Evaluating the Ecological and Environmental Impact of Urbanization in the Greater Toronto Area through Multi-Temporal Remotely Sensed Data and Landscape Ecological Measures

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Abstract Urbanization is a critical factor affecting the ecological and environmental balance of the Greater Toronto Area (GTA), the most populous metropolitan area in Canada, in the past three decades. The purpose of this chapter is to examine the relationship between landscape change and population increase patterns as well as to evaluate ecological impacts of urbanization in the GTA. Multi-temporal remotely sensed data have been used to derive vegetation changes from 1992 to 2003. Land use change is derived from historical land use maps. Five landscape fragmentation indices are calculated for different periods using FRAGSTATS software. Population change is compared with land use and vegetation changes. The landscape fragmentation rate is then compared with the population growth rate. Our results show that the mean normalized difference vegetation index (NDVI) is negatively correlated with the percentage of the urban settlement land and population density at the census tract (CT) level. Changes in the percentage of urban land use show relatively weak correlations with the five fragmentation indices. It was found that shape and fractal dimension indices are better at characterizing the urbanization process than the indices of diversity, contagion, and percentage of like adjacencies.

Keywords Urbanization · Landscape analysis · Remote sensing · Fragmentation · Environmental change

13.1 Introduction

Urbanization is a critical factor affecting the ecological balance of the earth system. One of the greatest challenges is to understand the impact of urban systems that evolve over time and space, as the outcome of the interaction between human behaviors and bio-physical processes. A wide variety of
processes may contribute to urban development. Over the last several decades, a range of models from social-economic, transportation, land use/cover change, and other perspectives have been developed to meet land management and planning needs (Brown et al. 2005; Muller and Middleton 1994; Pijanowski et al. 2005; Veldkamp and Lambin 2001; Verburg and Veldkamp 2005). Relatively, fewer studies have focused on the relationship among environmental, ecological, and social-economical changes caused by urbanization.

Landscape disturbance is a common problem caused by changing land covers and landscape patterns of urbanization (Wang and Moskovits 2001). Such disturbance could lead to low productivity of the ecosystem due to extra travel time, wasted space along borders, inability to use certain types of facilities, etc. Landscape complexity and heterogeneity are key aspects in assessing ecological processes and biodiversity within regions (Southworth et al. 2004). Past research has demonstrated that aspects of landscape pattern or structure influence the occurrence and distribution of species (Forman 1995). To measure landscape structure, indices describing landscape patterns, such as contagion, diversity and shape complexity, have been widely calculated from discrete landscape representations using software programs like FRAGSTATS (McGarigal et al. 2002). For continuous landscape representations, spatial statistics like local spatial autocorrelation measures and surface fractal dimension have been used (Pearson 2002; Read and Lam 2002; Seixas 2000; Southworth et al. 2004).

The GTA is one of the fastest growing and most populous metropolitan areas in Canada exhibiting rapid economic development, urbanization, and population growth in the past three decades (Bell et al. 1999; Bell 2001). Consequently this urbanization has led to a series of environmental problems including reduced farmland and biological diversity, high rates of soil erosion and water quality degradation, and air pollution (Yap et al. 2005). This change will continue to impact the structure and function of the ecosystem in this region (Blais 2000). Based on a forecast by the Urban Development Services of the Toronto City Planning, the population of the Greater Toronto Area will increase to 7.45 million by 2031. The increased population will add more anthropogenic pressure upon local lands, which, if not managed effectively, can eventually lead to further environmental degradation. In turn, such degradation can affect and potentially slow down if not threaten the pace of economic development in this region. Despite the importance of understanding the impact of past urbanization on sustainable development in this region, there have been few comprehensive analyses of land-use/cover, vegetation/other natural habitats, and socio-economic change across time and space in this heartland region of Canada.

Remotely sensed data is very useful for mapping vegetation and land use/cover changes in urban areas by overcoming many limitations of traditional surveying techniques to obtain a continuous and extensive inventory of ecosystems (Ridd and Liu 1998; Ward et al. 2003; Rogan and Chen 2004; Gillanders et al. 2008; Torres-Vera et al. 2009). With the use of remote sensing, it is possible to map and monitor the spatial extent of various factors influencing and contributing to environmental degradation, such as changes in vegetation
cover, impervious surface, land use type, and human activities. Remotely sensed data can also provide the necessary area-based land use/cover parameters to run different urban change models as well as plausible scenarios used to simulate future response to different planning/management scenarios (Clarke and Gaydos 1998; Veldkamp and Lambin 2001; Lo and Yang 2002; Sohl et al. 2007; Tang et al. 2007; Yuan 2009). However, prior research has predominantly focused upon land use/cover patterns caused by urban growth. There is a paucity of research analyzing the impact of land use/cover, population, and ecological change jointly as key urbanization factors.

This paper aims to evaluate the relationship between landscape change and population increase patterns as well as ecological impacts of urbanization in the GTA. Multi-temporal remotely sensed data are employed to derive vegetation changes from 1992 to 2003. Land use change is derived from historical land use maps. Population change at the census level is compared with land use and vegetation changes from 1992 to 2003. The landscape ecological indices are calculated from reclassified land use maps of the early 1990s and 2000s and compared with percentages of urban land use.

13.2 Method

13.2.1 Study Area

The GTA is located in the southern portion of Ontario, Canada covering 7,125 km² (Fig. 13.1), including regional municipalities of Halton, Toronto,
York, Peel and Durham regions. The total population of GTA was 3.89 million in 1991 and increased to 4.68 million in 2001. A large part of the GTA are covered by farmlands and forests protected by the Greenbelt. The land use in other GTA area is predominantly urban including major transportation routes and pockets of expanding urban development. Between 1990s and early this century, urban areas and associated land uses/covers have significantly expanded. Areas that are not urbanized comprise various agriculture lands, forests, wetlands and water bodies.

13.2.2 Data Sets

In order to analyze the relationship between population increase, land use, and vegetation changes from the early 1990s to the early 2000s, census data in 1991 and 2001 census years have been collected from Statistics Canada for each census tract (CT) in the GTA. This data is then linked to the census tract boundary file. Our analysis focused on the CT level of seven digits to ensure the CTs are geographically comparable between the two time instances. Population change from 1991 to 2001 is then calculated for each CT.

Multi-temporal Landsat TM images are used for vegetation change detection across different years. The ideal situation for change detection is that images are acquired at the same or very similar dates and times of different years. Two Landsat TM images acquired on June 3, 1992 and May 22, 2003, respectively, were ordered from the Canada Center for Remote Sensing (CCRS) containing no or minimal cloud cover. The TM images are compared for locational association and were found to need only a minor systematic translation to align to almost exact registration. All images, once aligned, were projected in the NAD 1983 UTM Zone 17 North projected coordinate system. Figure 13.2 shows the two TM images acquired in 1992 and 2003 in grey scale.

In order to measure the vegetation changes in GTA, a simple and well-known vegetation index, the normalized difference vegetation index (NDVI), is generated for each image to represent the continuum of landscape changes. NDVI is calculated from the reflectance measured in the red visible and near infrared bands by using the following equation (Jensen 2005):

$$\text{NDVI} = \frac{(V_{\text{NIR}} - V_{\text{RED}})}{(V_{\text{NIR}} + V_{\text{RED}})}$$

where $V_{\text{NIR}}$ and $V_{\text{RED}}$ represent the spectral values at the near infrared band (Landsat Band 4) and red visible band (Landsat band 3), respectively.

NDVI is often correlated to a variety of vegetation characteristics that include quantity, productivity, biomass, etc. By design, NDVI varies between –1 and 1. An area containing a dense vegetation canopy usually exhibits high positive values while free standing water and soils generally exhibit very low positive or even slightly negative NDVI values (Myneni et al. 1995). An NDVI
change map has been generated by subtracting the 1992 NDVI map from the 2003 NDVI map. The summary statistics of NDVI changes for each census tract have been generated by zonal analysis in ArcGIS.

Initially land use maps were to have been generated from the aforementioned TM images through image classification. However, after several tests, the classification results were found to be highly subjective and not conductive to this analysis given the producer’s/analyst’s choice and interpretation of classes, training sites, and accuracy measures. As such, two historical land use maps generated by the Ontario Ministry of Natural Resources (OMNR) using the Ontario Land Cover Data Base Classification Scheme have been collected. These maps depict the land use/cover within two time periods (early 1990s and early 2000s) approximately ten years apart. The former map is created solely based upon satellite imagery, while the latter is a compilation of data from various sources including topographic maps, aerial photographs, satellite imagery, and ground surveying. Based upon a review of the metadata for the maps, both are considered accurate. The later map (2000s) was provided in vector, it has been converted to raster from vector format to facilitate the subsequent analysis. As the classification schemes for the two maps differed, the original land use/cover classes were aggregated into five broad classes, which are: water, naturally vegetated land, agricultural land, settlement/developed land, and open land. The consistent classification schemes are necessary for temporal comparison. These classes are selected as being significant to this study and as per convention within studies of ecological and environmental impacts of urbanization.

Fig. 13.2 Landsat TM images acquired at (a) June 3, 1992 and (b) May 22, 2003
13.2.3 Landscape Ecological Measures

Landscape ecological measures capturing fundamental aspects of landscape pattern that influence ecological processes are calculated in FRAGSTATS for the two reclassified land use maps. Spatial heterogeneity or complexity in the landscape can be viewed as a continuum of variability and complexity ranging from low to high heterogeneity. This continuum can be measured either directly by measuring complexity and variability, or indirectly by measuring the departure from homogeneity (Li and Reynolds 1995). To date many landscape indices have been developed in the past (McGarigal et al. 2002). This study employs shape, diversity, and aggregation indices.

Patch shape complexity indices relate to the geometry of patches. Shape indices capture overall shape complexity rather than a value for each unique shape (Gustafson 1998; McGarigal et al. 2002). Shape index can be calculated with several methods, including perimeter-area ratios, complexity measurements of patch shape as compared to a standard shape (square), and fractal dimension (Milne 1988; Forman 1995). Most commonly used shape metrics are based on perimeter-area relationships. The area-weighted mean patch fractal dimension is a spatial configuration index that measures the degree of complexity, based on fractal analysis, whereas the area-weighted mean shape index compares the shape complexity to a standard shape.

The diversity indices include metrics such as richness, evenness, dominance and diversity, referring to the number of patch types, the relative abundance of different patch types, and a composite of both (McGarigal et al. 2002). As these composition metrics require integration over all patch types, the diversity metrics are only applicable at the landscape level (McGarigal et al. 2002). Multiple indices such as Shannon’s, Simpson’s and Modified Simpson’s evenness and diversity indices can be calculated to measure both landscape evenness and diversity in FRAGSTATS. All these diversity indices are composition metrics reflecting a composite measure of richness and evenness at the landscape level.

Contagion and interspersion indices assess the spatial aggregation in the landscape. Contagion can be defined as the tendency of cells of similar patch types to occur in large aggregated or contagious distributions. The contagion index (CONTAG), a spatial configuration metric, measures dispersion at the landscape level (McGarigal et al. 2002). The metric units are given as a percentage and a value approaching zero indicates that the patch types are maximally disaggregated and interspersed.

The study area has been divided into 112 grids (cells) each with a size of 6×6 km², to calculate landscape metrics for both reclassified landuse maps. Five landscape level metrics, including the shape dimension (SHAPE AM), the fractal dimension (FRAG AM), Shannon’s diversity index (SHDI), the contagion index (CONTAG), and the percentage of like adjacencies (PLADJ), were calculated within each grid.
13.3 Results and Analysis

Figure 13.3 maps the total population and population density changes at the CT level from 1991 to 2001. The total population increased from 3.89 million to 4.68 million from 1991 to 2001. It is evident in Fig. 13.3 that the population increase occurred mainly at the urban-rural fringe of the City of Toronto and other urban centers within the GTA.

From the early 1990s to early 2000s, the total area of settlement and developed land in the GTA has increased by 513 km². Meanwhile, the area of agricultural land and naturally vegetated land has decreased by 114 and 423 km², respectively. As evident in Fig. 13.4, most of the land use/cover changes, similar to population change, have occurred at the urban-rural fringe within the northern portion of the GTA. In this area agricultural lands and naturally vegetated lands had been converted to new settlement or development areas.

The NDVI change map between 1992 and 2003 is shown in Fig. 13.5. The NDVI change values range from −0.560 to 0.512. The mean NDVI for the entire GTA is 0.246 in 1992 and had a slight increase to 0.263 in 2003. This increase may be the result of vegetative growth from 1992 to 2003. As expected, the NDVI change occurs most in changed urban, suburban, and agriculture areas, while little change appears in the developed urban areas.

The Pearson’s product moment correlation coefficients between population density, percentage of settlement, and the mean NDVI changes at the CT level are listed in Table 13.1. As expected, mean NDVI is negatively correlated with the percentage of urban settlement land and population density. Urbanized areas tend to contain more impervious surfaces resulting in relatively low NDVI

![Fig. 13.3 Total population and population density changes from 1991 to 2001 at the census tract level in GTA](image)
Fig. 13.4 Land use maps of GTA for early 1990s (a) and early 2000s (b)

Fig. 13.5 The NDVI change from 1992 and 2003 TM images
values. In comparison, vegetated areas are normally associated with higher NDVI values. However, NDVI change is not significantly correlated to population density change. This observation likely indicates that population density change is not a major factor towards vegetation change at the CT level. Other factors such as land use planning strategies may be more significant factors.

At the grid level, the negative correlation between mean NDVI and the percentage of settlement and developed land and the population density became stronger than those at the CT level (Table 13.2). This increase is reasonable considering the impact of analysis scale and is consistent with the results from other research involving the Modifiable Areal Unit Problem (MAUP) studies (Cressie 1996). More particularly, population density has a very strong correlation (0.91 for 1990s and 0.87 for 2000s) with the percentage of settlement and developed land. It is reasonable that the percentage of settlement and developed land should be negatively correlated with the average NDVI, as urban development is often at a cost of vegetation reduction. The correlation strength (0.66 for 1990s and 0.62 for 2000s) between NDVI and population density is relatively weaker as shown in Table 13.2. The relationship between these two variables is more indirect with an NDVI value often reflecting the level of urbanization.

The five landscape fragmentation indices have been calculated at the grid level for each of two land use maps. These indices have been correlated with the percentage of settlement and developed land. The urban land use percentage is positively correlated with PLADJ and CONTAG, but negatively correlated with SHAPE, FRAG, and SHDI (Table 13.3). In particular, the correlations with FRAG, SHAPE, and PLADJ are stronger than those with SHDI and

<p>| Table 13.1 Correlation between NDVI, percentage of settlement and developed land, and population at the CT level |</p>
<table>
<thead>
<tr>
<th>Early 1990s</th>
<th>Early 2000s</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI vs. PSD</td>
<td>–0.58</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NDVI vs. POP</td>
<td>–0.42</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>PSD vs. POP</td>
<td>0.44</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

PSD represents percentage of settlement and developed land; POP represents population density

<p>| Table 13.2 Correlation between NDVI, percentage of settlement and developed land, and population at the grid level |</p>
<table>
<thead>
<tr>
<th>Early 1990s</th>
<th>Early 2000s</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI vs. PSD</td>
<td>–0.81</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NDVI vs. POP</td>
<td>–0.66</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>PSD vs. POP</td>
<td>0.91</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

PSD – percentage of settlement and developed land; POP – population density
Contag. However, the changes in percentage of urban land use show relatively weak correlations with the five fragmentation indices.

Each fragmentation index is compared spatially across grids within the individual image to examine the spatial patterns of landscape fragmentation. To foster fragmentation analysis at the grid level, the values of each index have been classified into three classes: low, middle, and the high-value classes. Figure 13.6 presents the spatial distributions of SHAPE index as an example for the five indices. The SHAPE index has shown a clear spatial gradient across the study site. This gradient generally corresponds to the three dominant land use areas: the urban, the urban-rural fringe, and the rural areas.

| Table 13.3 Correlation between percentage of settlement and developed land, and the fragmentation metrics at the grid level |
|---|---|---|
| Early 1990s | Early 2000s | Change |
| SHAPE vs. PSD | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ |
| FRAG vs. PSD | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ |
| SHDI vs. PSD | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ |
| CONTAG vs. PSD | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ |
| PLADJ vs. PSD | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ | $r$ | $p$ | $n$ |

PSD – percentage of settlement and developed land; FRAG – the fractal dimension; SHAPE – the shape dimension; SHDI – Shannon’s diversity index; CONTAG – the contagion index; PLADJ – the percentage of like adjacencies.

Fig. 13.6 Spatial patterns of landscape fragmentation measured by SHAPE metrics in the early 1990s and 2000s.
Similar maps with Fig. 13.6 have been generated and analyzed for the other four indices. These maps also indicate that the fragmentation indices reasonably characterize the urbanization processes. These five indices, however, characterize landscape fragmentation zones differently. From low to high values, SHAPE and FRAC metrics characterize the degree of urbanization from high to low. In other words, the urban area is the less fragmented zone, the urban-rural fringe is the more fragmented zone and the rural area is the most fragmented zone. In contrast, from low to high values, CONTAG and PLDJ indices characterize the degree of urbanization from low to high. Nevertheless, the spatial pattern of the SHDI index differs from those of other metrics in that the low value class characterizes the urban-rural fringe area. This finding implies that fragmentation indices do reveal the transition process of land use changes from the dominant land use of vegetation to agriculture and eventually to urban developed land.

Fragmentation indices have also been compared temporally for the two images on a grid basis to examine the impact of urbanization on landscape fragmentation during the decadal period. Figure 13.7 presents the spatial patterns of changes in SHAPE and FRAC indices during the decade. The large changes are generally located in the grid areas with significant land use changes in and outside of the urban region between 1990 and 2000. Similar maps for the other three indices are produced for visual interpretation and analysis. The maps of the spatial changes of these indices do not exhibit clear
patterns that correspond to the land use changes from 1990s to 2000s. This finding suggests that the SHAPE and FRAC indices are better to characterize the urbanization process compared to the other three indices.

13.4 Conclusions

This paper examines the relationship between land use, vegetation change, and population change patterns, and evaluates ecological impacts of urbanization in the GTA. Multi-temporal remotely sensed data have been employed to derive NDVI changes from 1992 to 2003. Land use change has been derived from historical land use maps. Population change is compared with land use and vegetation changes from 1992 to 2003 at both the census track (CT) level and across a grid of 6 km x 6 km cells. The five landscape fragmentation indices including the fractal dimension (FRAG), the shape dimension (SHAPE), Shannon’s diversity index (SHDI), the contagion index (CONTAG), and the percentage of like adjacencies (PLADJ) have been calculated at the grid level for the two land use maps. These indices are compared both spatially across grids and temporally over the decade to examine the spatial patterns of landscape fragmentation and the impact of urbanization on landscape fragmentation over the decadal period.

Results indicate that mean NDVI is negatively correlated with the percentage of urban settlement land and population density. This correlation is stronger at the grid level than at the CT level. However, NDVI change is not correlated with population density change. The changes in the percentage of urban land use show relatively weak correlations with the five fragmentation indices. It is found that fragmentation indices do capture the land use transition process from a dominant land use of vegetation to agriculture and eventually to urban developed land. The urban land use percentage is positively correlated with PLADJ and CONTAG, but negatively correlated with SHAPE, FRAG, and SHDI. However, spatial changes of PLADJ, CONTAG, and SHDI do not capture as clear patterns of land use change as SHAPE and FRAC do.

As many studies have demonstrated, landscape ecological measures and correlation analysis are strongly dependent on the analysis scale (Turner 1989; Cressie 1996; Lausch and Herzog 2002; Li and Reynolds 1995; Gustafson 1998). The impact of analysis scale is evident from the correlation analysis between NDVI, population density, and land use at the census tract and grid levels. Our landscape fragmentation analysis is based on the aggregated land use data at a regional scale. It should be noted that the correlation between fragmentation measures and land use change may change when the analysis is based on finer land use classification scheme and analysis scale. This dependence represents an opportunity for future study.
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