world. The Land Transformation Model (LTM) uses population growth, transportation factors, proximity or density of important landscape features such as rivers, lakes, recreational sites, and high-quality vantage points as inputs to model land use change. The model relies on Geographic Information Systems (GIS), Artificial Neural Network (ANN) routines, remote sensing and customized geospatial tools and can be used to help understand what factors are most important to land use change. Information derived from an historical analysis of land use change can be used to conduct forecasting studies (Pijanowski *et al.* 2002). Land use data from remote sensing is used for model inputs and calibration routines.

Artificial Neural Networks (ANN) are powerful tools that use a machine learning approach to numerically solve relationships between inputs and outputs. ANNs are used in a variety of disciplines, such as economics (Fishman *et al.* 1991), medicine (Babaian *et al.* 1991), landscape classification (Brown *et al.* 1998), image analysis

(Fukushima *et al.* 1983), pattern classification (Ritter *et al.* 1988), climate forecasting (Drummond *et al.* 1998), mechanical engineering (Kuo and Cohen 1998), and remote sensing (Atkinson and Tatnall 1997). The use of neural networks has increased substantially over the last several years because of the advances in computing performance (Skapura 1996) and of the increased availability of powerful and flexible ANN software. GIS is a powerful spatial data management and analysis tool that can be used to perform spatial-temporal analysis and modeling.

Recently, the United States Census Bureau released its year 2000 population census for the entire United States. Of the 14 counties in Michigan that experienced a 10,000-person or greater increase in population, 7 (50%) are located in counties along the Great Lakes coast. Four (Kent, Grand Traverse, Ottawa and Allegan) of these seven are located 30 miles or less from Lake Michigan.

Also in 2000, the United States Environmental Protection Agency (US EPA, 2000) issued a report updating its Lake Michigan Lakewide Management Plan (LaMP). This report outlined six major goals aimed toward improving the quality of the Lake Michigan ecosystem. One of these goals was to: "make land use, recreation, and economic activities sustainable and supportive of a healthy ecosystem". The Lake Michigan LaMP seeks to develop a systematic and comprehensive ecosystem approach that attempts to protect the sustainability of "open lake water and the watersheds that comprise the lake basin". One such approach is to develop indicators of ecosystem health that can be applied lake basin wide.

The purpose of this paper is to: (1) present our approach of the modeling of land use change using the Land Transformation Model along Lake Michigan's coastal watersheds; (2) summarize the results of the model executions; (3) apply several ecological assessment metrics to past, current and future land use changes along Lake

Michigan's coastal watersheds; and, (4) discuss the implications of the model results in the context of the Lake Michigan LaMP.

BACKGROUND

Artificial Neural Networks

Artificial Neural Networks (ANN) are computer simulation tools designed to emulate the functionality of mammalian neurons (Rosenblatt 1958). ANNs typically consist of many hundreds of simple processing units, which are wired together like synapses in a complex communication network. Each unit or node is a simplified model of a real neuron which fires (sends off a new signal) if it receives a sufficiently strong input signal from the other nodes to which it is connected. The strength of these connections may be varied in order for the network to perform different tasks corresponding to different patterns of node firing activity. ANNs are specified by a variety of factors, such as network topology, node functions, training algorithms and learning rules (Principe *et al.* 2000).

There are several benefits to using neural networks over using alternative approaches, such as mathematical models that have explicit equations. First, neural nets possess the ability to perform well on data that it has not seen before. This feature of neural nets is referred to as *generalization*. A second possible benefit of using neural nets over a mathematical model is that neural nets are not adversely affected by *errors* in the original data and therefore may not require data to be free of errors. Therefore, datasets created from imperfect methods, such as the classification of land use from satellite remote sensing, where all locations may not have the correct land use assignment for use, may not overly affect the outcomes of a neural network model.

Neural nets are also very useful if state equations have not been developed that describe the relationship that is being modeled. This is usually the case in systems that have strong anthropogenic factors acting in complex ways, such as in the process of land use change. Because neural nets are nonlinear systems, it is likely that a neural net will reach a solution numerically that adequately describes the relationship between input and output.

The Land Transformation Model

Detailed descriptions of the Land Transformation Model can be found else where (Pijanowski *et al.* 2000, Pijanowski *et al.* 2002). Briefly, the LTM modeling process includes the following procedures.

We first *process the inputs* to the model using a series of base layers stored and managed within a GIS. These base layers store information about land uses (such as agriculture parcels and urban areas) or features in the landscape (e.g., roads, rivers, and lakeshores). Grid cells are coded to represent predictors as either binary (presence="1" or absence="0") or continuous variables (e.g., elevation) depending on the type of attribute. Figure 1A shows a map of example predictor cells for highways where the presence of a highway is coded in the GIS as a "1" (black) and the absence as a "0" (white).

Next, we use the GIS to *apply spatial transition rules* that quantify the spatial effects that predictor cells have on land use transitions (see Pijanowski *et al.* 2002, for details). We use four classes of transition rules: (1) neighborhoods or densities; (2) patch size; (3) site specific characteristics; and (4) distance from the location of the nearest predictor cell. 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 likelihood of land use transition. Site-specific characteristics are values assigned to a cell based on a biophysical or social characteristic that is specific to each grid cell. An example site-specific characteristic is the location of high quality views. The distance spatial transition rule relates the effect of the Euclidean distance between each cell and the closest predictor variable. Figure 1B shows a map of distance to highway predictor variable created using the GIS on predictor cells from Figure 1A.

Certain locations are coded so that they do not undergo transitions. This is necessary for areas within which development is prohibited, such as public lands. We code cells with a "1" if a transition cannot occur; all other locations are assigned a "0". All such layers are then multiplied together to generate one single layer which we call the "exclusionary zone."

In our next step, we *integrate all predictor variables* (Pijanowski *et al.* 2002) using one of three different integration methods: multi-criteria evaluation (MCE), artificial neural networks (ANN), and logistic regression (LR). Each integration procedure requires a different type of data normalization. With all of the integration methods, the cell size (e.g., 100 x 100 meters in the present analysis) and analysis window are set to a fixed base layer. The output from this step is a map of "change likelihood values," which specifies the relative likelihood of change for each cell based on the result given for the cell's vector of predictor variable values.

In the final step, which is called *temporal indexing*, the amount of land that is expected to transition to urban over a given time period is determined using a "principle index driver" or PID (Pijanowski *et al.* 2002). This can be thought of as the "demand function". Most often, a PID is based on population forecasts developed from a demographic or economic analysis scaled to the amount of urban land in use. Such per capita requirements for land (i.e., the number of hectares of developed land per person) are calculated such that the total amount of new urban land at a later time is:

$$U_i(t) = \left(\frac{d_i P}{d_i t}\right) * A_i\,(t) \qquad (1)$$

Where U is the amount of new urban land required in the time interval t, i is the unit (e.g., county) of for which the population statistics are available, P is the population size in any given area in a given time interval and A is the per capita requirements for urban land.

The LTM creates an output that assigns locations with a "1" if it is projected to transition to urban and a "0" if no such transition is expected. The PID is used to determine the number of cells that need to transition to urban. Projections are made by selecting the appropriate number of cells in priority order, which is based on the change likelihood.

METHODS

Study Area Description

Nine coastal watersheds (Figure 2) located along the eastern shores of Lake Michigan were selected for this study; these nine watersheds correspond to the United States Geological Survey's 1:250,000 hydrological unit codes (HUC). These 9 watersheds are located in 39 of Michigan's 83 counties. Located in the coastal watersheds are the major cities of Grand Rapids, Kalamazoo, Battle Creek, Holland, Muskegon, Traverse City, Charlevoix and Petoskey. These watersheds encompass approximately 29% of the entire land area for the state of Michigan (including the Upper Peninsula).

We used the Michigan Resource Information System (MiRIS) land use database which was developed by the Michigan Department of Natural Resources. This database contains land use/cover to Anderson Level III (Anderson *et al.* 1976) for areas larger than 2.5 acres. Land use/cover was interpreted from 1:24,000 aerial photography from

1978. Many Michigan counties have updated their MiRIS land use databases; these updates were used in the analysis and modeling exercises following the procedures outlined below in Urbanization Trend Analysis. Landscape features were also derived from the MiRIS line database. Each of these layers, such as rivers, roads, railroads, and political boundaries were extracted by county and joined using the Arc/Info 8.0 GIS (ESRI 1999). Locations of public lands, which are assumed not to undergo development, were acquired from the Michigan Department of Natural Resources Land and Water Management Division. Population data by minor civil division (MCD) for each of the 39 counties were obtained from the Michigan Information Center (MIC) web site and joined to the Michigan MCD GIS database. All data were converted into an Albers Equal Area projection for modeling.

Figure 3 shows a map of the study area and its land use in 1978. Areas in red denote urban (residential, commercial, retail, industrial), yellow denotes agriculture, green denotes forest, blue is open water and brown is wetlands. In 1978, over a third (34%) of the area was agriculture, nearly 44% was forest, and slightly less than 5.6% was in urban. Other land uses in the study area in 1978 include: open water (3%), wetlands (4%) and barren/dunes (< 1%).

Urbanization Trend Analysis

We conducted an analysis of the relationship between urban growth and population change to parameterize our model. Changes in the amount of urban area in 1978 (as contained in the MiRIS land use database) were compared to land use databases from 17 counties that updated their land use GIS data. Seventeen counties, including 8 located in the current study, were included in this analysis. Between this 17-year (1978 to 1995) period, the amount of urban in these counties increased from 474,574 hectares to 595,321 hectares, representing a 25.22% increase in urban. During this same time period, the total population of these 17 counties increased from 6,128,158 to 6,304,7000 people; a 2.88% increase in population. This ratio, which we call the urban expansion index, represents an 8.76 fold increase of urban usage in relation to the population increase. This large ratio of urban increase to population increase is likely due to: 1) a large exodus of residents from inner cities to the suburbs and more rural locales; and 2) larger parcels for residential use especially in the more rural communities (Wyckoff 2002).

The Planning and Zoning Center (Rusk 1999), Lansing, Michigan, conducted an independent analysis of the proportion of urban increase to population increase and found that many areas in Michigan undergo different rates of urban expansion to population expansion. They found that the Ann Arbor metropolitan area, which is located outside our study area, had the lowest urban expansion index in the state at 2.3.

We examined the consequences of future urban expansions using the LTM applying an urban expansion rate of 2.3 (which we call the “non-sprawl” scenario) and a second condition that assumes the statewide average trend of 8.76. We consider the latter trend as an “urban sprawl” scenario. The model was executed using a 1978 (hereafter as referred to as 1980) as a baseline and forecasting to 1995, 2020 and 2040. We also compare here “sprawl” versus “non-sprawl” growth scenarios for 2020 and 2040.

Parameterization of the Land Transformation Model

We created a “base” GIS layer that was used to register all spatial calculations. This base layer contained cells that were 100m x 100m (one hectare) in size in a grid with 4503 rows and 1713 columns. There were 4,254,077 active cells in this grid. Note that some of the cells were located in the grid but were inactive because they fell outside the coastal watershed study area. The following driving variables were developed statewide (the area was reduced for this current analysis):

Distance to Transportation. Previous studies (see Pijanowski *et al.* 2002) have found a strong correlation between the proximity to county road and future urban development. We used the GIS to calculate the distance each cell is from the nearest county road. In addition, we also calculated the distance each was from the nearest highway and highway interchange.

Proximity to Amenities. We also calculated the distance each cell was from the nearest urban cell (as a surrogate to proximity to urban services), the distance from lakes and rivers (high demand development locations) and to the nearest Great Lakes shoreline.

Exclusionary Zone. Areas that cannot be developed were aggregated into one GIS layer and used to prohibit the model from assigning land use change probabilities to these locations. All public lands, previous urban (including transportation) and locations of surface water were assigned to the exclusionary zone.

Population Forecasts. Decadal population total census data by Minor Civil Division (MCDs) were obtained from MSU's Center for Remote Sensing. Decadal total population for 1950-1990 were used in Microsoft's Excel 2000 trend analyzer to extrapolate total population for each MCD to the year 2000, 2020 and 2040. Statewide population totals for the forecasts were then compared to the US Census Bureau's Michigan statewide population forecasts and then adjusted evenly across all MCDs to match statewide forecast numbers (decreased our totals for 2020 by 8% and our 2040 totals by 12%). In addition, the amount of urban per MCD was calculated using equation (1) above so that a per capita urban use per unit (i.e., MCD) was derived. This per capita urban use requirement value was then used to adjust the urban use demand for future years based on population forecasts. We calculated the amount of future urban by using the 2.3 and 8.76 ration for urban use increase to population increase, for non-sprawl and sprawl scenarios, respectively.

Neural Network. Driving variables stored in the GIS were written to ASCII grid representations and then converted to a tabular format such that each location contained its spatial configuration value (i.e., each location was an input vector into the neural net) from each driving variable grid. This reformatting to a tabular arrangement was necessary for input to the neural net software. The neural net model was based on Pijanowski *et al.* (2002). Details of how neural net operate are found in Appendix A of this paper for readers requiring additional technical information.

Ecological Assessment of Urbanization

The United States Environmental Protection Agency has embarked on a series of pilot projects in the Mid-Atlantic region of the United States that attempt to develop landscape pattern metrics that can be used to assess ecological quality of watersheds and communities. A recent study conducted by Jones *et al.* (1997) examined how over twenty different landscape metrics could be used to assess the ecological condition of watersheds within the region. We selected several of these metrics for use in this current study and examined how they changed over time and across the two urbanization trends. The metrics used here are:

Percent urban in watershed. The total amount of all urban, including residential, retail, industrial, was calculated for each watershed and then divided by the watershed size. As watersheds become more urban, hydrologic properties are expected to change. More urbanization will result in more surface runoff, less recharge into groundwater and more water evaporated back into the atmosphere (Leopold 1973).

Human Use Index (HUINDEX). Humans generally use the land for two primary purposes: for housing and to grow food. These uses generally negatively impact wildlife populations. The U.S. Environmental Protection Agency has developed a land use metric that quantifies the amount of urban or agriculture within a fixed neighborhood window. We used this approach as part of our ecological assessment using the same window size proposed by Jones *et al.*'s (1997) – storing the number of cells that were urban or agriculture within a 250 m x 250 m neighborhood window.

Amount of Forest Along Streams. Forested riparian zones are well known to reduce sedimentation and nutrient loadings to streams as well as provide habitat for important plant and animals. We calculated the amount of forest cover buffering streams in all watersheds and divided this by the total length of all streams in that watershed. We examined the proportion of streams buffered by forests across the nine major watersheds in this study area.

Nitrogen Loading from Uses. Agriculture and urban uses may have negative impacts on stream water quality by increasing the amount of nutrients into surface and ground waters (Daniel *et al.* 1998). Sources of these nutrients include fertilizers and human/animal waste. Following Jones *et al.* (1997), we used a nitrogen export coefficient adopted by the United States Environmental Protection Agency's (Young *et al.* 1996) to estimate the amount of nitrogen that might result from all land uses in each minor watershed. This total was then adjusted to account for each watershed's size and reported in kg/ha/yr.

Loss of Prime Farmland. A large proportion of Michigan's southern Lower Peninsula contains soils suitable for many important crops, such as corn, soybeans and wheat. We used the Michigan Comprehensive Resource Inventory and Evaluation System's GIS database containing the status of prime agricultural soils. This information, stored in a 1 km grid database, codes the proportion of soils in a large survey area that is prime farmland. We extracted from the database all areas that contained more than 80% of the area with prime farmland. These areas were then examined in relation to locations of current and future urban areas.

Distance of Urban from the Great Lakes Shoreline. We calculated the distance each urban cell is from the nearest Lake Michigan shoreline. In many areas in the Great Lakes Basin, the most rapid urban development is occurring along coastal environments. Increasing the population density of people along the shoreline is likely to increase negative anthropogenic impacts on the Great Lakes ecosystem. We plotted the amount of urban for each time period and urbanization trend at 1 km intervals from the shoreline.

RESULTS

In 1980, over 5% of the study area was composed of urban (Figure 4). By 1995, we estimate that over 7% of the study area is urban. Population of the area is expected to increase by 10% between 1995 and the year 2020. Scaling the amount of urban use as a ratio that is the same as 1980 will result in urban taking up as much as 8% of the nine watersheds. By the year 2040, using the same ratio as the 1980 population per capita urban use, nearly 10% of the study area will be composed of urban. However, if we assume that the amount of urban being used per person is the same as that in 1995, then over 12% of the study area will be urban by 2020 and over 21% of the study area will be urban by the year 2040. This latter value represents a quadrupling of the amount of urban with only a 25% increase in population.

The percentage of urban usage per watershed over the modeling time frame and with and with out sprawl is shown in Figure 5. Nearly all watersheds begin in 1980 with less than 10% urban; one, the Manistee Watershed, which is composed mostly of state forest land, is less than 3% urban. By 1995, we estimate that three watersheds (Kalamazoo, Lower Grand and the Black-Macatawa) will exceed 10% urban use in total area. By the year 2040, assuming constant urbanization rates, these same three watersheds will be over 15% urban. In contrast, if we assume a sprawl scenario, by the year 2020, six of the nine will be composed of 10% or more urban use; one (the Black-Macatawa), will be over 33% urban. By the year 2040, again assuming sprawl ratios, all but one will be more than 10% urban; the Black-Macatawa watershed will be nearly 44% urban.

We used the GIS to calculate the percentage of urban use within each of the smaller watersheds in order to examine impacts at smaller spatial scales (Figure 6). Note that in 1980, only a few watersheds contained 50% or more urban. These watersheds represented the larger cities (e.g., Grand Rapids, Kalamazoo) that are located in the study area. Assuming a constant rate of urbanization, by the year 2040, more than twice the number of small watersheds will contain 50% of more urban. Several of these will be located along the coast of Lake Michigan. However, assuming a sprawl trend, by the year 2040, a majority of the coastal watersheds located in the southern half of the Lake Michigan study area will contain 50% or more urban. In addition, the cities of Grand Rapids and Kalamazoo will also have their neighboring watersheds have increased amounts of urban.

Estimates of nitrogen export, derived from the simple United States Environmental Protection Agency's nitrogen export land use based coefficient model, shows that increasing the amount of urban will likely result in reduced nitrogen loadings to the study areas watersheds (Figure 7). This is probably a result of the loss of agricultural lands in the area which contribute more nitrogen to the land than does any other land use.

The human use index, which is designed to assess the amount of human use of the land for agriculture and urban across scales, is shown in Figure 8A. In 1980, a majority of the study area is light colored, reflecting the low level of human use of the land. In contrast, a large portion of the Black-Macatawa watershed is colored dark, indicating that its use is mostly urban or agriculture. Still, large portions of the northern area remain light colored. These areas, which are state forested lands, are assumed to remain as forests.

Figure 8B shows two different human use index change calculations that were made between 1980 and the non-sprawl trend to 2040 and 1980 and the sprawl trends to 2040. The 2040 sprawl trends clearly show a much greater increase in human use along the coastline of Lake Michigan.

Figure 9A shows the locations of prime farmland in the study area. In 1980, slightly more than 2% of the entire study area's prime agricultural land was urbanized (Figure 9B). By 2040, we estimate that nearly 4% of this area (almost a doubling) of the prime farmland will be converted to urban. Assuming a sprawl trend, the LTM estimates that 8% of the study area's prime farmland will be lost to urban development. In addition to this loss, many areas that support specialized crops, such as fruits and vegetables, which are currently not considered prime farmland, may also be lost. These specialized crops (e.g., apples, blueberries) are high income crops.

The percentage of the length of all streams in each watershed that are buffered by forests (e.g., that contain a riparian zone), is shown in Figure 10. Many of the watersheds should experience relatively small changes in the stream cover composition. Only one (Black-Macatawa), will have less than 30% of its stream length composed of non-forest cover given a sprawl trend to the year 2020 and 2040. One (Manistee), because it is located in a state forest, will have nearly 80% of all stream banks buffered by forest.

The amount of urban use, expressed in total hectares, as a function of distance from Lake Michigan, is illustrated in Figure 12. Note that even in 1980, there was more urban located within 10 km of the Lake Michigan shore than any other distance from lakeshore category. In addition, the greatest differential impact of urban sprawl occurs between 20-30 km from the shoreline.

DISCUSSION

We used the GIS and artificial neural network (ANN) Land Transformation Model to forecast urban use to the years 2020 and 2040 using two trends: the most historically conservative urban to population expansion ratio, 2.3, we called the "non-sprawl" scenario, and a statewide average urban to population expansion ration of 8.7. In the first trend, we estimate that the entire study area, composed of the none major coastal watersheds of eastern Lake Michigan, will be composed of 8.2% and 9.6% urban in the years 2020 and 2040, respectively. For the sprawl scenario, we estimate that the study area will be composed of 13.2% and 20.4% urban in 2020 and 2040 respectively.

Of the nine major watersheds in the study area, under a non-sprawl scenario, the Lower Grand watershed would contain the great proportion of urban use. However, under a sprawl scenario, the Black-Macatawa and the Kalamazoo watersheds would contain the great proportion of urban. The Black-Macatawa watershed could be as much as 40% urban by the year 2040. A majority of this growth will occur along the small coastal watershed communities in southwestern Michigan.

The results of the LTM simulations also suggest that the Black-Macatawa watershed could experience the greatest loss of forested riparian cover. This is important because this watershed currently contains the least amount of forest cover along its streams.

There is also the potential for a significant loss of prime farmland in this study area. We estimate that there could be a loss that is proportional to the amount of urban growth. Although it is possible for there to be greater loss of prime farmland, because significant urban development will not occur over large areas of prime farmland, more than 8% of the study area's prime farmland could be lost by the year 2040 under a sprawl scenario. This loss is irreversible.

Another significant finding of our work is that many of the small coastal watersheds in this study area will be more than 50% urban by 2040 assuming a sprawl scenario. Thus, inputs from the urban environment are likely to have the largest impact along the Lake Michigan shoreline.

We also found that the Human Use Index proposed by Jones *et al.* (19XX) is useful to visualize large-scale and long term impacts of urban changes. The original work by Jones and his colleagues was conducted on static digital land use maps. We show that it is also a useful metric for temporal sequences of changes as well.

Finally, we were able to show that one possible benefit of future urbanization trends might be reduced nitrogen loadings into the surface and ground water system. This would result from a large loss of agricultural land, especially in the southern portion of our study area. However, if our simple nitrogen loading model underestimates the amount of fertilizer being applied to urban areas, then this benefit may not result from the protected urbanization.

Policy Implications of the LTM Forecasts

The purpose of the United States Environmental Protection Agency's Lakewide Management Plan (LaMP) is to develop a strategy to assess, restore, protect and monitor the ecosystem health of a Great Lake. A LaMP helps to coordinate the work being conducted by all government and non-government agencies responsible for developing environmental and economic policies impacting the health of a Great Lake. All plans are open to public review and input so that all potential stakeholders can have a “voice” in the content of the LaMP and subsequently on the health of the Great Lakes.

One of goals of the Lake Michigan LaMP was to: “make land use, recreation, and economic activities sustainable and supportive of a healthy ecosystem”. The LaMP seeks to develop a systematic and comprehensive ecosystem approach that attempts to protect the sustainability of “open lake water and the watersheds that comprise the lake basin”.

The LTM forecasts presented here can be used to anticipate the potential consequences of future changes so that policy can be developed that may mitigate any negative impacts to the quality of the watersheds that comprise the lake basin. Developing sound policies that increase the efficiency of decision-making and the ability to respond in timely manner so that anticipated changes are mitigated is a common goal in any policy formulation (Heathcote 1998).

In its assessment of the potential environmental impacts from land use changes, the LaMP identified several specific types of land use trends were of major concern. These land use trends, and the implications from our study follow:

- *Loss of natural habitat:* Natural habitat provides needed resources for wildlife. The Human Use Index calculated on land use changes projected by the LTM show clearly that coastal natural habitats are likely to be greatly impacted in 20 to 40 years and that wildlife habitat in the southern extent will become greatly reduced in the future.

- *Threats to coastal-inland wetland systems*. Land use change alters land surface characteristics which in turn modify surface and ground water interactions. Reducing ground water recharge may negatively impact wetland hydrologic dynamics (Salama *et al.* 1999). Our results show that a majority of the small watersheds in the southern half of our study area will undergo so much future urbanization that they will become hydrologically impaired.
- *Threats to coastal lake shore system, including the Lake Michigan sand dunes*. The coastal sand dunes are clearly sensitive environments which are potentially threatened by expanding residential development along the shoreline of Lake Michigan. LTM projections indicate potentially severe impacts to these sensitive habitats due to extensive residential and sprawled development along the Lake Michigan shoreline.
- *Impairment of surface water quality such as rivers and inland lakes.* The intricate system of tributaries contributing to the Lake Michigan is clearly subject to impacts from urban and suburban land use changes and its population-related implications. Impacts resulting from practices such as channelization, dredging and filling, damping, sedimentation, loss of riparian vegetation, eutrophication, flooding, etc., are all positively correlated with urbanization. LTM methodology and estimations are capable of identifying specific areas of concern where policy measures and possibly specific best management practices (BMP's) can be implemented in order to ease or mitigate anticipated impacts.
- *Human health and non-point source pollution impacts from water quality* is often caused by pathogens and drinking water contamination, a direct result of urbanization. LTM estimations can reliably correlate and indicate potential areas and sources of concern.

Summary

A land use forecast model, such as the LTM, can generate useful information about possible environmental impacts of future urbanization. We were able to show that the greatest amount of new urban will be along the coastal watersheds of Lake Michigan, that some watersheds will become hydrologically impaired from increased amount of imperviousness from urbanization, that some riparian habitats might be lost along major rivers draining to Lake Michigan, that the amount of natural habitat will be reduced thus threatening the sustainability of wildlife populations, and that the amount of prime farmland lost will be proportionally greater than the increase in urban areas. In addition, the model predicted that the Black-Makatawa watershed is likely to have the greatest impact from future urbanization. We suggest that this watershed be examined more carefully by policy makers and resource managers.

FIGURE LEGENDS

Figure 1. An example of how the LTM spatially codes drivers (A) and spatial interaction values (B).

Figure 2. Hydrology of the study area shown in relationship to the entire Great Lakes Basin (A). The nine major watersheds (B) are also shown. The study area's major streams and rivers are shown in C.

Figure 3. The distribution of land uses in 1980 across the study area (A) and in the largest populated area around Grand Rapids (B).

Figure 4. The percentage of urban use in the study area over the temporal periods and between the baseline and sprawl conditions.

Figure 5. The amount of urban (in percent) in the nine major Michigan watersheds of Lake Michigan. Both urbanization trends, non-sprawl and sprawl, are shown.

Figure 6. A map of small watershed basins and the percent composed of urban.

Figure 7. Nitrogen loading (in kg/ha/yr) for each of the small watershed basins in the study area.

Figure 8. The human use index (A) for 1980 and 2020 sprawl scenarios. A comparison of 1980 to 2040 non-sprawl and 1980 and 2040 sprawl is shown in B.

Figure 9. The amount of prime farmland (A) replaced by urban use for 1980, 2040 non-sprawl and 2040 sprawl scenarios. A map (B) illustrating the distribution of the prime farmland is also shown.

Figure 10. Percentage of major river banks composed of forest by major watershed.

Figure 11. The amount of urban (in hectares) as a function of distance from the Lake Michigan shoreline.

Figure A1. An illustration of an artificial neural network and the two main types of calculations that are made: feed forward of weights and back propagation of errors.

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APPENDIX A

This appendix is designed to provide some of the technical details of how the artificial neural network is configured for use in the LTM. In addition, where appropriate, some historical context is also presented.

The Land Transformation Model (LTM) uses what is referred to as a multi-layer perceptron (MLP) neural net. The MLP was first described by Rumelhart *et al.* (1986) and it is one of the most widely used ANNs. The MLP consists three different types of layers: input, hidden, and output (Figure A1) and thus can be used to identify relationships that are non-linear in nature. ANN algorithms calculate weights for input values, input layer nodes, hidden layer nodes and output layer nodes by introducing the input in a feed forward manner, which propagates through the hidden layer and to the output layer. The signals propagate from node to node and are modified by weights associated with each connection. The receiving node sums the weighted inputs from all of the nodes connected to it from the previous layer. The output of this node is then computed as the function of its input called the *activation function*. The data moves forward from node to node with multiple weighted summations occurring before reaching the output layer. The mathematical expressions for each component of the neural network are, following from Reed and Marks (1999):

$$U_i = \sum_j w_{ij} x_j + b_i \quad (1)$$

where w_{ij} is the j^{th} synaptic weight assigned to a node i, and x_j contains the output value from node j of the previous layer; U_i is the summed scalar of all weights and output values from the previous layer. A scalar bias or threshhold, b_i, is added to optimize the number output values can be placed into the correct output category. The scalar, u_i, is then passed through a nonlinear function, which is sometimes referred to as the *squashing function* or *activation function*, such as:

$$y_i = f(u_i) \qquad (2)$$

where the function in (2) is either a logistic, tanh or step function. Logistic functions are used most often. Logistic functions create output values that range from 0.0 to 1.0.

Weights in an ANN are determined by using a training algorithm, the most popular of which is the back propagation (BP) algorithm. The BP algorithm randomly selects the initial weights, then compares the calculated output for a given observation with the expected output for that observation. The difference between the expected and calculated output values across all observations is summarized using one of several statistics, such as the sums of squares, or more preferably, the mean squared error (MSE). After all observations are presented to the network, the weights are modified according to a one of several different types of *learning rules*. The Widrow-Hoff learning rule or *delta* rule (Skapura 1996) is used most often and it has the following form:

$$\Delta w = \eta(t - u)\frac{x}{\|x\|^2} \qquad (3)$$

where η is the constant learning rate, t is the value of the *target* or true output, u is the value of the estimated output and x is the value of the input at location j. Learning rules are applied so that the total error is distributed among the various nodes in the network. This process of feeding forward signals and back-propagating the errors is repeated iteratively (in some cases, thousands of times) until the error stabilizes at a low level.

ANN Parameterization of the LTM

The Stuttgart Neural Network Simulator (SNNS) was utilized for training and testing. To reduce the possibility that the neural network would “overtrain” during training, every other cell was presented to the neural network. The SNNS "batchman" utility was used to create, train and test the neural network. A back propagation, feedforward neural network, with one input layer, one hidden layer and one output layer was utilized. The neural network input layer contained seven nodes (one node for each driving variable) and six nodes in the hidden layer. The output layer contained binary data that represented whether a cell location changed to urban (1= change; 0= no change) during the study period for the training exercise (1978 to 1995). Cells located within the exclusionary zone were removed from both the training and testing exercises.

Each value in an entire predictor variable grid was standardized a linear normalization that transforms the input so that there is a mean of zero with a unit standard deviation:

$$x_s = \frac{x_j - \bar{x}}{\sigma_j} \qquad (5)$$

where x_s is the scaled value, x_j is the raw value, $\bar{x}$ is the mean of all x_j, and σ_j is the standard deviation of all x_j.

The neural network contained a logistic activation function with a bias (Reed and Marks 1999). The Widrow-Hoff learning rule or *delta* rule (Skapura 1996) was used for training. The learning rule was applied so that the total error is distributed among the various nodes in the network.

Following Pijanowski *et al.* (2002), the neural net trained on the input and output data for 500 cycles. Previous experience of training urban change data showed that 500 cycles gave a minimum mean square error between the modeled output and presented data. After training was completed, the network information containing all of the weights, biases and activation values was saved to a file. This file was examined for unusual values in activation functions or bias.

The testing exercise that followed used driving variable input from all cells (except those located in the exclusionary zone) in the study locations but with the output values removed. The network file generated from the training exercise was used to estimate output values for each location. 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 testing exercise is called a "result" file. The actual number of cells undergoing transition during the study period for each county was then used to determine how many cells from each county "result" file should be selected to transition. Cells with values closest to 1.0 were selected as locations most likely to transition. A C program was written that performed this calculation such that if cells possessed the same value but only a subset of them needed to be selected to transition, then the necessary number of cells of equal value was randomly selected from the pool of available cells. We converted the file back into a GIS format by reintroducing those locations taken out as part of the exclusionary zone. Once in the GIS, the output was analyzed per the procedures outlined in the Results section of this paper.

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