Exurban Development: 
Mapping, Locating Factors, and Ecological Impact Analysis 
using GIS and Remote Sensing

by

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Abstract

Anthropogenic disturbance in a landscape can take various forms, including residential development, which has substantial impact on the world’s ecosystems. Exurban development, characterized by low density residential development outside urban areas, was and continues to be one of the fastest growing forms of residential development in North America. It has disproportionately large ecological impacts relative to its footprint, yet is mostly overlooked in scientific studies. Specifically, a lack of spatially explicit (disaggregate) data on exurban development at regional level has contributed to a very limited understanding of this interspersed low density development.

The main goal of this dissertation is to provide an increased understanding of exurban development in terms of its location, locating factors, and conservation and ecological implications at regional level, especially to enable incorporation of exurban information in the decision making processes. For this I asked four specific questions in this dissertation: (i) Where exactly is exurban development? (ii) What are the most likely factors that influence exurban development location? (iii) How does current and future development conflict with conservation goals? And (iv) What is the extent of the exurban development’s ecological impacts? Using a
heterogeneous landscape, the County of Peterborough (Ontario, Canada), as the case study this dissertation undertook a number of separate yet related analyses that collectively provided the improved understanding of exurban development. The investigation of traditionally used surrogates for development, like roads and census data, and a more direct remote sensing method, using moderate resolution SPOT/HRVIR imagery, provided insights and contributed to development of spatially explicit data on exurban development. The evaluation of several commonly hypothesized locating factors in relation to exurban development revealed some of the major influences on the location of this development, especially in the context of Ontario.

This research contributed to our understanding of the future risks of land conversion and identification of potential conflict areas between development and conservation plans in the study area. Lastly, examining the ecological impact of exurban development including associated roads, in terms of functions such as barrier effects and landscape connectivity, highlighted the importance of these seldom included anthropogenic disturbances in land and conservation planning.

The contributions of this research to the existing body of knowledge are threefold. First, this dissertation reveals the limitations associated with existing methods used to map exurban development and presents a relatively easy, effective, automated and operational method to delineate exurban built areas at regional level using GIS and remote sensing. Second, the analyses conducted in this dissertation repeatedly highlights the importance of incorporating fine level details on exurban development in land and conservation planning as well as ecological impact assessments and presents methods and tools that can systematically and scientifically integrate this information in decision making framework. Third, this study conducted one of a kind, comprehensive and spatially explicit study on exurban development in Canada, where there
is near absence of such research. With the rarely available exurban built footprint data delineated for the study area, this study not only identified the potential locating factors, future conversion risk, and conflict areas between development and conservation plans, but also quantified ecological impact in terms of landscape function, namely barrier effects and landscape connectivity, using a relatively novel circuit theoretic approach that can directly inform land and conservation decision planning process.
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Chapter 1: Introduction

1.1 BACKGROUND

Human activities in the landscape often result in conversion or loss of land cover types and fragmentation of remaining land cover into smaller, more isolated elements (Saunders et al. 1991, Forman and Alexander 1998, Trombulak and Frissell 2000, Fahrig and Rytwinski 2009). Chapin et al. (2000) estimated that almost half of the world’s ice free surface has been transformed into agricultural and urban covers by humans. This recent, rapid landscape transformation threatens efforts to conserve biotic resources throughout North America and other parts of the world (Dale et al. 2000, Miller et al. 2009). Among various forms of anthropogenic causes of landscape transformation, land use and roads associated with residential development is a leading cause of species imperilment in North America (Wilcove et al. 1998, Miller and Hobbs 2002, Fahrig 2003, Benitez-Lopez et al. 2009). Thus, it is important to consider residential development threats to wildlife and their habitat while making conservation management plans in order to properly prioritize limited resources available for conservation (Cassidy et al. 2001, Theobald 2003 b, Theobald 2010).

Establishment of conservation areas has been a common approach used to reduce anthropogenic threats to biological conservation (Margule and Pressey 2000, Pressey et al. 2007, Moilanen et al. 2011). However, limited resources and widespread conflict with human interests often hinders protection of areas that are necessary for achieving conservation goals. A complementary approach of taking conservation initiatives beyond public and protected areas into private lands
is gaining widespread acceptance (Theobald and Hobbs 2002, Theobald 2004, Donovan et al. 2009, Radeloff et al. 2010). Private lands support high levels of biological diversity (Bean and Wilcove 1997, Knight 1999), but the listed species on private land have been declining more rapidly than those on public land (Noss et al. 1997). Though there are various reasons for this rapid biodiversity loss, most of them are directly or indirectly related to land use changes on these private lands; usually from wild land and resource extraction uses to agricultural and then to low and high density urban uses (Hansen and Brown 2005, Huston 2005).

In the past half century, low density residential development, also known as exurban development, has been the most rapidly growing form of land use, predicted to cover 25% of the conterminous United States by 2005 (Nelson 1992, Brown et al. 2005, Theobald 2005 a, Gude et al. 2006, Irwin et al. 2007). Exurban development evolved from the term “exurbia”, coined by Spectorsky in his 1955 book called “The exurbanites”. Spectorsky used it to describe the far flung commuter settlements of the New York Metropolitan region. In literature there are various definitions and terminologies used to refer to exurban development, specifics of which depend mostly on geographic location and purpose of the study (Davis et al. 1994, Brown et al. 2005, Radeloff et al. 2005, Stewart et al. 2005, Irwin et al. 2007, Ban and Ahlquist 2008, Platt 2010, Newburn and Berck 2011). In general there is a consensus that exurbia is the kind of settlement pattern spanning the landscape between contiguous urban development and rural countryside (Troughton 1983, Nelson 1992, Nelson and Sanchez 1999). Quantitatively it is often characterized as low density housing of approximately 6 to 25 homes per square kilometer in a

1.2 DISSERTATION CONTEXT

Exurban development is one of the leading anthropogenic causes of landscape transformation on private lands in North America (Joseph and Smit 1983, Troughton 1983, Nelson 1992, Hansen et al. 2005, Theobald 2005 a, Brown et al. 2008). Since the location of exurban developments are often non-random relative to biodiversity, as both are strongly influenced by biophysical factors, their ecological effects may be disproportionately large relative to the area of the development itself (Hansen et al. 2005). In addition, exurban development is advancing at an unprecedented pace, impacting previously undisturbed areas to a large extent or increasing the intensity of the impact through redevelopment of the previously developed lands. Advances in information technology are allowing more and more people to flee the cities and to adopt small-town lifestyles near the natural amenities of rural landscapes (Hansen et al. 2005, Huston 2005, Gude et al. 2006). With ever increasing technological advances, a flexible work environment that encourages tele-commuting and affluent retiring population, this trend is expected to continue in future. Also, it is expected that the land use intensity will be much higher in exurban areas because of the conversion of seasonal homes into permanent households, specifically in the context of natural amenity rich areas. Consequently, additional substantial changes will be inflicted upon the landscape through transformation of more land into residential land use outside incorporated urban areas, especially in natural amenity rich areas close to major urban
centers. Thus, it is critical for conservationists, geographers, ecologists, and planners alike to examine and improve our understanding of these extensive and widespread causes of landscape transformation, especially in the ecologically sensitive areas. Without such knowledge, land cover and land use changes due to exurban development will not only continue, but will also threaten existing efforts and initiatives targeting natural resources and biodiversity conservation in the landscape.

1.2.1 Exurban development: Where exactly is it?

The significance of exurban development and its potential ecological consequences are recognized by many in the literature (Hansen et al. 2005, Brown et al. 2005, Gude et al. 2006, Compas 2007). Especially in the past decade there have been a number of studies pertaining to the ecological consequences of exurban development, which have contributed to the increased understanding of the relationship between exurban development and ecological impacts at local (site) level through empirical species / community specific studies (Odell and Knight 2001, Hansen et al. 2005, Schlossberd et al. 2011) and at regional (national) level through use of fragmentation indices (Radeloff et al. 2005, Theobald 2005 a). These dedicated researches have been successful, to a large extent, in highlighting the importance of exurban development in land and conservation planning. Despite these efforts it is still largely difficult to incorporate exurban development in land and conservation planning decision making process. One of the major hindrances has been the lack of spatially explicit or spatially disaggregate data reflecting exurban development, which are crucial for ecological inferences and decision making process (Theobald 2003 a, Hammer et al. 2004, Brown et al. 2005, Hansen et al. 2005, Hawbaker et al. 2005, Gude
et al. 2006, Clark et al. 2009). The need to identify and map the extent and spread of natural as well as anthropogenic disturbances in the landscape has been emphasized in the literature time and again (Turner et al. 2001). Unless spatially explicit information on exurban development is available, any subsequent analysis examining its pattern as well as its implications on the landscape is difficult, if not impossible.

In the past decade, researchers have explored the benefits and limitations of various mapping methods to develop fine resolution spatially explicit (disaggregate) data on exurban development. Some of the direct methods examined include remote sensing techniques, such as sub-pixel classification of Landsat imagery to derive percent impervious surface in exurban landscapes using a Classification and Regression Tree approach (McCauley and Goetz 2004), Artificial Neural Networks (Lee and Lathrop 2006), and linear spectral mixture analysis (Small 2001). Others used different approaches, like Defense Meteorological Satellite Program Operational Linescan System nighttime satellite imagery with classification based on emitted light intensity (Cova et al. 2004), and straightforward digitizing of aerial photos (Hawbaker et al. 2005). The indirect methods involved the use of ancillary data such as census housing density data (Radeloff et al. 2005), spatial road data to weigh county-level census housing data (Theobald 2005 a, Brown et al. 2005) or section-level aggregated housing data from County Tax Assessor’s Offices (Gude et al. 2006).

Though limited in number, these studies highlighted the potential and the challenges associated with direct and indirect mapping of low density residential developments. The direct methods involving remote sensing seem appropriate and have been increasingly used to map urban
development patterns (Cova et al. 2004, McCauley and Goetz 2004). However, their utility in low density settlements have not been explored much in the literature, except at very high spatial resolutions (1-4m) that are prohibitively expensive and would require a very high data volume when mapping large spatial extents (McCauley and Goetz 2004, Lee and Lathrop 2006).

Relatively lower spatial resolution, such as Landsat images, have also been widely explored for land cover mapping at regional extents but these are usually limited to coarse categories extending over a large number of contiguous pixels, thus they are generally not appropriate for mapping scattered low density exurban development.

The indirect mapping techniques often use population density, housing/dwelling density and other information from census data (Theobald 2005 a, Clark et al. 2009). However, the U.S. and Canadian censuses either aggregate data into relatively large areal units or have data available for smaller areal units but only within city limits, which make exurban or low density areas difficult to study. Also, census data is typically tied to the primary place of residence and seasonal and second homes are not well represented, thus measures based on population may underestimate settlement patterns and associated landscape change (Theobald 2005 a). Housing density is more complete in that sense, but again the aggregated data over large areal units lack the geographic precision needed for ecological inference or for detailed studies on settlement patterns. With rapid technological development, increasing numbers of local municipalities are developing digital spatially explicit property parcel data that can provide the required details on housing development over large areas (Compas 2007), but these data are still unevenly available and often only encompass the urban / city extent.
1.2.2 Exurban development correlates, conversion risk, and conflict with conservation plans

A critical but often overlooked aspect of land and ecological conservation is an understanding of future threats to the landscape. Anthropogenic threats may come in the form of land use conversion and/or intensification resulting in land cover modification. Within a given region, various socioeconomic, biophysical, spatial, and policy factors all influence the location of a particular form of land use, such as residential development (Conway 2005, Platt 2006). Spatial accessibility to population and/or employment centers is a primary locating factor in metropolitan areas (Troughton 1983, Verburg et al. 2004). In exurban regions, however, access to natural amenities such as protected areas, lakes, and trails may also influence the location of residential development (Gustafson et al. 2005, Conway 2005, Hansen et al. 2005, Radeloff et al. 2005). Huston (2005) identified three broad phases of development that are characterized mainly by (i) natural resource constraints, including biophysical conditions that facilitate or limit humans settlements in certain areas, (ii) transportation expansion that allows development to move away from the source of production and/or employment but remain accessible, and (iii) pursuit of natural amenities, facilitated by recent advancement in information technology which has allowed people to move further away from urban centers into perceived “natural” areas. These three phases, though identified to be temporally sequential, can occur simultaneously in a landscape and can even interact to influence land change. To better understand these threats associated with future residential developments, including exurban developments, it is crucial to examine the relationship between their current locations and the potential driving factors. Such knowledge will allow the broader planning process to be more proactive than reactive, and will
facilitate timely intervention before the particular land use conversion becomes unmanageable (Nelson 1992).

Recent attempts to streamline the identification of areas requiring immediate conservation attention have resulted in the development of prioritization procedures that identify areas of high conservation interest or biodiversity hotspots facing large threats in near future (Reyers et al. 2001, Wessels et al. 2003, Reyers 2004). Complementary approaches that focus more on common species before they become threatened, such as U.S. gap analysis (Scott et al. 1996), provide a set of tools for land managers to work with for proactive conservation planning at regional and national level. Also, with advances in GIS technologies other sophisticated spatial prioritization tools like Marxan (Ball et al. 2009) and Zonation (Moilanen 2007) are used widely around the world to prioritize the conservation efforts based on several bio-physical and socio-political parameters in the face of increasing natural and anthropogenic threats.

Since land uses are not static, the identification of land likely to be transformed to some form of land use can provide essential information required for proactive conservation planning (White et al. 1997). Thus, in addition to identifying the areas of high biodiversity conservation value, identification of areas that are currently threatened or likely to be so in the near future by some form of dominant land use, provides an opportunity to evaluate the potential conflict areas and take timely actions.

1.2.3 Ecological implications of exurban development
Anthropogenic disturbances such as residential development and roads impose distinct patterns on the landscape and influence a wide range of ecological processes (Forman and Alexander 1998, Turner et al. 2001, Fahrig 2003). Habitat for wildlife is directly removed during construction and, once constructed, built surfaces create a physical and chemical environment different from that of surrounding areas (Trombulak and Frissel 2000, Sanderson et al. 2002, Hansen et al. 2005). These changes are mostly irreversible, and can stimulate further changes in the landscape. For example, expansion of a road network to serve new settlement can lead to further development due to the increased accessibility. These interspersed development patches connected by linear infrastructure, like roads, result in landscape fragmentation, which has various ecological ramifications.

In addition to inflicting irreversible changes in the landscape, exurban development is also expanding at exceptional rates (Brown et al. 2005, Radeloff et al. 2005, Theobald 2005 a, Clark et al. 2009, Theobald 2010). As it is often located near ecologically sensitive areas, it has disproportionately larger ecological impact relative to its physical footprint (Maestas et al. 2003, Hansen et al. 2005). The effects of exurban development range from direct loss and/or fragmentation of habitat to alteration of ecological processes such as fire and flood regimes (in-depth review refer to Hansen et al. 2005). Though each of these ecological effects of exurban development is important and deserves a better understanding, habitat fragmentation, in particular, is of concern as it has various direct and indirect effects on wildlife in the landscape. Exurban development not only perforates the major land cover types that provide refuge to various wildlife, but the incision and dissection by associated linear infrastructures imposes
further fragmentation effects (Forman 1995, Jaeger 2000). This result in multiple undesired ecological effects those are direct and visible, such as edge effects, structural and compositional changes in vegetation communities. Other effects are indirect and only observable over long time periods, such as reduced landscape connectivity, which can subdivide populations, make resource inaccessible, increase human-wildlife conflict including road mortality, leading to a substantial cumulative impact on the species’ ability to persist in the landscape (Forman 1995, Forman et al. 2002 a, Jaeger et al. 2005).

In the past decade there have been a number of studies pertaining to the ecological consequences of exurban development, which have contributed to the increased understanding of the relationship between exurban development and ecological impacts at local (site) level through empirical species and/or community specific studies (Odell and Knight 2001, Hansen et al. 2005, Schlossberd et al. 2011) and at regional and national level through use of fragmentation indices (Radeloff et al. 2005, Theobald 2005 a, Irwin and Bockstael 2007). These studies have been successful in highlighting the importance of exurban development in land and conservation planning. Nevertheless, despite these efforts it is still largely challenging for decision makers to incorporate exurban development in land and conservation planning in decision making process. The major hindrance has been the lack of easily accessible spatially explicit data on exurban development (Theobald 2003 a, Hansen et al. 2005, Gude et al. 2006, Clark et al. 2009), though this is beginning to change (Cova et al. 2004, Shrestha and Conway 2011). In addition to this, there a scarcity of studies that explore analytical methods to quantify the functional impacts of exurban development at the regional level, which can directly facilitate decision making process.
as in other anthropogenic disturbances such as roads. Nevertheless, advances in road ecology over the past decade (Forman and Alexander 1998, Trombulak and Frissell 2000, Forman and Deblinger 2000, Forman et al. 2002 b, Jaeger 2005, Roedenbeck et al. 2007, Eigenbrod et al. 2009, Summers et al. 2011) have provided a much needed conceptual and technical foundation for quantifying the anthropogenic disturbance in the landscape that can be applied to exurban development.

1.3 STUDY AREA

The study area, Peterborough County (Ontario, Canada), covers 4379 km$^2$ of which only 101 km$^2$ is formerly incorporated in an urban area (Figure 1, Statistics Canada 2006). Thus, about 98% of the total study area is located outside of a designated urban area. It is these unincorporated lands that are the focus of the research.

The 2006 population and number of private dwelling units for Peterborough County were 133,080 and 67,281, of which 35% and 44% respectively are located outside of an urban area (Statistics Canada 2006). The county is a popular part of Ontario’s ‘cottage country’ and is rich in natural amenities such as forests and lakes. The region is within a two hour drive of two major urban centers, Toronto to the south and Ottawa to the east. These two cities include almost half of Ontario and 1/5th of Canada’s population. Peterborough County is located near the largest provincial park in Ontario, Algonquin Provincial Park, and is home to a newly created provincial park, Kawartha Highlands Signature Site. The combination of these characteristics makes the county an ideal setting for exurban development.
Ecologically, Peterborough County is located in an ecotone between two distinct Ecozones (Wicken 1986): the Mixedwood Plains in the South and the Boreal Shield in the North. The Mixedwood Plains cover most of the densely populated regions of southern Ontario along the Windsor – Quebec City corridor. The surficial geology is characterized by gently rolling hills and plains, with glacial and fluvial deposits that make the soil some of the most productive in Canada. In Peterborough, this Ecozone was cleared for agriculture in the 19th Century. At that time, a regular road grid was laid down and rectangular farm parcels of 40 to 80 ha were delineated to attract agriculture (MacIlwraith 1997), which is still present in the landscape.

The Boreal Shield Ecozone covers a large swath of land in Ontario, including northern Peterborough County. The area is located on the Canadian Shield and is characterized by granite barrens (with less than 15 cm of soil cover) and water bodies interspersed throughout a primarily forested landscape dominated by boreal vegetation. This part of Peterborough lacks a regular pattern to the road network, partly because it was never considered a significant location for agriculture. Nevertheless, it is popular for recreational activities and is the location of numerous cottages and seasonal homes.

Ecozones can be further broken down into Ecodistricts, which are more homogeneous in terms of their regional landform, local surface form, soil development, textural group, vegetation cover/land use classes, range of annual precipitation, and mean temperature (Marshall and Schut 1999). In the study area, Ecodistricts were used to define three distinct zones: the Mixedwood Plains in the South, the Boreal Shield in the North, and the transition zone in the middle.
The strong north-south gradients in the study area, defined by surface geology, land cover, land use and road pattern captures the range of conditions where exurban development is often found in North America. In addition, this landscape is important from an ecological perspective, since ecotones act as a ‘zone of control’, facilitating or impeding important functions such as fluxes of materials and wildlife (Wiens et al. 1985). However, the increasing encroachment by exurban development is threatening such processes through landscape fragmentation and transformation. Therefore, there is interest from local land conservationists to develop accurate maps of exurban development to aid land preservation efforts.
Figure 1: Peterborough County, Ontario
1.4 RESEARCH GOAL AND DISSERTATION OVERVIEW

The main goal of this dissertation is to investigate exurban development from a geomatic perspective, by mapping its physical footprint, identifying its locating factors, and assessing its conservation and ecological implications at a regional level. A heterogeneous landscape, the County of Peterborough (Ontario, Canada) is used as the case study, which is representative of many exurban landscapes. The contributions of this research to the existing body of knowledge are threefold. First, the analysis reveals the limitations associated with existing methods used to map exurban cover and highlights the potential of using a combination of GIS and remote sensing approaches. Second, it provides insight relevant to conservation planning by explicitly illustrating differences in inference when rarely included exurban development is incorporated into landscape-level conservation planning and ecological impact analysis. Third, this study is a one of a kind spatially explicit investigation on exurban development in Canada, where there is a near absence of such research. To achieve the overall goal, I ask several questions organized in four distinct, but related dissertation chapters.

Chapter 2 investigates the utility of readily available ancillary data and GIS techniques to map exurban settlements over large spatial extents. In this study, the utility of the two commonly used indirect approaches, (i) road network as the surrogate, and (ii) dasymetric mapping incorporating census data to specifically map exurban development over large spatial extents is examined. While often used, there has been a lack of formal assessment on the accuracy of these methods in exurban development mapping. Thus, this chapter contributes basic but critical information on
the utility of these approaches. Additionally, the impact of different contexts and scales used to derive these indirect measures of exurban development are assessed.

Chapter 3 examines the use of medium resolution remotely sensed data to map exurban development over large spatial extents. In this study, we explore a simple and effective method for rapid and accurate delineation of built cover associated with exurban development across large spatial extents with and without post-classification structural and contextual processing. In particular, this method is based on NDVI recoding of moderate spatial resolution (10 m) multispectral imagery acquired from Système Pour l’Observation de la Terre / High Resolution Visible and Infrared (SPOT 5/ HRVIR) satellite. The most successful approach included usage of spectral information along with the contextual post-classification processing based on property parcel size.

Chapter 4 identifies proximate drivers that are correlated with exurban development locations to infer information about the processes driving them. This is then used to assess the risk of future exurban conversion, and to identify the potential conflict areas between conservation goals and developmental potential. Three types of location factors are considered in the study: biophysical, accessibility, and natural amenity based characteristics. As in previous chapters, the analysis was conducted separately for the three zones to determine if the significant locating factors vary between the zones. Future exurban development locations are then identified, using the significant locating factors, and compared with the Great Lakes Conservation Blueprint for Biodiversity (Hensen et al. 2005).
Lastly, Chapter 5 assesses the ecological impact of exurban development and associated roads in terms of barrier effects and its influence on landscape connectivity. This study specifically seeks to compare the estimates of barrier effects and landscape connectivity measures using (i) original or standard land cover data, (ii) refined land cover, (iii) land cover and weighted roads, and (iv) land cover, weighted roads, and weighted exurban development to determine if there are substantial differences in the results. This study also examines the applicability of a recently proposed tool, Circuitscape, which uses circuit theoretic framework (McRae et al. 2008) for assessing landscape connectivity for wildlife with limited dispersal ability in an exurban context. The study area is the exurban portions of the Peterborough County, Ontario (Canada). A case study species, Blanding’s turtle, was used to ensure the barrier effects mapping and landscape connectivity assessment was ecologically relevant as measures of both are species dependent.

Taken together these four chapters of this dissertation provide a comprehensive understanding of exurban development location, locating factors, and its ecological impacts in terms of barriers to wildlife movement and landscape connectivity. The management implications and areas for future research are then explored in the concluding chapter.
Chapter 2: Mapping exurban development: Can road and census data act as surrogates?

ABSTRACT

Exurban development, characterized by low density residential development, is one of the leading anthropogenic causes of land transformation. A major hindrance to studying this phenomenon is a lack of spatially explicit data. In this study two commonly employed indirect approaches that use readily available roads and census data as surrogates of exurban development are examined as a way to delineate exurban development across large spatial extents. The study area is the heterogeneous Peterborough County (Ontario, Canada). Mixed results were obtained when comparing correlations between road density, dasymetric maps and reference data at multiple scales. Comparison between the two methods indicated that dasymetric maps of dwelling counts performed better, but only when the census blocks were of relatively smaller size. These results highlight that heterogeneity contained within a study area can greatly obscure relationships that may be evident at smaller spatial extents, where conditions are relatively more homogeneous, making use of such indirect methods challenging across large spatial extents. In particular, the geographic and historic context of the study area influences the effectiveness of these methods. Additionally, when surrogates are used, the distribution of the surrogate itself may be context dependent (e.g. roads being built regardless of settlements) thereby affecting the overall effectiveness of the mapping approach. Thus caution should be taken while using these methods.

2.1 INTRODUCTION

For many years, researchers either ignored or dismissed exurban development, mainly because data limitations hid its prevalence (Irwin et al. 2007). In recent years, however, the “exurbs” have gained more attention as a result of the recognition that these rapidly expanding areas have major implications for regional land use and conservation planning (Irwin et al. 2007, Hansen et al. 2005). Many contributions in the ecological and planning literatures have also recognized the ecological significance of exurban development (Hansen et al. 2005, Brown et al. 2005, Gude et al. 2006). Despite this, there are still a limited number of scientific studies pertaining to exurban
development. One of the major hindrances is the lack of spatially explicit data reflecting exurban development, which are crucial for making ecological inferences or to conduct detailed analyses regarding its pattern, causes, or consequences (Theobald 2003 a, Hammer et al. 2004, Brown et al. 2005, Hansen et al. 2005, Hawbaker et al. 2005, Gude et al. 2006).

In response to the increasing need to gain spatially explicit data on the various forms of urban land uses, including exurban, many studies in the literature have explicitly focused their efforts on urban mapping. Various indirect and direct approaches have been explored using available GIS data and/or remote sensing datasets. Indirect mapping makes use of existing data that can act as a surrogate to reflect certain phenomenon of interest that are difficult to measure directly, such as level of development in the landscape. To date, little work has explored direct approaches to mapping exurban development outside very small spatial extents or using prohibitively costly methods (see Chapter 3 for details on direct approaches).

The first and one of the commonly used surrogates in indirect mapping of land use intensity is road network data, which are increasingly more detailed and accessible (Mladenoff et al. 1995, Greenburg and Bradley 1997, Stoms 2000, Reyers et al. 2001, Theobald 2005 a). The relationship between the road network and human activities are inextricably intertwined (Forman 2000). Roads are the primary means of access for human use of adjacent areas, and they influence patterns of settlement and land use change, which in turn may induce new travel demands resulting in expansion of the current road network (Hess et al. 2001, Hawbaker and Radeloff 2004). One is unlikely to find settlements mutually exclusive of roads in most parts of North America. Likewise, it is also unlikely that a similar road pattern will always result in
similar intensity of settlements around them, especially in exurban areas. As a result, the assumption that the road network can act as an effective surrogate for human activities in the landscape may not hold true and any ecological or other inferences based on this may be misleading.

Another common surrogate approach utilizes publicly available demographic datasets, such as those generated by a national census (Merrill et al. 1999, Theobald 2003 a and b, Brown et al. 2005). Generally, population density is the preferred attribute used to study settlement patterns. However, since census data is typically tied to the primary place of residence, seasonal and second homes are not well represented. Thus, settlement patterns and associated landscape change may be underestimated if measures based on population are used (Theobald 2003 a). Dwelling count information is more complete in that sense, but again the aggregated nature of the data over large areal units, especially outside urban centers, lacks the geographic precision needed for ecological inference or for detailed studies of settlement patterns.

A variety of analytical problems have been associated with aggregated census data and the arbitrary nature of its areal units (Mennis 2003). One prominent issue is the Modifiable Areal Unit Problem (MAUP), defined as the situation when changes in boundary and/or scale of data aggregation significantly affect the results of spatial data analysis (Openshaw 1983). Also, presentation of such aggregated data by its administrative unit, often in choropleth map format, gives an impression that the data is distributed homogeneously within each areal unit, when in reality it is rarely so (Dorling 1993, Mennis 2003). This is especially true when the areal unit is large and distribution is highly non-uniform, as is the case for most census units in exurban
areas. A surface based representation of demographic data has been proposed as a potential solution to these problems, where data are modeled as continuous fields (raster format) instead of a set of individual geographic entities or objects with aggregated demographic values (vector format) (Mennis 2003). A raster GIS environment allows for development of continuous fields for aggregated demographic data using various areal interpolations (Goodchild et al. 1993) and dasymetric mapping techniques (Eicher and Brewer 2001, Mennis 2003).

The second indirect approach, dasymetric mapping, was first popularized by Wright (1936) and is defined as the particular type of areal interpolation process that redistributes the aggregated numbers from census zonal units using other ancillary information (e.g. roads, land cover, land use) to create smaller spatial units possessing greater internal consistency in the density of the variable being mapped (Langford 2003). These ancillary data can range from a simple set of habited and uninhabited regions as indicated on topographic maps (Wright 1936) to detailed land use datasets derived from remotely sensed imageries such as Landsat Thematic Mapper multispectral imageries (Langford et al. 1991). Likewise the redistribution model also can range from simple areal weighting, with each grid cell receiving a certain percent of the total value based the percent area of the host areal unit it occupies (Wright 1996) to complex systems based on percent “habitable” area each cell occupies, major land use type, and predetermined population distributions within given land use types (Langford et al. 1991, Eicher and Brewer 2001, Mennis 2003, Langford 2006).

In exurban studies, road data combined with land cover data has been used to weigh census dwelling counts, assuming that higher dwelling density is located closer to the road network on
developable land cover (Theobald 2005 a, Brown et al. 2005, Gude et al. 2006). Since the
dasymetric mapping approach is informed by empirical data collected on the ground, such as
census dwelling count data in addition to other ancillary data, this may be a superior approach to
map exurban development compared to using any surrogate measures.

Despite repeated use of roads and census data as surrogate for development, there has not been
any empirical evaluation of their appropriateness. In this study, the utility of these two
commonly used indirect approaches, (i) road network as the surrogate, and (ii) dasymetric
mapping incorporating census data to specifically map exurban development over large spatial
extents is explicitly examined. Additionally, the analyses were conducted at multiple scales
(extent and resolution) to assess the sensitivity of these surrogates to the scale of analysis.

2.2 MATERIALS AND METHODS

2.2.1 Data

Multiple geomatic datasets that were examined in this project to extract exurban development
over a large spatial extent are given in Table 1.
The Ontario Road Network Route File (2005) used includes detailed road network attributes (e.g. route hierarchy, rush hour traffic presence, speed limits, and travel time) for different road types in Ontario (Figure 2 a). In addition, the dwelling count data and related spatial boundary files were acquired for the finest census unit available, census blocks (Figure 2 b) (Statistics Canada 2001). There are a total of 2460 census blocks within the county of which only 1309 census blocks are outside the incorporated urban areas. To normalize for the differences in census block area, the dwelling count density was computed using only the habitable area within each census block (excluding non-habitable areas like water and protected land).

Digital property parcel data for Peterborough (in AutoCad format) from Peterborough County was converted to GIS polygon data (.shp), which was used as the reference data. In addition to the spatial location and lot size information, this data provides broad ownership status information (private, crown, and municipal) for individual parcels. A major limitation of this data is that the built status of individual parcels is not reflected. Thus, some initial processing was conducted to extract the parcels that would define exurban development from the overall
private parcel dataset. First, only private parcels were extracted and categorized into lot size classes that correspond to the parcel lots sizes used in the exurban literature (McCauley and Goetz 2004, Theobald 2005a, Brown et al. 2005, Hansen et al. 2005). Since the data lacks information on parcel’s built status, orthophotos were used to determine which parcels were actually built. The orthophotos, obtained from the southern Ontario orthophotos inventory, had a 20 cm resolution. Since a significant portion of the county was not covered by this database, additional air photos were sought from other sources (e.g. National Air Photo Library), but due to limited dates and resolution of the data, were not considered further. Out of the 601 orthophotos for Peterborough County, a ten percent random sample of usable imagery (67) was obtained.

A five percent random sample was taken for each lot size category within areas where orthophotos were available. Based on the percent of different lot sizes that actually had built structures, smaller than eight hectares parcels were considered as exurban parcels. This is smaller than the 16 hectares lot size that has been used in literature to define exurban parcels (mainly in the western United States), but reflects conditions in Peterborough County (Figure 2c).
Figure 2: County of Peterborough (a) roads, (b) census blocks with dwelling counts, and (c) exurban parcels and orthophotos (available and selected)
2.2.2 Evaluation of road network as a surrogate

In the potential exurban regions of the study area – which excludes water, protected areas, and urban areas – road density was calculated using a simple line density algorithm. This algorithm calculates the magnitude of linear data (road segments) per unit area within a certain specified neighbourhood radius around each output cell. Depending on how large the neighbourhood is, road density values will change. Initially, multiple neighbourhood radii, from as small as 0.5 km, which is assumed to be a reasonable walking distance for a person, to as large as 10 km was examined to assess the effect of neighbourhood scale changes on the road density calculation. Presumably using a smaller neighbourhood radius (0.5 km) will depict local variation better than the larger neighbourhood radius (10 km), but at the expense of broader spatial pattern and vice versa. Only the results pertaining to the neighbourhood radii of 0.5 km or 500m and 1.5 km are presented in this chapter as larger neighbourhood area did not provide necessary details for local exurban mapping.

The road density rasters at 500 m and 1500 m neighbourhood radii were computed using (i) all roads un-weighted (UWRD), (ii) only major and local roads (MLoRD), assuming they reflect residential housing presence better, and (iii) weighting roads by their speed limits (WRD), which varies by road type. Initially, multiple resolutions (cell or pixel size of 10 m, 25 m, 100 m, 300 m, 500 m, and 1000 m) were examined to identify a suitable output resolution to compute road density rasters. A resolution of 100 m sufficiently captured the local variations in road density without resulting in unmanageably large data volume, however to match the resolution of the SPOT multispectral images used in the direct approach (Chapter 3) all indirect approach analyses
were conducted at 10 m resolution. At the Peterborough extent, however, 100 m resolution was used since even the one percent random sample of 10 m raster resulted in computational difficulties.

The three variants of road density (summarized in Table 2) at two neighbourhood radii were then correlated with exurban parcel density data, based on the reference data, using a non-parametric correlation test (Spearman’s Rho) at multiple spatial extents covering (i) County of Peterborough, (ii) three major zones, and (iii) six smaller sample areas capturing the heterogeneity of the landscape (Figure 3). The multi-scale correlation analysis was important to reveal any underlying context-dependent patterns in the correlation results that could provide important information on the effectiveness of the road network as the surrogate for development.

Table 2: Three variants of road density as surrogates

<table>
<thead>
<tr>
<th>Road Density Variant</th>
<th>Abbrev.</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Un-weighted road density</td>
<td>UWRD</td>
<td>using all roads (un-weighted)</td>
</tr>
<tr>
<td>Major and Local road density</td>
<td>MLoRD</td>
<td>using only major and local roads</td>
</tr>
<tr>
<td>Weighted road density</td>
<td>WRD</td>
<td>using all roads weighed by speed limit</td>
</tr>
</tbody>
</table>
Figure 3: Multiple spatial extents at which indirect approach effectiveness was evaluated (overlaid on exurban parcel density at 500m neighbourhood radius)
2.2.3 Evaluation of dasymetric dwelling count data

To create the dasymetric map, the aggregated dwelling count data from the census (Statistics Canada 2001) collected at the level of smallest areal unit available, census blocks, was redistributed into continuous data. A binary dasymetric approach was used, whereby disaggregated dwelling count values are assigned only to the habitable areas (Wright 1996, Mennis 2003). The obvious “non-exurban areas” were excluded from analysis, as in the previous approach. With the road density rasters as the underlying surface, the dwelling count data was redistributed such that higher road density cells were assigned a higher percentage of the dwelling count within the particular census block. Corresponding to the three variants of road density, three dasymetric dwelling count maps were created using the equation 1 (Table 3). All maps preserved the pycnophylactic property (Tobler 1979), which means that “people [or dwelling count] are not destroyed nor manufactured during the redistribution process” (Langford and Unwin 1994, 24).

\[ y_i = \left( \frac{x_i}{z_i} \right) \times k \]  

\text{Equation 1}

where, \( y_i \) = new dwelling count dasymetric map using road density raster, \( i \)

\( x_i \) = road density raster, \( i \)

\( z_i \) = zonal summary of the road density raster, \( i \) (CB as zones)

\( k \) = dwelling count of the census block
The non-parametric correlation test (Spearman’s Rho) was again used to compare the output dasymetric dwelling count rasters and the reference data using the same set of spatial extents as described in the previous section.

Table 3: Three variants of dasymetric dwelling count maps

<table>
<thead>
<tr>
<th>Dasymetric dwelling count Variant</th>
<th>Abbrev.</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dasymetric dwelling count using UWRD</td>
<td>UWDDC</td>
<td>computed using UWRD</td>
</tr>
<tr>
<td>Dasymetric dwelling count using MLoRD</td>
<td>MLoDDC</td>
<td>computed using MLoRD</td>
</tr>
<tr>
<td>Dasymetric dwelling count using WRD</td>
<td>WDDC</td>
<td>computed using WRD</td>
</tr>
</tbody>
</table>

2.3 RESULTS

2.3.1 Evaluation of road network as a surrogate

The multi-scale non-parametric correlation results for (i) Un-weighted Road Density (UWRD), (ii) Major and Local Road Density (MLoRD), and (iii) Weighted Road Density (WRD) rasters at 100m resolution for the county and zonal extents and at 10m resolution for sample subsets extent are presented in Table 4 and Figure 4.

Table 4: Correlation coefficients of road density verses exurban parcel density at multiple scales*

<table>
<thead>
<tr>
<th>Extent</th>
<th>500m</th>
<th>1500m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UWRD</td>
<td>MLoRD</td>
</tr>
<tr>
<td>Peterborough</td>
<td>.558</td>
<td>.075</td>
</tr>
<tr>
<td>Zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>.621</td>
<td>.591</td>
</tr>
<tr>
<td>Mid</td>
<td>.675</td>
<td>.650</td>
</tr>
<tr>
<td>South</td>
<td>.558</td>
<td>.545</td>
</tr>
<tr>
<td>Sample Subset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S1</td>
<td>.662</td>
<td>.662</td>
</tr>
<tr>
<td>S2</td>
<td>.503</td>
<td>.098</td>
</tr>
<tr>
<td>S3</td>
<td>.760</td>
<td>.760</td>
</tr>
<tr>
<td>S4</td>
<td>.537</td>
<td>.537</td>
</tr>
<tr>
<td>S5</td>
<td>.633</td>
<td>.651</td>
</tr>
<tr>
<td>S6</td>
<td>.518</td>
<td>.526</td>
</tr>
</tbody>
</table>

*All correlations significant at the 0.01 level (2-tailed)
Figure 4: (a and b) Un-weighted road density, (c and d) weighted road density, and (e and f) major and local road density at 500 m and 1500 m neighbourhood radii
At the Peterborough extent, results indicate that there is a significant positive correlation between the road density rasters and reference data however the strengths of correlations were relatively weak. Among the multiple road density variants, the UWRD with smaller neighbourhood radius yielded the strongest positive correlation of 0.558. Unlike expected, differentiating between different road types and using only local roads did not yield as strong a correlation. Likewise, using a larger neighbourhood radius of 1500 m also resulted in similar, if not weaker, correlation strength for all road density variants.

The observed weak correlation strengths between the road density raster and the reference data is possibly a result of the spatial extent of the study area and the heterogeneity contained within it. In a large spatial extent such as Peterborough County, the distribution of any surface feature, including road network, is rarely homogeneous. For example, most of the highways (thus high weights in WRD) are situated in the south. Likewise, even the local road network is more extensive in the South, which may or may not reflect residential developments. Historically, the local roads in this region were laid down in a grid pattern to attract potential future agricultural and residential land use (Peter Alley, local resident, personal communications). Since, the road density was not strictly tied to house development throughout the County, when correlation analysis is conducted at a County-level, these sub-regional patterns may be obscured.

At the zonal level, all variants of road density showed stronger significant positive correlations with the reference data. The strongest correlations were observed for the middle zone (0.65-0.78), followed by the northern zone (0.51-0.71), and then the southern zone (0.46-0.56). The strength of correlation was lowest for the South when a larger neighbourhood was used in the
density calculation. This might be attributed to the inclusion of more road grids (characteristic of the South) regardless of development. However, in the other two zones a larger neighbourhood resulted in stronger correlation coefficients.

At a finer spatial extent, represented by the six sample subset areas, the correlation results indicated mixed results. The road density of some samples (1, 3, and 5) showed stronger correlation with the reference data (0.54-0.85), while others (2, 4, and 6) showed much weaker correlation (0.10-0.54), especially at the larger neighbourhood radius. These results highlight an interesting local pattern that was not clearly evident at larger spatial extents. Subsets 2, 4, and 6 are different from subsets 1 and 3 in that they lack distinctly clustered developments and associated road network (e.g. shoreline development). Also some are located in the South, which has the gridded road network regardless of development; thereby a lower association between roads and exurban development exists.

2.3.2 Evaluation of dasymetric dwelling count data

The multi-scale non-parametric correlation results of the three variants of dasymetric dwelling count maps are presented in Table 5 and Figure 5.
Table 5: Peterborough extent correlation coefficients of dasymetric dwelling count vs. exurban parcel density

<table>
<thead>
<tr>
<th>Extent</th>
<th>500m</th>
<th>1500m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DDC_UWRD</td>
<td>DDC_MLoRD</td>
</tr>
<tr>
<td>Peterborough</td>
<td>.092</td>
<td>.083</td>
</tr>
<tr>
<td>Zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>.314</td>
<td>.018</td>
</tr>
<tr>
<td>Mid</td>
<td>.598</td>
<td>.588</td>
</tr>
<tr>
<td>South</td>
<td>.443</td>
<td>.438</td>
</tr>
<tr>
<td>Sample Subset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S1</td>
<td>.676</td>
<td>.676</td>
</tr>
<tr>
<td>S2</td>
<td>.521</td>
<td>.102</td>
</tr>
<tr>
<td>S3</td>
<td>.680</td>
<td>.680</td>
</tr>
<tr>
<td>S4</td>
<td>.555</td>
<td>.555</td>
</tr>
<tr>
<td>S5</td>
<td>.638</td>
<td>.643</td>
</tr>
<tr>
<td>S6</td>
<td>.505</td>
<td>.506</td>
</tr>
</tbody>
</table>

*All correlations significant at the 0.01 level (2-tailed)*
Figure 5: Dasymetric dwelling count maps using (a and b) un-weighted road density, (c and d) weighted road density, (e and f) major and local road density at 500 m and 1500 m neighbourhood radii
Results suggest that similar to road density, there are positive correlation between the dasymetric dwelling count maps and the reference data at the extent of Peterborough County. However, unlike expected, it did not yield substantially better results than using road density alone. In fact, unlike road density, using a smaller neighbourhood gave much weaker correlations regardless of the road density type used in the dasymetric dwelling count map. Using a larger neighbourhood resulted in similar correlation strengths as the road density maps. This suggests that the supplementary information provided by census dwelling count data did not add value to the indirect exurban mapping approach. Nonetheless, recognizing that the large spatial extent could have been a contributing factor, further assessment at smaller spatial extents was conducted.

The zonal level correlation analysis showed that the correlation between most variants of dasymetric dwelling count and reference data were substantially stronger at the zonal level. Nonetheless, a comparison of the two methods at the zonal level revealed that in general road density fares comparatively better, with larger correlation coefficients, than its dasymetric dwelling count counterparts. This is especially pronounced in the North and the Middle, and to a lesser extent in the South. This reestablishes the previous notion that the census dwelling count data does not seem to enhance indirect mapping results. However, it is worth noting that in the South, dasymetric dwelling count showed promise, especially when a larger neighbourhood was used. This observed trend may be attributed to a limitation of the census data, which typically has large census blocks in the northern and middle zones and much finer blocks in the south, thereby affecting the results of the dasymetric dwelling count mapping approach.
At the finer spatial extent of the subset areas, the dasymetric dwelling count maps correlation results showed mixed results, similar to road density. However, the dasymetric dwelling count of the southern sample subsets (5 and 6) have slightly stronger correlations than for road density. Again, this may be due to the smaller census block sizes in the South, which provided detailed dwelling count data.

2.4 DISCUSSION

On the whole, the multi-scale analysis of the multiple variants of two indirect approaches clearly illustrate two major points: (i) the examined indirect approaches perform well only for certain geographic locations, neighbourhood radius, and spatial extents, thus context and scale matters, and (ii) unlike expected the indirect approach that uses additional information, such as census data, does not always yield better results in mapping exurban development.

First, the mixed results obtained from each level of the multi-scale correlation analysis of road density and dasymetric dwelling counts clearly highlight that when large spatial extents are involved, the heterogeneity contained within the study area can greatly obscure the overall results. This is the case of Peterborough County extent, where the correlation results show a relatively weak relationship. However, at smaller spatial extents, where conditions are more homogeneous, the indirect approaches produced maps that relate more strongly with the reference data, indicating that they may be better surrogates for exurban development than depicted by the larger scale results.
The strong performance of the indirect approaches in the middle and subsets 1 and 3 for road density at the 1500m neighbourhood imply that these areas have something that others do not. One common characteristic among them, which is absent elsewhere, is that each contains large water bodies and is dominated by shoreline development. It seems that though water bodies, a major natural amenity in many exurban areas, are not directly included in the mapping approach, they are creating a contextual basis on which the surrogate (road network) distribution is dependent. When existing data is being used as a surrogate for development, the distribution of the surrogate itself may be highly context dependent, thereby affecting the overall effectiveness of the mapping approach. Therefore, in areas like the southern Peterborough, where roads were historically laid down regardless of development and in some parts of northern Peterborough, where presence of “wilderness” roads were extensive, the indirect approaches performed poorly. While in other areas like the middle region of Peterborough County and some parts of the North (mainly around major natural amenity such as large water bodies), the indirect approaches performed better.

In the light of above discussion, it is safe to say that the multi-scale analysis revealed that though the road network can be an effective surrogate for development, it is highly dependent on the context of the study area (geographical and historical). If exurban development is mostly concentrated around a non-uniform road network, as in natural amenity dominated areas like the Middle zone in this study, roads can act as surrogate for development. But, if it is not the case, such as in the South, then caution should be taken when using the roads and its derivatives as a
surrogate for exurban development. Needless to say, the analyst’s knowledge of the study area is crucial, when considering the use of the indirect approaches for exurban mapping.

Second, the relatively similar (and in some cases poorer performance) of the dasymetric dwelling count mapping approach as compared to the road density maps, revealed that incorporating census data may not necessarily yield better results than using simple surrogate measures. The census dwelling count data seemed to improve the result of the indirect mapping approach only when the census blocks were relatively smaller in size, such as in southern zone and sample subsets 5 and 6. This suggests that though the census data did not prove to be as useful in improving the indirect mapping results in this study, the reason behind it is attributed more to the a limitation of the data rather than a limitation of the methodology itself. When the census block units are very large and the road network distribution is not tied to human settlements (presence of “wilderness” roads without developments as in the North, and roads regardless of development in the South), a dasymetric approach is not able to allocate the dwelling counts correctly. In contrast, if the road network is tied to the residential development and the census block boundaries are fine, such as in case of the middle zone (shoreline developments served by local roads), it allows for more precise reallocation of the dwelling count resulting in better performance of a dasymetric dwelling count approach. Thus, the dasymetric mapping approaches examined in this study has high potential to be used in exurban mapping only if fine resolution census data is available.
2.5 CONCLUSION

In response to the increasing need for spatially explicit data on the various forms of urban development, including exurban areas, many studies have focused their efforts on urban mapping. However, the focus is still mostly on urban and suburban areas with high density settlement patterns, the results of which may or may not be applicable to low density urban environments such as exurban areas (McCauley and Goetz 2004). Indirect approaches have primarily been explored in literature as a way to map exurban development, though there has not been explicit evaluation of the appropriateness of these methods (Langford et al. 1991, Stuckens et al. 2000, Eicher and Brewer 2001, Mennis 2003, Theobald 2005 a). In this chapter, I have particularly addressed this issue by exploring the applicability of two specific indirect methods to map exurban development in the study area at multiple spatial scales.

This study demonstrated that the indirect mapping approaches using readily available datasets (such as the detailed road network data and the census dwelling count data collected at the finest spatial unit) can be successfully used as surrogates to map exurban developments in areas. However, there are two major concerns that need to be taken into consideration when doing so: scale and context. When these surrogates are assessed at large spatial extents, the heterogeneity contained within the study area can greatly obscure the overall results, thereby not clearly reflecting when surrogates are effectively capturing exurban development. This problem is largely mitigated by conducting assessments at smaller spatial extents, where conditions are relatively more homogeneous. The multi-scale analysis of the surrogates also revealed that the geographical and historical context of the study area is an important factor in deciding their
effectiveness. When ancillary data are used as a surrogate for development, the distribution of
the surrogate itself may be highly context dependent (such as roads being built to serve the
residences, or being built regardless of the development, or being built as wilderness roads)
thereby affecting the overall effectiveness of the mapping approach, and thus caution should be
taken while using these measures. The areas where roads are spatially tied to the exurban
development, as in natural amenity dominated landscapes such as the North and Middle zones of
Peterborough, roads seem to be the useful surrogate. In locations like the South, where roads
were present regardless of development, additional information on census dwelling counts
proved to be useful.

Among the two examined indirect approaches using (i) road density as the surrogate, and (ii)
dasymetric dwelling counts with census data, the latter seemed to perform better only when the
census blocks were of relatively smaller size (higher resolution data). Also, multiple variants of
the road data did not yield substantially different results, except when highways were excluded
from analysis, in which case the result was very poor for some areas in the study area.

Though this research has clearly illustrated the potential and the challenges associated with the
examined indirect approaches for mapping exurban development over large spatial extents, this
study has a number of limitations. A major limitation in this study is that the parcel data, used as
reference data, is not complete and up-to-date. There were areas (e.g. identified to be Indian
Reserves) where the census and the road data showed dwelling count values and local roads
respectively, but parcel data had no records at all thereby creating a false impression that the
indirect approach was incorrect. In addition, the road network data did not include private
roads, which would probably have better reflected exurban developments. In the future, it may be worth trying to include the private road data, which currently does not exist. Lastly, the year each dataset reflects is not a perfect match (census data is from 2001 whereas road data and property parcel data were last updated in 2005), which might have affected the strengths of correlation results negatively. All the stated limitations, however, only contribute to the underestimation of the effectiveness of the indirect approaches, therefore, with more up-to-date and better geo-referenced datasets the indirect approaches may actually show better results than what is demonstrated in this study.
Chapter 3: Delineating exurban development footprint using SPOT imagery and ancillary data

Published in:

ABSTRACT

Exurban development, characterized by low density residential development, is one of the leading anthropogenic causes of land transformation. A major hindrance to studying this phenomenon is a lack of spatially explicit data. In this paper, we explore a simple method based on NDVI recoding of SPOT 5 imagery (10 m resolution) to delineate exurban built pixels across large spatial extents. The study area is the heterogeneous Peterborough County (Ontario, Canada). While an accuracy assessment of the initial NDVI recoding had a producer’s accuracy of approximately 80%, the user’s accuracy was extremely low (20%) reflecting high commission error. To improve the latter, post-classification structural and contextual processing using readily available data were examined. The structural processing produced slight improvement, but the user’s accuracy was still mostly below 50%. The contextual processing using water, roads, and a dasymetric map also showed only slight improvement. Alternatively, the inclusion of parcel boundary data proved to be the most effective method for exurban mapping in the study area, with the user’s accuracy in most sections of the study area over 65% and the producer’s accuracy approximately 80%. This study highlights how the low density, dispersed nature of the exurban development compounds the normal challenges associated with mapping built cover, making most of the traditional post-classification processing methods ineffective. An exception to this appears to be contextual processing based on parcel size.

3.1 INTRODUCTION

Today, exurban development is used to define the landscape between contiguous urban development and the rural countryside (Nelson 1992). Quantitatively, it has been characterized as low density housing, with approximately 6 to 25 homes per square kilometer within a landscape dominated by natural cover (Brown et al. 2005).

Exurban development is advancing at unprecedented rates. With ever increasing technological advances, a flexible work environment that encourages tele-commuting and an affluent retiring population, this trend is expected to continue into the future (Gude et al. 2006, Hansen et al. 2005, Huston 2005). Since the location of exurban development is often non-random relative to biodiversity, as both are strongly influenced by biophysical factors, the ecological effects of exurban development may be disproportionately large relative to the area it covers (Hansen et al. 2005). Thus, it is critical for geographers, ecologists, conservationists, and planners alike to improve our understanding of this widespread cause of landscape transformation. However, a major challenge to studying exurban development is a lack of spatially explicit data, which is mainly a result of urban land cover datasets excluding these low density areas (Hansen et al. 2005).

Most remote sensing techniques used to map urban cover are spectrally based, attempting to capture buildings and other impervious surface covers’ distinct spectral signatures (Campbell 2007). Exploiting the unique spectral profile, indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI), have been developed to automate the land cover mapping process in areas with built cover (Zha et al. 2003). However, most research has focused on high density urban and suburban areas, the results of which may not be applicable to low density urban environments such as exurban landscapes (McCauley and Goetz 2004).

One challenge in mapping urban land cover is the heterogeneous nature of such a landscape due to the variety of materials or cover types (i.e. concrete, asphalt, trees, grass, water, soil, and a variety of roofing material) present. This heterogeneity makes it difficult to define a spectrally distinct ‘built’ class (Jensen 2007). An additional challenge is that urban materials may be spectrally similar to other non-urban cover types, such as bare rocks or fallow fields, causing further confusion (Zhang et al. 2002). These challenges become more so when small, isolated patches of urban cover exist within a vegetated landscape, as is the case with exurban development.

Various attempts have been made to overcome the challenges associated with urban land cover mapping (Mesev 2003). One approach has been to use high spatial resolution data, which are fine enough to distinguish between different cover types within urban areas (Jensen 2007, Lu and Weng 2007). However, as the spatial extent of the study area increases, obtaining very high resolution imagery (1-4 m) becomes prohibitively expensive and involves unmanageably large
data volumes (McCauley and Goetz 2004). Also, recent studies have concluded that even with increased spatial resolution, mixed pixel problems were pervasive, along with between class spectral confusion and within class spectral variation (Gao and Skillcorn 1998, Zhang et al. 2003).

Others map urban land cover by attempting to tackle the problem of mixed pixels and spectral confusion directly. McCauley and Goetz (2004) developed an impervious surface map of the Chesapeake Bay area in the Eastern US, with sub-pixel classification of Landsat imagery using a Classification and Regression Tree (CART) approach. Likewise, Artificial Neural Networks (Lee and Lathrop 2006) and Linear Spectral Mixture Analysis (Small 2001 and 2002) have also been explored to overcome the problem of spectral mixtures. In addition, spatial information provided by satellite images, such as structural measures (e.g., shape, size), textural measures and contextual information, have been used to provide supplementary information to differentiate among classes when spectral information alone was insufficient (Lackner and Conway 2008, Stuckens et al. 2000, Zhang 1999, Zhang et al. 2003, ). Finally, ancillary data have also been used to provide additional information to delineate urban cover from other cover types (Zhang et al. 2002).

Though these techniques can accurately map high density urban land cover, the utility of these techniques in exurban regions has not been fully explored. Some exceptions in the current literature involve studies at very high spatial resolutions (1-4 m) across small spatial extents that are not realistic for large geographic extents (Lee and Lathrop 2006, McCauley and Goetz 2004). Alternatively, Treitz et al. (1992) used SPOT 10 m panchromatic and 20 m multispectral data to
classify eight land cover types in the urban-rural fringe of Toronto. They employed a two-stage
digital analysis algorithm incorporating a spectral-class frequency-based contextual classification
resulting in an overall accuracy of 78%. Gao and Skillcorn (1998) also used SPOT 20 m data to
produce detailed land cover maps at the urban-rural periphery with acceptable accuracy levels.
However, to our knowledge, no study has evaluated the capabilities of SPOT 5 / HRVIR data,
which has a relatively high spatial resolution (10 m) across all multispectral bands and the wide
image swath (60 km) needed to extract exurban pixels that are dispersed across large geographic
areas.

In this study, we explore a simple and effective method for rapid and accurate delineation of
built cover associated with exurban development across large spatial extents. In particular, this
method is based on NDVI recoding of moderate spatial resolution (10 m) multispectral imagery
acquired from Système Pour l’Observation de la Terre / High Resolution Visible and Infrared
(SPOT 5/ HRVIR) satellite, with and without post-classification structural and contextual
processing. The study area is the County of Peterborough (Ontario, Canada), a biophysically
diverse area that has experienced over fifty years of exurban development.
3.2 MATERIALS AND METHODS

3.2.1 Satellite Data

Portions of five leaf-on SPOT 5 / HRVIR multispectral (MS) images (10 m) were needed to cover the study area (Table 6). The selection of the sensor data was based on factors that included the objective of the study, the spatial scale (resolution and extent), characteristics of the study area, image availability, and cost constraints (Phinn 1998, Lu and Weng 2007).

Table 6: Specifications of SPOT 5 / HRVIR imagery

<table>
<thead>
<tr>
<th>K / J</th>
<th>Cols x Rows</th>
<th>Date (yy/mm/dd)</th>
<th>Time</th>
<th>Incidence Angle</th>
<th>Viewing Angle</th>
<th>Sun Azimuth</th>
<th>Sun Elevation</th>
<th>Coordinate System</th>
</tr>
</thead>
<tbody>
<tr>
<td>615/260</td>
<td>7214x7182</td>
<td>05/06/28</td>
<td>16:13</td>
<td>-5.69</td>
<td>-5.02</td>
<td>142.92</td>
<td>65.34</td>
<td>UTM 17N</td>
</tr>
<tr>
<td>616/259</td>
<td>5565x4929</td>
<td>05/06/07</td>
<td>16:17</td>
<td>2.27</td>
<td>1.97</td>
<td>149.82</td>
<td>65.14</td>
<td>UTM 18N</td>
</tr>
<tr>
<td>616/260</td>
<td>7322x7156</td>
<td>06/05/27</td>
<td>16:07</td>
<td>-11.30</td>
<td>-9.98</td>
<td>145.99</td>
<td>63.20</td>
<td>UTM 17N</td>
</tr>
<tr>
<td>617/260</td>
<td>7550x7536</td>
<td>05/07/03</td>
<td>16:16</td>
<td>4.16</td>
<td>3.66</td>
<td>146.48</td>
<td>65.45</td>
<td>UTM 18N</td>
</tr>
<tr>
<td>617/261</td>
<td>7554x7540</td>
<td>05/07/03</td>
<td>16:17</td>
<td>4.16</td>
<td>3.66</td>
<td>145.58</td>
<td>65.79</td>
<td>UTM 18N</td>
</tr>
</tbody>
</table>

Each scene subset was co-registered with the others using identifiable features in the scenes, such as road pixels, to ensure the spatial location of a particular pixel relative to the other subset. Though all five images were taken around the same phonological time of the year (late spring/early summer), only two were from the exact same date, and a range of different years were represented. Thus, image normalization was deemed important to match the image radiometric signals so that they are consistent between images (Olthof et al. 2005).

Various methodologies and algorithms (Chavez 1975 and 1988) have been proposed in the remote sensing literature to perform image normalization, where all scenes of a composite are matched to a reference scene selected as the least atmospherically contaminated scene. With
each method there are limitations associated with error propagation from reference scene outwards since normalization is done in a recursive manner (Guindon 1997), difficulty in automation, in-situ data unavailability, as well as biases that may result when selected invariant objects area not strictly invariant (Huang et. al. 2000). In addition, most of these methods assume homogeneity within the scene, which is rarely the case, especially over large spatial extents. They are also known to create more problems when cloud, shadow, and/or haze are present in the image. Thus, in the light of the above issues, as proposed by Huang et al. (2000) only first order normalization was performed on each SPOT scene, which were relatively cloud free, to achieve image normalization to the extent possible.

The first order normalization was done by converting raw DN values of each SPOT 5 scene to at-satellite reflectance values using two sets of standard equations. First, DNs were converted to radiance using equation 2 (Chander and Markham 2003).

\[
L_\lambda = \frac{(L_{\lambda_{max}} - L_{\lambda_{min}})}{Q_{cal_{max}}} Q_{cal} + L_{\lambda_{min}}
\]  

Equation 2

where \(L_\lambda\) is the spectral radiance at the sensor’s aperture in Wm\(^{-2}\)sr\(^{-1}\)\(\mu m\)^{-1}, \(Q_{cal}\) is the quantized calibrated pixel value in DNs, \(Q_{cal_{min}}\) is the minimum quantized calibrated pixel value corresponding to \(L_{\lambda_{min}}\), \(Q_{cal_{max}}\) is the maximum quantized calibrated pixel value corresponding to \(L_{\lambda_{max}}\), \(L_{\lambda_{min}}\) is the spectral radiance that is scaled to \(Q_{cal_{min}}\) in Wm\(^{-2}\)sr\(^{-1}\)\(\mu m\)^{-1}, and \(L_{\lambda_{max}}\) = spectral radiance that is scaled to \(Q_{cal_{max}}\) in Wm\(^{-2}\)sr\(^{-1}\)\(\mu m\)^{-1}.

Then the radiance value of each pixel is converted to at- satellite reflectance value using equation 3 (Chander and Markham 2003).
\[ \rho_p = \frac{\pi L_\lambda d^2}{(E_{\text{SUN}} \lambda \cos \theta_s)} \]  

Equation 3

where \( \rho_p \) is the unit less planetary reflectance, \( L_\lambda \) is the spectral radiance at sensor’s aperture, \( d \) is the Julian day specific earth and sun distance in astronomical units (au), \( E_{\text{SUN}} \lambda \) is the band specific mean solar exoatmospheric irradiance, and \( \theta_s \) is the solar zenith angle in degrees.

Nevertheless, as with many other normalization techniques (Chavez 1988, Huang et al. 2000), the first order normalization could not completely eliminate inconsistencies in reflectance values among the scenes. Therefore, a scene-by-scene classification using five scene-specific training datasets was completed to minimize error. For all scenes, water bodies, protected areas and land within the incorporated urban areas, including the City of Peterborough, were masked out using the ancillary data.

3.2.2 Binary recoding of NDVI

The goal of the classification was to create a binary map separating built cover associated with exurban development from the rest of the landscape, hereafter called exurban built pixels and other, respectively. The general approach used to capture exurban built pixels, including pre-processing steps, is summarized in Figure 6.
Figure 6: Schematic of Methodology
Multiple classification methods – unsupervised ISODATA clustering, supervised per-pixel maximum likelihood classification, and an arithmetic manipulation of binary recoded Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) – were initially examined for a sub-set of the study area to determine the best approach. In the end, the simple technique using only NDVI recoding achieved the highest accuracy levels. Thus, we decided to further examine this simple yet potentially effective method’s utility in mapping exurban pixels over large geographic areas. NDVI for SPOT 5 MS data is defined in equation 4.

$$NDVI_{SPOT5} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} = \frac{\text{Band 3} - \text{Band 2}}{\text{Band 3} + \text{Band 2}} \quad \text{Equation 4}$$

NIR and Red stand for the spectral reflectance measurements acquired in the near infrared and red regions. NDVI values range from –1.0 to +1.0, with dense vegetation canopy having positive values due to low Red reflectance, while the classes that have high reflectance in the visible part of the spectrum (e.g. clouds, snow, and built pixels) are characterized by negative values (Campbell 2007). The relative simplicity of the algorithm and its capacity to broadly distinguish vegetated areas from other surface types has made NDVI one of the most successfully used indices in remote sensing, including urban applications (Masek et al. 2000, Zha et al. 2003, Jensen 2007).

The first step in the binary recoding of the NDVI raster was choosing scene-specific thresholds for each image to distinguish between the two classes. For each SPOT scene, a number of training points representing exurban built pixels were digitized based on orthophotos and parcel boundary data. To determine the NDVI threshold values to be used in recoding, the NDVI value
at each training point was extracted (Table 7). Based on the descriptive statistics of these training points, several threshold options were examined.

Table 7: NDVI value range for the SPOT scenes and the scene specific training points

<table>
<thead>
<tr>
<th>Scene No.</th>
<th>Scene NDVI_min</th>
<th>Scene NDVI_max</th>
<th>Training Points NDVI_min</th>
<th>Training Points NDVI_max</th>
</tr>
</thead>
<tbody>
<tr>
<td>615 260</td>
<td>-0.412</td>
<td>0.615</td>
<td>-0.012</td>
<td>0.424</td>
</tr>
<tr>
<td>616 260</td>
<td>-0.250</td>
<td>0.755</td>
<td>0.171</td>
<td>0.486</td>
</tr>
<tr>
<td>617 260</td>
<td>-0.444</td>
<td>1.000</td>
<td>0.148</td>
<td>0.671</td>
</tr>
<tr>
<td>617 261</td>
<td>-0.310</td>
<td>1.000</td>
<td>0.161</td>
<td>0.458</td>
</tr>
</tbody>
</table>

Accuracy assessment results indicated that using a threshold value defined as the mean NDVI of the built training pixels plus 1 standard deviation ($\text{NDVI}_{\text{mean}} + 1 \ \text{NDVI}_{\text{SD}}$), which statistically would include 68% of the built training sample (Rogerson 2001), captured built pixels reasonably well. It yielded high producer’s accuracy and relatively higher user’s accuracy compared to a more generous threshold value of ($\text{NDVI}_{\text{mean}} + 2 \ \text{NDVI}_{\text{SD}}$) or a commonly used fixed threshold value of zero (Zha et al. 2003). Thus, scene-specific thresholds defined by ($\text{NDVI}_{\text{mean}} + 1 \ \text{NDVI}_{\text{SD}}$) were used to recode the NDVI rasters for the five SPOT scenes. The resulting binary images were then mosaicked together to create a single binary map of the study area.

3.2.3 Post-classification processing

In urban remote sensing, high commission error (i.e. low user’s accuracy) is often a problem (Griffiths 1988, Lu and Weng 2007, Jensen 2007, Sim et al. 2005, Zhang et al. 2002). The overestimation of built pixels, due to spectral confusion among built land cover and other classes of interest, such as barren agricultural fields and bare rocks, is a challenge that is hard to resolve with spectral information alone. In this study, such confusion was evident with the NDVI
recoding technique, which had a high producer’s accuracy but very low user’s accuracy.

However, it was apparent that some of the incorrectly classified built pixels could be easily separated using additional information, such as structural attributes and contextual information (Groom et al. 1996).

Thus, to further distinguish among the classes of confusion, post-classification structural and contextual information was explored. The structural processing used spatial information from the initial classification results to filter out incorrectly classified built pixels, while the contextual processing incorporated ancillary data (roads, water, dwelling units, and parcel boundaries) that are often correlated with the presence of exurban development (Table 8). In all, seven additional classifications were created (Table 9).
Table 8: Summary of data used in the contextual processing

<table>
<thead>
<tr>
<th>Data</th>
<th>Data Type</th>
<th>Date</th>
<th>Spatial Resolution</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water Bodies</td>
<td>Raster</td>
<td>05 - 06</td>
<td>1 ha</td>
<td>SPOT classification</td>
</tr>
<tr>
<td>Dasymetric Dwelling</td>
<td>Raster</td>
<td>01 - 02</td>
<td>10 m</td>
<td>Census and Road data</td>
</tr>
<tr>
<td>Road Network</td>
<td>Vector</td>
<td>05</td>
<td>-</td>
<td>DMTI Spatial</td>
</tr>
<tr>
<td>Parcel Boundaries</td>
<td>Vector</td>
<td>05</td>
<td>-</td>
<td>County of Peterborough</td>
</tr>
</tbody>
</table>

Table 9: Structural and contextual processing variants of the NDVI recoding

<table>
<thead>
<tr>
<th>Processing Levels</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural Processing</td>
<td></td>
</tr>
<tr>
<td>NDVI_10 000</td>
<td>Retained built pixel clusters &gt;=2 and &lt;=100 pixels</td>
</tr>
<tr>
<td>NDVI_5 000</td>
<td>Retained built pixel clusters &gt;=2 and &lt;=50 pixels</td>
</tr>
<tr>
<td>NDVI_2 500</td>
<td>Retained built pixel clusters &gt;=2 and &lt;=25 pixels</td>
</tr>
<tr>
<td>Contextual Processing</td>
<td></td>
</tr>
<tr>
<td>NDVI_water</td>
<td>Retained built pixels within 250 m of a water body</td>
</tr>
<tr>
<td>NDVI_roads</td>
<td>Retained built pixels within 200 m of a road</td>
</tr>
<tr>
<td>NDVI_dasy</td>
<td>Retained built pixels where value &gt; 0 in dasymetric dwelling count map</td>
</tr>
<tr>
<td>NDVIParcel</td>
<td>Retained built pixels on parcels less than 8 ha</td>
</tr>
</tbody>
</table>

**Structural processing**

Structural processing was explored because it could potentially eliminate misclassified barren fields, since agricultural fields tend to be much larger than the footprint of exurban development (Griffiths 1988). The first step in the structural processing was creating unique clumps of classified built pixels, using a four-pixel rule. Clumps greater than 25 pixels (2 500 m²), 50 pixels (5 000 m²) and 100 pixels (10 000 m²) were then sieved out on separate runs. It was expected that exclusion of built pixel clumps larger than 2 500 m² would remove all agricultural fields, but at the expense of some correctly classified exurban built pixels. Thus, filtering out larger clump sizes was also explored as a way to minimize omission error. Additionally, for each
classification, including the contextual processing variants, single pixel built clusters were removed as they primarily represented noise.

**Contextual processing**

Contextual processing was explored to address the misclassification of both barren agricultural fields and bare rock by filtering out locations where exurban development was unlikely to exist. Different kinds of contextual information, such as housing and population density, the road network, temperature, precipitation, digital elevation models and soil maps, is often incorporated into a classification procedure to improve accuracy (Lu and Weng 2007). A critical step, however, is to develop relevant rules so that the classes of confusion can be separated (Lu and Weng 2007). For example if the class of interest (i.e. exurban development) is spatially associated with certain features (i.e. near large water bodies) then this contextual information can be used to develop filter rules to isolate the class of interest.

The study area covers a large geographic area and is highly heterogeneous in nature, in terms of both biophysical and land use characteristics, so several types of contextual information were explored to separate exurban built pixels from bare rock and barren fields: (i) proximity to water bodies, (ii) proximity to roads, (iii) dasymetric dwelling counts, and (iv) property parcel size.

Since the study area is a popular location for second homes, especially in the North on the Canadian Shield, much of the exurban development is in close proximity to lakes and rivers. Thus, these shoreline developments may be isolated from spectrally similar covers by removing pixels far from water bodies. Though water bodies could provide good insight into locating built
pixels in the northern part of the study area, in the southern part it might not work as well since there are fewer lakes and the demographic situation is quite different. Here, factors such as the historic presence of a regular-grid road network may primarily influence the location of exurban development. Thus, in both cases a buffer distance from these features was determined using training data. All exurban pixels outside the buffer were then reclassified as ‘other’.

A Dasymetric Dwelling Count (DDC) map was employed for the third contextual processing variant. A dasymetric map is a type of areal interpolation that redistributes aggregated values from census areal units using other ancillary data (e.g. roads, land cover, land use) to create smaller spatial units possessing greater internal consistency in the density of the variable being mapped (Langford 2003). A dasymetric dwelling count map was created at 10 m spatial resolution based on 2001 census data and local road density. Only locations with a dasymetric dwelling count value equal to or greater than one are considered likely to have exurban development. Thus all pixels with a value of zero were reclassified as ‘other’.

The last contextual variant used spatially explicit private property parcel boundary data as a contextual filter. This data did not contain the built status of individual properties, but did provide the location and size of each privately-owned parcel. Based on a comparison between samples of parcels of varying sizes and orthophotos, it was established that most parcels less than eight hectares included some kind of built structure. Thus, any exurban built pixels from the initial classification located on parcels larger than eight hectares were re-classified as ‘other’.
3.2.4 Accuracy Assessment

In this study, an accuracy assessment of the initial binary recoded NDVI map and the structurally and contextually corrected variants was conducted using 2002 20 cm orthophotos as the reference data. First, nine different sample sites, three in each zone (North, Middle, and South), were selected to limit the data volume required for the accuracy assessment without compromising the ability of the accuracy assessment to capture the heterogeneity of the study area. Each sample site covered an extent of three orthophotos (Figure 7). Sample site selection was based on available orthophotos and presence of exurban property parcels.
Figure 7: Location of the nine sample sites for accuracy assessment
A stratified random sample from the classified map was used to conduct the accuracy assessment. This is a commonly adopted method in remote sensing where a random sample of each class from a classified map is compared against the reference data, and the relationship between the two datasets is summarized in an error matrix (Congalton 1991). An error matrix is an N x N matrix of "observed" and "classified" cells corresponding to N land cover classes that depicts the classified class versus the reference class. The diagonal cells indicate correct classification according to the reference data. The off-diagonal cells indicate a misclassified cell. This is an effective way to represent accuracy since accuracy of each class is clearly described along with both the producer’s accuracy and the user’s accuracy. Producer’s accuracy is a measure of how accurately the analyst classified the image by class (columns) and details the errors of omission (pixel is omitted from its correct class). It is calculated by dividing the correct number of pixels by the column or reference total. User’s accuracy is a measure of how well the classification is performed in the field by category (rows) and details the errors of commission (pixel is committed to an incorrect class). It is calculated by dividing the correct number of pixels by the row or classified total.

In this study, for each of the eight classified maps 300 random sample points (150 each for the built and the others classes) were selected within the nine sample sites, with 50 points from each zone for each class. These points were used to determine the producer’s and user’s accuracy for (1) all of Peterborough County and (2) individually for the three zones.

Theoretically a stratified random sample of pixels from different classes in a classified map should be able to capture both producer’s accuracy and user’s accuracy well, thereby providing
an accurate measure of overall accuracy of a classification technique. However, problems arise
when a class of interest is rare on the map: the random sample of the classified pixels often fails
to include an appropriate number of representative sample points for the rare class, thereby
potentially overestimating its producer’s accuracy indicating low omission error. In this research
the class of interest, exurban built, is rare. Thus, relying on a random (simple or even stratified)
sample selection approach may lead to an inflated producer’s accuracy while hiding the fact that
potentially not enough sample points have been considered representing actual exurban built
pixels. This is especially true in the North zone where all classified built pixels may be correctly
classified, but still the omitted built pixels may not be reflected in the other class due to its
extreme rarity in the landscape.

To overcome this problem, it was deemed necessary to include a sample of exurban built pixels
digitized directly from the reference data, in addition to the stratified random sample from the
classified image. A total of 72 reference built points were digitized using the orthophotos and
SPOT scenes and proportion of correctly classified points were used to estimate the omission
error for each classified map. Relying only on a sample from the reference data such as this, as is
the case in some urban remote sensing studies (Zha et al. 2003), is not desirable as it will fail to
reflect the user’s accuracy (commission error) since the sample is limited to only the actual built
class locations.
3.3 RESULTS

Figure 8 shows the original NDVI raster, the simple binary recoded NDVI raster for the study area, and the best structurally and contextually-processed variants. Based on an initial visual inspection, it is apparent that the simple NDVI recoding includes small patches of exurban pixels scattered throughout the study area, with a higher density of patches located in the southern zone (Figure 8 b). A similar scatter pattern is evident in the structural processing variant (Figure 8 c), although many patches in the South have been removed from the original classification. With all contextually-processed variants, the exurban patches follow the pattern of the ancillary data used as the filter. For example, the use of exurban parcels as a filter retained exurban built patches where there are relatively small ownership parcels: along roads, due the subdivision of large agricultural parcels along the road frontage, and close to water bodies (Figure 8 d). Since, the class of interest in this study is the built class, which is also a ‘rare’ class, most of the discussion is focused on the producer’s and user’s accuracy of this class in the following sections.
Figure 8: (a) NDVI rasters, (b) Recode with $\text{NDVI}_{\text{mean}} + 1$ std. dev threshold, (b) NDVI recode with structural processing (2 to 50 pixel), and (c) NDVI recode with contextual processing (private parcels <8ha)
3.3.1 Binary recoding of NDVI

The assessment of the simple binary NDVI classification using the stratified random sample points yielded a producer’s accuracy of 89%, but a much lower user’s accuracy of about 21% (Table 10). This was expected since a relatively generous threshold value was chosen to minimize the omission errors.

Table 10: Summary of Producer’s Accuracy (PA) and User’s Accuracy (UA) of exurban built class

<table>
<thead>
<tr>
<th></th>
<th>Peterborough PA (%)</th>
<th>Peterborough UA (%)</th>
<th>North PA (%)</th>
<th>North UA (%)</th>
<th>Middle PA (%)</th>
<th>Middle UA (%)</th>
<th>South PA (%)</th>
<th>South UA (%)</th>
</tr>
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<tbody>
<tr>
<td>NDVI recoding</td>
<td>89</td>
<td>21</td>
<td>100</td>
<td>22</td>
<td>80</td>
<td>16</td>
<td>86</td>
<td>24</td>
</tr>
<tr>
<td>Structural Processing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI_10000</td>
<td>78</td>
<td>36</td>
<td>86</td>
<td>24</td>
<td>76</td>
<td>44</td>
<td>77</td>
<td>40</td>
</tr>
<tr>
<td>NDVI_5000</td>
<td>86</td>
<td>40</td>
<td>86</td>
<td>38</td>
<td>77</td>
<td>40</td>
<td>95</td>
<td>40</td>
</tr>
<tr>
<td>NDVI_2500</td>
<td>76</td>
<td>41</td>
<td>80</td>
<td>32</td>
<td>78</td>
<td>58</td>
<td>70</td>
<td>32</td>
</tr>
<tr>
<td>Contextual Processing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI_water</td>
<td>49</td>
<td>27</td>
<td>93</td>
<td>26</td>
<td>61</td>
<td>50</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>NDVI_roads</td>
<td>80</td>
<td>40</td>
<td>86</td>
<td>36</td>
<td>66</td>
<td>38</td>
<td>92</td>
<td>46</td>
</tr>
<tr>
<td>NDVI_dasy</td>
<td>74</td>
<td>27</td>
<td>73</td>
<td>22</td>
<td>68</td>
<td>26</td>
<td>80</td>
<td>32</td>
</tr>
<tr>
<td>NDVI_parcelas</td>
<td>79</td>
<td>67</td>
<td>83</td>
<td>60</td>
<td>76</td>
<td>68</td>
<td>79</td>
<td>74</td>
</tr>
</tbody>
</table>

The accuracy assessment conducted at the sub-regional level revealed that the producer’s accuracy is high for all zones with the highest estimate for the northern zone (Table10). The 100% in the northern zone indicates that there are zero omission errors whereas it was obvious from orthophotos that it was not so. Thus, as discussed earlier, the digitized reference points were used to re-examine the omission error, which indicated that only 65% of the reference points in the North were actually captured in the classified map (Table 11). This illustrates the problem with the traditional accuracy assessment method when the class of interest is extremely rare. For the middle and southern zones the results were relatively similar between the two
accuracy assessment methods, thus are not of much concern in this study. The relatively higher omission error in the North was likely due to the presence of older buildings with smaller footprints, and denser mature vegetation shadowing the built areas. The best producer’s accuracy was observed for the southern zone, which has open farmland and less dense vegetation, so that exurban sites could be easily captured by the 10 m resolution imagery.

| Table 11: Producer’s Accuracy (%) based on analyst selected built points |
|-------------------------------|-----------|---------|---------|---------|
|                               | Peterborough | North  | Middle | South  |
| NDVI recoding                 | 81         | 65      | 80      | 96      |
| Structural Processing         |            |         |         |         |
| NDVI_10000                    | 71         | 50      | 80      | 85      |
| NDVI_5000                     | 69         | 50      | 75      | 85      |
| NDVI_2500                     | 65         | 50      | 75      | 73      |
| Contextual Processing         |            |         |         |         |
| NDVI_water                    | 47         | 65      | 70      | 12      |
| NDVI_roads                    | 76         | 62      | 70      | 96      |
| NDVI_dasy                     | 74         | 62      | 70      | 89      |
| NDVI_parcel                  | 79         | 62      | 80      | 96      |

All three zones showed low user’s accuracy, indicating high commission error for the entire study area. The northern and middle zones have the lowest probably due to the substantial presence of bare rock in the Boreal Shield. In the South, the low user’s accuracy can be attributed to the spectral confusion between built cover and bare agricultural fields prevalent in this area. It is likely that using SPOT images acquired later in the season when the bare agricultural fields are grown out (August) could eliminate this problem; however the unavailability of five relatively cloud free SPOT 5 images ruled out this option. Overall, these results highlight a clear challenge when using an NDVI recoding technique to map exurban
3.3.2 Structural Processing

Elimination of patches of varying sizes tended to decrease the producer’s accuracy (Tables 10 and 11) and only moderately increased the user’s accuracy of the exurban built class (Table 10), suggesting many actual exurban development patches were being re-classified as non-built. This was true at the county and zonal extents. The lower cut-off values (2,500 and 5,000 m$^2$) had the highest user’s accuracies, but also substantial decreases in the producer’s accuracies as compared to the initial classification.

Overall, the structural processing results suggest that a structural filter could not uniformly improve the initial NDVI classification, although this type of post-classification processing did help in cases where there was confusion between built patches and barren agricultural fields by almost doubling the user’s accuracy. In particular, excluding patches greater than 5,000 m$^2$ in the southern zone substantially removed misclassified agricultural fields without greatly compromising the accuracy level of correctly classified patches of exurban development. However, the level of user’s accuracy was still far below acceptable levels (40%).

3.3.3 Contextual Processing

The post-classification contextual processing also produced mixed results (Tables 5 and 6). At the extent of Peterborough County, using proximity from water bodies substantially reduced the producer’s accuracy (49%) as compared to the initial classification, while the other contextual
filters lead to only a slight change. User’s accuracy increased in all cases, and did so substantially when ownership parcel boundary data was used.

Using proximity to water bodies to filter built pixels yielded a lower producer’s accuracy not only in the South, where lakes are scarce, but also in the North, which has numerous lakes and shoreline development. But substantial improvement is seen in the middle zone, mainly because this region had a high proportion of shoreline development around a few large lakes. As expected, the road filter produced the highest user’s accuracy for the southern zone, but it is still below acceptable levels. The use of a dasymetric map proved no better than the road filter, even with the added information associated with housing density.

The most dramatic improvements were observed when ownership parcel data was used to extract built pixels from the initial NDVI classification. At the study area extent, the producer’s accuracy was at acceptable level (79%) and user’s accuracy was also higher (67%) than any other method examined in this study. Though 67% is still considered lower than acceptable level using common remote sensing standards (>70%), it is a substantial improvement from the initial 20%. The producer’s accuracy also remained high for the three zones (>75%), and uniformly produced the highest user’s accuracy. Thus, given the challenges associated with mapping low density and dispersed development such as exurban development, using parcel size as a filter was determined to be the appropriate approach to minimize the commission error in the study area.
3.4 **DISCUSSION**

This paper describes an effort to directly map exurban development with operationally efficient remote sensing data using a method that can be applied across large spatial extents (regional level). While binary recoding of NDVI was able to produce results with acceptable producer’s accuracy, additional processing was needed to increase the user’s accuracy. This research suggests that 10 m SPOT 5 MS imagery has sufficiently fine resolution to capture the relatively small, isolated clusters of pixels associated with exurban development. Although, where canopy cover is very high lower accuracies were achieved. Additionally, ancillary information was needed to reach acceptable user’s accuracies, through separation of built cover from barren agricultural fields and bare rocks. Such confusion is not surprising (Jensen 2007, Lu and Weng 2007, Zhang *et al.* 2002) and may be pronounced when mapping exurban development, which often occurs within agricultural landscapes and/or is located on rugged terrain where rocky outcroppings may be common.

Recognizing the limitation of using the spectral information alone, we examined post-recoding structural and contextual processing to try to minimize the commission error without increasing the omission error in the process. High commission error has always been an issue in urban remote sensing, mainly because urban pixels are spectrally similar to other common cover types such as bare rocks, barren fields, and shorelines (Jensen 2007, Lu and Weng 2007, Sim *et al.* 2005, Zhang *et al.* 2002). In cases where the focus is not explicitly on the built land cover, this problem is mostly ignored by creating a combined ‘built/bare’ class and acknowledging the limitation (Zhang *et al.* 2002).
Another approach to avoid such commission error usually involves removing ‘noise’ through a filtering process to create a smoothed map with minimal salt-and-pepper effect (McCauley and Goetz 2004). However, when the target of interest is exurban built cover, both of these approaches are flawed, since the built pixels need to be separated from other spectrally similar cover types and they are likely to be present in small clusters, which may be mistaken for noise if a standard filtering process is applied. In this study, the commission error within the study area was significantly reduced through post-recoding processing.

The success of the post-classification structural processing, however, was slight, while the contextual processing was more varied. The water and road filters showed some potential in different zones. The most impressive result was obtained when contextual processing was conducted using the ownership parcel boundaries, probably because the non-residential properties in the study area tend to be much larger than the typical exurban building lot. This is particularly true in the southern zone, where most non-exurban properties are 40 or 80 hectares (100 or 200 acres) as a result of 19th century land division (MacIwlraith 1997). In the North, uniform parcel boundaries were never delineated, which may explain why the parcel filter was less successful.

The methods used in this paper do have a number of limitations. First, there is a temporal difference between the reference data, orthophotos from 2002, and the SPOT 5 MS data (2005/2006). This meant that non-built areas shown in the orthophotos may actually have been built during the three or four year time gap. However, this limitation will not affect the overall usefulness of the final exurban map since its producer’s and user’s accuracy are within the
acceptable range for this study, and if there were additional built areas it would mean that the accuracy assessment actually underestimated the user’s accuracy (less commission error).

A second limitation of the approach was the use of leaf-on imagery, which likely caused lower accuracy where there is dense canopy cover. While the southern zone’s results suggest that 10 m leaf-on imagery is sufficient, use of leaf-off imagery should be explored as a way to improve the classification in the North. Despite these limitations, use of a simple NDVI threshold with parcel boundary-based contextual processing showing potential to map exurban development.

3.5 CONCLUSION

This study explored a relatively simple remote sensing technique using binary recoding of NDVI values from SPOT 5 / HRVIR imagery and post-classification processing to map exurban development in a relatively large, heterogeneous landscape. While binary recoding of NDVI alone was able to produce results with acceptable producer’s accuracy, user’s accuracy was very low due to confusion between exurban built cover, barren agriculture fields, and bare rocks. Our results showed that contextual post-classification processing could improve the user’s accuracy, with the level of increase dependent on the local landscape context and the specific method used. The structural processing proved to only have limited effectiveness even in areas where the major class of confusion has substantially larger patches than the target class. It performed worst in places where the major class of confusion does not have a distinct patch size. The effectiveness of the contextual processing also varied across the study area. The most promising
approach was inclusion of a parcel boundary filter, which was able to produce the best user’s accuracy, while maintaining high producer’s accuracy across the heterogeneous study area.
Chapter 4: Exurban development: An assessment of the locating factors, conversion risk, and conflict with conservation plans

ABSTRACT

Exurban development is one of the leading anthropogenic causes of land transformation. Expanding at unprecedented rates, it is impacting previously unaltered areas, including those with high conservation value. The significance of the potential ecological consequences of exurban development is recognized by many in the literature, however, there are few studies documenting it on the landscape. In this study, the relationship between biophysical conditions, socio-economic accessibility, natural amenity features and exurban development is compared to determine the factors influencing exurban developments’ location. Future risk maps were then created based on these relationships. These maps were compared with previously identified conservation priority areas for biodiversity protection to begin to understand the extent of exurban threats to conservation goals in the study area, Peterbourgh County, Ontario. The analysis of potential locating factors using logistic regression and classification trees indicates that accessibility factors consistently play an important role in exurban development patterns, but many other factors had significant influence in only one or two sections of the study area. The creation of the risk maps suggests that based on existing conditions the study area is not under substantial threat of future exurban conversion, primarily due to a lack of suitable developable areas. Finally, the comparison of the conversion risk map with the conservation priority areas indicates that though a substantial portion of the priority areas is not located in areas with a high risk of development, a large portion of the priority areas is unprotected, thus is vulnerable to any future changes in the landscape.

4.1 INTRODUCTION

A critical but often overlooked aspect of land and ecological conservation is an understanding of future threats to the landscape (Conway 2005). Many anthropogenic threats come in the form of land use conversion and/or intensification through modifications of natural land cover. Such land conversion can bring irreversible changes to the landscape, as mostly pervious land covers are converted into impervious surfaces (i.e. buildings and roads). This results in loss and/or
fragmentation of natural cover that may provide refuge to wildlife. Wilcove et al. (2000) argue that conversion to residential development, and associated land uses, is the leading cause of species imperilment on private lands in North America. One particular type of residential development, exurban development, may warrant special concern because it is often located near ecologically sensitive areas. Thus, it may have a disproportionately large ecological effect relative to its physical footprint (Hansen et al. 2005).

Exurban development is advancing at an unprecedented pace, often impacting previously undisturbed areas (Hansen et al. 2005, Brown et al. 2005, Theobald 2000). Advances in information technology are allowing more people to flee cities to adopt small-town lifestyles near the natural amenities of rural landscapes (Hansen et al. 2005, Huston 2005, Gude et al. 2006). With a growth in flexible work environments that allow tele-commuting and a burgeoning affluent retiring population, this trend is expected to continue in future (Hansen et al. 2005). Consequently, the irreversible changes associated with exurban development in natural amenity rich areas typically outside incorporated urban centers will continue.

Recent research has focus on predicting future development based on spatial and socioeconomic correlates of recent development. When considering future residential development in metropolitan areas, the primary locating factor is often spatial accessibility to population and/or employment centers (Verburg et al. 2004). However, in exurban regions access to natural amenities, such as parks, nature reserves, and lakes may have a stronger influence on the location of development (Gustafson et al. 2005, Conway 2005, Hansen et al. 2005). To better understand the processes behind land conversion and the threats associated with future conversions, it is
crucial to examine the relationship between current land use and potential locating factors in a landscape. Such an understanding will allow the broader planning process to be more proactive than reactive, and will facilitate timely management of land conversion (Nelson 1992).

The goals of this chapter are to explore the proximate drivers of exurban development in the study area, assess future land conversion risks associated with exurban development, and identify potential conflict areas with existing conservation goals. Three types of location factors are considered in the study: biophysical, accessibility, and natural amenity based characteristics. As in previous chapters, the analysis was conducted separately for the three zones to determine if the significant locating factors vary between the zones. Future exurban development locations are then identified, using the significant locating factors, and compared with the Great Lakes Conservation Blueprint for Biodiversity.

4.1.1 Potential Locating Factors

Landscape change is dependent on drivers that are often complex and regionally dependent (Kasperson et al. 1997). Considerable attention has been given to identifying both large scale driving forces and more local determinants of land use, and consequent land cover change. Large-scale driving forces include socioeconomic conditions and biophysical factors (Lambin et al. 2001), such as shifting economic conditions, technological innovations, population growth, and climate change (Meyer and Turner 1994). Alternately, the specific location of change is usually assumed to be related to accessibility to transportation corridors, biophysical characteristics, spatial policies and zoning laws, and socioeconomic and natural amenities-based factors that affect site or neighborhood characteristics (Verburg et al. 2004, Conway 2005).
Based on these potential factors, Huston (2005) proposed three distinct stages of development that result in land change, which can be temporally sequential or may occur simultaneously and potentially interact with each other. The first stage is characterized by development locations that are mostly dependent on biophysical characteristics (elevation, slope, aspect, surficial geology, and existing land cover) that constrain or facilitate changes. The second stage is defined by the growing transportation network, which provides easy accessibility to employment centers thus development follows their pattern. The third stage is characterized by advanced information technology, which has allowed development to overcome the previous two factors, and in which development can occur almost anywhere. In this stage of development, natural amenity is increasingly becoming the significant influencing factor in land change.

When identifying significant locating factors, land prices (Geoghegan et al. 1997), population density (Turner et al. 1995), and available services (Bockstael 1996) are considered important socioeconomic factors in determining location of urban development. However, accessibility to urban or employment centers remains a common focus in predicting exurban development location (Schneider and Pontius 2001, Conway 2005). The emphasis on accessibility is a result of assumptions associated with equilibrium maximizing individuals, whereby each individual is seeking to meet their need to access the services to the maximum, inherent in many of these analyses (Verburg et al. 2004). Nevertheless, in nature rich exurban landscapes the importance of such variables may or may not be as significant due to the value residents place on the perceived “naturalness” of the area (Patel 1980, Fernandez et al. 2005). In these situations, development tends to occur in isolation and / or closest to natural amenities regardless of ease of
access to urban centers (Theobald and Hobbs 1998). However, if exurban development is situated in an agricultural landscape within the “commutershed” of major urban centers, accessibility-based variables may be more pronounced than in a nature rich landscape where natural amenities may be the most significant factors (Conway 2005, Gustafson et al. 2005, Gude et al. 2006).

When defining accessibility-based variables, there is no single measure employed (Handy and Niemeier 1997). Euclidean (Schneider and Pontius 2001) and / or functional distance (Turner et al. 1996, Wear and Bolstad 1998) to a given urban center is often used. In cases with no clear urban or employment centers, such as many exurban areas, Euclidean or functional distance to highway exits following the local road network (Verburg et al. 2004, Conway 2005) and to nearest urban site (Pijanowski et al. 2002) can be useful measures. Alternately, the amount or percent of certain land covers, such as built cover, within a specified neighborhood is another way of defining access (Geoghegan et al. 1997).

Outside accessibility factors, analyses of exurbanizing landscapes often included a number of biophysical and natural amenity based characteristics as potential locating factors. Existing land cover may be used to represent the ease of clearing for development, slope angle is assumed to be related to difficulty of construction, while elevation has been used to represent vegetation and climatic differences (Turner et al. 1995). Other factors such as flooding potential (Schneider and Pontius 2001), view of natural features (Geoghegan et al. 1997, Wear and Bolstad 1998), and access to water and protected open space (Conway 2005) have also been considered as relevant locating factors.
4.1.2 Land Conversion Modeling

Empirical modeling is an important tool for studying land use and land cover change due to its ability to integrate measurements of land cover changes and associated drivers (Lambin et al. 1999). Numerous modeling frameworks have been used to study land conversions and the locations of particular anthropogenic activities in the landscape, with the choice of modeling approach based on the specific purpose of the study (Verburg et al. 1999).

Empirical, spatially-explicit land use and land cover models provide a way to explore current spatial patterns, understand the processes driving them, and project future conditions in the landscape (Lambin 1997, Schneider and Pontius 2001, Conway 2005), which in turn can facilitate proactive development and biodiversity conservation planning. Developing models of future landscape change to facilitate the land use decision making is increasingly common. In addition to evaluating threats to existing agricultural lands and future rates of fragmentation and loss of natural cover, these models can be used to examine the consequences of various build-out scenarios on biodiversity (Turner et al. 2001, Theobald and Hobbs 2002). However, in most of the cases, these models focus primarily on continuous urban areas and thus are of limited use to project increases in low density residential developments, such as exurban development (Merenlender et al. 2005).

Methodological approaches employed to model the potential location of future land conversions include two broad approaches, spatial transition-based models and regression-based models (Theobald and Hobbs 1998). The spatial transition-based models are based on a stochastic Markov-chain technique, where a single step or Markov transition function at each times step
\( t+1 \) is a function of the state at time \( t \) (Zhou and Liebhold 1995). It is a form of stochastic cellular automata, which assume that the influence of neighbouring areas affect the transition probabilities of any particular area (Zhou and Liebhold 1995).

Alternately, regression-based models establish relationships between a wide range of explanatory variables and the probability of land use change (Theobald and Hobbs 1998, Schneider and Pontius 2001). It is commonly used to understand historical, current, and future patterns of land conversion. This approach is data demanding for spatially explicit studies, yet analytically simple and is widely used in land conversion modeling (Turner et al. 1996, Schneider and Pontius 2001, Verburg et al. 2004, Conway 2005, Gustafson et al. 2005, Gude et al. 2006). In this study a logistic regression model, which is appropriate for dichotomous or binary response data (presence / absence), was used to establish the relationship between current exurban development and potential locating factors.

A conceptually different approach that has been used extensively in ecological modeling, but has not been examined in much detail in land conversion studies, is decision based trees such as Classification and Regression Trees (CART) (Breiman et al. 1984, Iverson and Prasad 1998, Guisan and Zimmermann 2000, Miller and Franklin 2002). While regression models fit the data to a pre-specified model CART models are data driven, allowing development of a model whose form is directly a function of the particular dataset (Miller and Franklin 2002). Rather than estimating a mean value for a range of explanatory variables associated with the response variable, decision trees identify specific thresholds associated with each variable above or below which the response variable can be found (Moore et al. 1991). If the response variable is
continuous, such as species abundance, then regression trees are used and if it is categorical, such as species type, then classification trees are used. In this study a dichotomous categorical response variable (presence / absence) is used, thus a classification tree approach was explored as a second method to establish the relationship between exurban development and potential locating factors.

Regardless of the modeling approach used, the data from two or more dates is typically employed. The first set of data (i.e. training data) is used to detect change and to establish the relationship with the locating factors and the second set (i.e. test data) is used to validate the established relationship with actual change in the landscape (Conway 2005). In cases where time series data is not available, the spatial relationship between the location of particular land cover and the locating factors can be used to establish the relationship. Such approaches are common practice in predictive studies in ecology, such as predictive vegetation distribution mapping (Franklin 1995, Iverson and Prasad 1998, Miller and Franklin 2002) and habitat distribution mapping (Mladenoff et al. 1995, Wahlberg et al. 1996, Pearce and Ferrier 2000, Hirzel et al. 2002). In this study, due to the lack of time series data, a similar approach was adopted where the relationship between the potential locating factors and existing exurban development was established.
4.2 MATERIALS AND METHODS

4.2.1 Exurban land cover

The location of exurban development mapped using SPOT/HRVIR imagery, described in the previous chapter, is used as the response variable in this analysis. All exurban built cells within a single property parcels boundary were considered as a single observation. An equal sample of presence (exurban built cells) and absence (non-built cells) locations were included to support a robust analysis. The presence (1) sample was based on all exurban development locations, for a total of 21,342 cells within Peterborough County. An equal number of absence (0) cells were identified through a constrained random sample of non-built cells located outside the property parcels containing exurban built cells. All undevelopable lands were excluded from the sample. Areas that were deemed unavailable for exurban development included protected areas (based on the Ontario parks dataset), all locations designated as urban areas (by Statistics Canada), and all water bodies larger than 5 ha. The absence cells were selected from only those areas that were relatively similar to exurban locations: cells within 250 m of roads and water bodies. The sample was selected to achieve an equal number of presence and absence cells for not only the entire study area, but also for each of the three zones (Table 12).

Table 12: Exurban development presence and absence by zone

<table>
<thead>
<tr>
<th>Zone</th>
<th>Total Presence (1)</th>
<th>Random Sample of Absence (0)</th>
<th>Total Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>4924</td>
<td>4924</td>
<td>9848</td>
</tr>
<tr>
<td>Mid</td>
<td>8214</td>
<td>8214</td>
<td>16428</td>
</tr>
<tr>
<td>South</td>
<td>8204</td>
<td>8204</td>
<td>16408</td>
</tr>
<tr>
<td>Total</td>
<td>21342</td>
<td>21342</td>
<td>42684</td>
</tr>
</tbody>
</table>
4.2.2 Explanatory variables

A total of 18 potential locating factors were used in the analysis (Table 13), selected based on the literature, data availability, and characteristics of the study area. These variables are broadly categorized as (i) biophysical conditions, (ii) accessibility, and (iii) natural amenity-based characteristics.

Table 13: Potential locating factors

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable code</th>
<th>Source</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Biophysical</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i. Elevation</td>
<td>Elev</td>
<td>NRCan</td>
<td></td>
</tr>
<tr>
<td>ii. Slope</td>
<td>Slop</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td>iii. Stoniness</td>
<td>Ston</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td><strong>Accessibility</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i. Road density within 0.5 km</td>
<td>UWRD_5</td>
<td>DMTI</td>
<td>2006</td>
</tr>
<tr>
<td>ii. Road density within 1.5 km</td>
<td>UWRD_15</td>
<td>DMTI</td>
<td>2006</td>
</tr>
<tr>
<td>iii. Euclidean distance to Roads</td>
<td>ED_road</td>
<td>DMTI</td>
<td>2006</td>
</tr>
<tr>
<td>iv. Euclidean distance to Railway</td>
<td>ED_rail</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td>v. Euclidean distance to Urban Area</td>
<td>ED_urba</td>
<td>StatCan</td>
<td>2001</td>
</tr>
<tr>
<td>vi. Euclidean distance to Airfields</td>
<td>ED_airf</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td>vii. Euclidean distance to Health Centers</td>
<td>ED_heal</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td>viii. Euclidean distance to Schools</td>
<td>ED_Scho</td>
<td>OMNR</td>
<td></td>
</tr>
<tr>
<td>ix. Functional distance to Toronto</td>
<td>FD_toro</td>
<td>StatCan</td>
<td>2001</td>
</tr>
<tr>
<td>x. Functional distance Highway Ramps</td>
<td>FD_ramp</td>
<td>DMTI</td>
<td></td>
</tr>
<tr>
<td>xi. Percent developed within 1km radius</td>
<td>Dev_1km</td>
<td>OFRI</td>
<td>2000</td>
</tr>
<tr>
<td>xii. &lt;8ha Parcel Density within 0.5 km</td>
<td>ExDen_5</td>
<td>Teranet</td>
<td>2006</td>
</tr>
<tr>
<td><strong>Natural Amenity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i. Euclidean distance to water body</td>
<td>ED_wate</td>
<td>SPOT classification</td>
<td>2005/06</td>
</tr>
<tr>
<td>ii. Euclidean distance to protected areas</td>
<td>ED_capa</td>
<td>OMNR</td>
<td>2006</td>
</tr>
<tr>
<td>iii. Percent forest cover within 1km</td>
<td>For_1km</td>
<td>OFRI</td>
<td>2000</td>
</tr>
</tbody>
</table>

Three biophysical variables were included: elevation, slope, and a variable describing the surficial geology in terms of stoniness of the land. The accessibility characteristics were represented by two road density variables, defined as the length of road within a 0.5 km and 1.5...
km neighbourhood respectively, reflecting the extent of the road network in the vicinity of each cell. A number of proximity variables were created to reflect the Euclidean distance of each cell to the nearest feature of interest such as the road network (excluding freeways), railway lines, urban areas, airfields, health centers, and schools. Also, functional distance, defined as the distance following the road network, to major accessibility centers (i.e. Toronto and freeway ramps) was computed. The last accessibility variables were the percent of land with built land cover within 1 km and the density of <8 ha property parcels within 0.5 km, to represent each site’s surrounding neighbourhood. Lastly, natural amenity based characteristics were represented by the amount of forest cover within 1 km and the two proximity variables: Euclidean distance from water bodies and conservation and protected areas. Each locating factor was computed for an area 100 km beyond the study area boundary to avoid boundary effects.

4.2.3 Locating factors analysis

The relationship between the response variable, presence or absence of exurban development, and the multiple explanatory variables were examined using two specific modeling approaches: logistic regression and classification trees. Once determined, the relationship defined by both methods was then used to project the likelihood of future land conversion to exurban development and generate the land conversion risk maps for the study area.

**Logistic Regression**

Logistic regression was used in this analysis primarily because the response variable was binary, defined as exurban built (1) or other (0), with exurban built as the predicted outcome. The
logistic function is based on a curvilinear response between the response and the explanatory
variables, defined in equation 5.

\[ E(Y|x) = \frac{e^{(\beta_0 + \beta_1x)}}{1 + e^{(\beta_0 + \beta_1x)}} \]  

Equation 5

where the expected value of \( Y \) for a given \( x \) \((E(Y|x))\) is bounded between 0 and 1 in the binomial
model. To test for multicollinearity, correlations among the 18 explanatory variables were
determined using Spearman’s \( r \), since it does not require the variables to have a normal
distribution and can account for possible non-linear relationships (Daniel 1990). Based on the
observed correlations and scatterplots, seven different sets of potential locating factors (Table
14) were included in separate runs, to determine which variable sets best explains the location of
existing exurban development while minimizing multicollinearity.

Table 14: Variable sets included in the logistic regression

<table>
<thead>
<tr>
<th>Variable Set</th>
<th>Variables Included</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>All potential locating factors included</td>
</tr>
<tr>
<td>1</td>
<td>All variables but FD_tor and Uwrd_15</td>
</tr>
<tr>
<td>2</td>
<td>Elev, Slop, Ston, UWRD_5, UWRD_15, Dev_1km, Exden5, For_1km</td>
</tr>
<tr>
<td>3</td>
<td>Elev, Slop, Ston, ED_rds, ED_ua, ED_air, ED_sch, ED_rails, FD_rmp, ED_wtr, ED_capa, For_1km</td>
</tr>
<tr>
<td>4</td>
<td>Set 3 plus exden5</td>
</tr>
<tr>
<td>5</td>
<td>Set 4 plus UWRD_15</td>
</tr>
<tr>
<td>6</td>
<td>Set 4 plus UWRD_5</td>
</tr>
<tr>
<td>7</td>
<td>Elev, Slop, Ston</td>
</tr>
</tbody>
</table>

Within each variable set, the most significant explanatory variables were identified using a step-
wise selection process (Pearce and Ferrier 2000). Each zone was analyzed separately to account
for the potential differences in the locating factors across the study area.
Four general goodness-of-fit measures were used to evaluate the results. First, Akaike's Information Criterion (AIC) helps to identify the most parsimonious model that best explains the data with the fewest number of independent variables. Lower values indicate a better fit. Second, the percent concordant is calculated by examining all possible pairs of 0-1 observations. If the observation with a dependent value of 1 has a higher predicted value than the paired observation then the pair is concordant (Allison 1999). Larger concordant values are associated with a better fit. Third, the widely used Receiver Operating Characteristic (ROC) statistics was calculated. This provides a more complete description of classification accuracy by estimation the area under the ROC curve that plots the probability of detecting true signal and false signal for an entire range of possibility (Hosmer and Lemeshow 2000, Pontius and Schneider 2001). The area under the curve ranges from zero to one, and values closer to one indicating the model’s greater ability to discriminate between true and false signals and in case of map comparison, this indicates higher level of agreement between the maps. The fourth and the final global goodness-of-fit measure is the pseudo R-square, a measure of the explanatory power of the independent variables. A pseudo R-square greater than 0.2 is considered a good fit (Pampel 2000).

All possible future exurban locations were then determined by eliminating areas that could not convert to exurban (i.e. protected as open space, designated urban centers, and locations that were already developed) and applying the equation derived from the logistic regression to the remaining land, this calculates a likelihood value for each cell that represents its probability of converting to exurban development based on the level of shared characteristics with already
converted sites. The probability maps for each zone were created separately using the zone specific equations, and then combined to create a single map of Peterborough County.

**Classification Trees**

Full grown classification trees were created with the same presence and absence sample data that was used in the logistic regression and all 18 explanatory variables. Since the tree size is not limited in the growing process, a tree may be more complex than necessary to describe the data. To minimize over fitting, the full grown trees are generally pruned to achieve parsimonious description by reducing the nodes on a tree (S-Plus 2005). Pruning successively snips off the least important splits, where the importance is measured by the cost-complexity measure based on the deviance (or misclassification error rate) of the sub-tree and the number of terminal nodes (for details refer to S-PLUS 2005, pp 17). Figure 9 shows the reduction in misclassification rate with addition of tree size or nodes for the North. Since over three-fourth of the misclassification rate was explained by the first five nodes in the full tree, 70 nodes were pruned keeping only those first five (Figure 9). The summary of the full tree and the resulting pruned tree were compared to assure that the simplified pruned model did not substantially compromise the misclassification rate. Likewise, for the Middle and the South zones the full grown tree was pruned by 82 and 93 nodes respectively.

The pruned tree that represented the simplest model with minimum difference in misclassification rate as compared to the full grown tree was used to create the probability of exurban conversion map. The results of the classification tree analysis were evaluated using the ROC as the general goodness of fit measure. The probability of conversion map was created
using StaModZone for ArcView (Gerrard 2003). Similar to the logistic regression procedure, the probability maps for each zone were created separately using the zone specific classification trees model.
Figure 9: Classification tree of the North zone (a) Tree Size (x-axis) plotted against the Misclassification Error Rate for the full grown tree, and (b) Tree pruned by 70 nodes
Comparison of the two approaches

A confusion matrix was used to examine differences in output between the two methods. The probability maps resulting from the logistic regression and the classification trees methods were compared in terms of total number of cells allocated to five different conversion probability classes; >75%, 50-75%, 25%-50%, 10%-25%, and <10%.

4.2.4 Future land conversion risk and conflict with biodiversity conservation

Both probability maps were then used to assess future land conversion risk in Peterborough County. The probabilities of exurban conversion modeled by both methods were stratified into the same five risk classes as used in the confusion matrix. The total area within each risk class was calculated and compared at the county and the zone level.

The areas with a high risk of exurban conversion were also compared with two existing datasets that defined (i) high value areas for biodiversity conservation as identified by the Great Lakes Conservation Blueprint for Biodiversity (GLCBB) (Henson et al. 2005) (Figure 10 a) and (ii) the state of greenlands protection (Fraser and Neary 2004) (Figure 10 b) to identify the potential conflict areas between development interests and biodiversity conservation.
Figure 10: (a) The Great Lakes Conservation Blueprint for Biodiversity and (b) The State of Greenlands Protection
4.3 RESULTS

4.3.1 Locating factor analysis

Logistic Regression

Table 15 shows the results of the logistic analysis for each set of variables across the two regions. Not surprisingly, the “All” set, forcing all variables to be included, performed the best, because adding additional independent variables will always increase the amount of variation explained, but does so at the expense of greater complexity. Variable Set 2, where all Euclidean and functional distance variables are excluded, performed the worst in all three zones, indicating the general importance of accessibility measures. Interestingly, the equation that only included the three biophysical variables (Sel 7) performed reasonably well. Finally, every variable set explained the location of exurban development better in the northern zone than in the other two zones; while the best variable set was different for each zone.
Table 15: Goodness of fit for eight sets of stepwise logistic regression models

<table>
<thead>
<tr>
<th></th>
<th>AIC</th>
<th>Concord.</th>
<th>ROC(c)</th>
<th>P. Rsq (L&amp;F)</th>
<th># of Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>7053</td>
<td>92.7</td>
<td>0.928</td>
<td>0.485</td>
<td>13</td>
</tr>
<tr>
<td>Sel 1</td>
<td>7097</td>
<td>92.7</td>
<td>0.928</td>
<td>0.482</td>
<td>13</td>
</tr>
<tr>
<td>Sel 2</td>
<td>11196</td>
<td>80.0</td>
<td>0.801</td>
<td>0.181</td>
<td>9</td>
</tr>
<tr>
<td>Sel 3</td>
<td>9300</td>
<td>86.2</td>
<td>0.862</td>
<td>0.320</td>
<td>8</td>
</tr>
<tr>
<td>Sel 4</td>
<td>7239</td>
<td>92.6</td>
<td>0.926</td>
<td>0.471</td>
<td>5</td>
</tr>
<tr>
<td>Sel 5</td>
<td>7174</td>
<td>92.6</td>
<td>0.927</td>
<td>0.476</td>
<td>8</td>
</tr>
<tr>
<td>Sel 6</td>
<td>7165</td>
<td>92.7</td>
<td>0.927</td>
<td>0.477</td>
<td>10</td>
</tr>
<tr>
<td>Sel 7</td>
<td>7448</td>
<td>92.6</td>
<td>0.927</td>
<td>0.455</td>
<td>4</td>
</tr>
<tr>
<td>Middle</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>14168</td>
<td>88.8</td>
<td>0.888</td>
<td>0.379</td>
<td>14</td>
</tr>
<tr>
<td>Sel 1</td>
<td>14177</td>
<td>88.7</td>
<td>0.888</td>
<td>0.379</td>
<td>13</td>
</tr>
<tr>
<td>Sel 2</td>
<td>18210</td>
<td>80.9</td>
<td>0.810</td>
<td>0.201</td>
<td>7</td>
</tr>
<tr>
<td>Sel 3</td>
<td>17162</td>
<td>82.2</td>
<td>0.823</td>
<td>0.247</td>
<td>9</td>
</tr>
<tr>
<td>Sel 4</td>
<td>14324</td>
<td>88.5</td>
<td>0.886</td>
<td>0.372</td>
<td>11</td>
</tr>
<tr>
<td>Sel 5</td>
<td>14309</td>
<td>88.5</td>
<td>0.886</td>
<td>0.373</td>
<td>10</td>
</tr>
<tr>
<td>Sel 6</td>
<td>14205</td>
<td>88.7</td>
<td>0.887</td>
<td>0.377</td>
<td>10</td>
</tr>
<tr>
<td>Sel 7</td>
<td>14776</td>
<td>88.4</td>
<td>0.885</td>
<td>0.352</td>
<td>3</td>
</tr>
<tr>
<td>South</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>15127</td>
<td>88.7</td>
<td>0.888</td>
<td>0.336</td>
<td>11</td>
</tr>
<tr>
<td>Sel 1</td>
<td>15124</td>
<td>88.8</td>
<td>0.888</td>
<td>0.336</td>
<td>11</td>
</tr>
<tr>
<td>Sel 2</td>
<td>19603</td>
<td>78.0</td>
<td>0.781</td>
<td>0.139</td>
<td>8</td>
</tr>
<tr>
<td>Sel 3</td>
<td>19475</td>
<td>78.3</td>
<td>0.784</td>
<td>0.145</td>
<td>8</td>
</tr>
<tr>
<td>Sel 4</td>
<td>15157</td>
<td>88.7</td>
<td>0.888</td>
<td>0.335</td>
<td>10</td>
</tr>
<tr>
<td>Sel 5</td>
<td>15153</td>
<td>88.7</td>
<td>0.888</td>
<td>0.335</td>
<td>11</td>
</tr>
<tr>
<td>Sel 6</td>
<td>15124</td>
<td>88.8</td>
<td>0.888</td>
<td>0.336</td>
<td>11</td>
</tr>
<tr>
<td>Sel 7</td>
<td>16093</td>
<td>87.5</td>
<td>0.877</td>
<td>0.293</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 16 shows the variables that were retained in the final equations for all three zones.

Logistic coefficients can be generally interpreted based on their sign. In the North, exurban development is less likely to occur far from highway entrance ramps, far from local roads, in areas with high local forest density, higher elevations, greater stoniness, and high local road density. Exurban development is more likely to occur near existing urban and exurban areas. In the Middle, a similar relationship exists for all of those variables, while distances to nearest
airfield and water body were also retained: exurban development was more likely to be closer to water body, as expected in nature rich areas, but away from the airfields, probably to avoid noise.

In the South, many of the variables and relationship remained the same but a new variable, distance to school, was also retained. The South contains most of the urban areas of Peterborough County and is less of a nature rich area, thus it was not surprising to see that a social amenity plays an important role here. This may also indicate the more suburban nature of development in the South.

Table 16: Most parsimonious stepwise logistic regression model coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beta Coefficient</th>
<th>Variable</th>
<th>Beta Coefficient</th>
<th>Variable</th>
<th>Beta Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.9587</td>
<td>Intercept</td>
<td>4.6242</td>
<td>Intercept</td>
<td>0.7701</td>
</tr>
<tr>
<td>FD_ramp</td>
<td>-0.0003</td>
<td>FD_ramp</td>
<td>-0.0001</td>
<td>FD_ramp</td>
<td>-0.0001</td>
</tr>
<tr>
<td>ED_urba</td>
<td>0.0683</td>
<td>ED_urba</td>
<td>0.0775</td>
<td>ED_road</td>
<td>-6.6565</td>
</tr>
<tr>
<td>ED_road</td>
<td>-0.8062</td>
<td>ED_road</td>
<td>-2.1230</td>
<td>ED_airf</td>
<td>0.0178</td>
</tr>
<tr>
<td>For_1km</td>
<td>-0.0005</td>
<td>ED_airf</td>
<td>0.0251</td>
<td>ED_scho</td>
<td>-0.0542</td>
</tr>
<tr>
<td>Elev</td>
<td>-0.0153</td>
<td>ED_wate</td>
<td>-0.2492</td>
<td>ED_wate</td>
<td>0.0346</td>
</tr>
<tr>
<td>Ston</td>
<td>-0.0338</td>
<td>For_1km</td>
<td>-0.0004</td>
<td>For_1km</td>
<td>-0.0001</td>
</tr>
<tr>
<td>ExDen_5</td>
<td>0.0987</td>
<td>Elev</td>
<td>-0.0185</td>
<td>Elev</td>
<td>-0.0053</td>
</tr>
<tr>
<td>UWRD_5</td>
<td>-0.3806</td>
<td>Ston</td>
<td>-0.0240</td>
<td>Slop</td>
<td>-0.0344</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ExDen_5</td>
<td>0.0494</td>
<td>Ston</td>
<td>0.0476</td>
</tr>
<tr>
<td></td>
<td></td>
<td>UWRD_5</td>
<td>-0.2783</td>
<td>ExDen_5</td>
<td>0.0523</td>
</tr>
</tbody>
</table>

The potential of future exurban development based on the logistic regression is given in Figure 11. Overall, most sites have a very low likelihood of converting (less than 0.1) because they share limited characteristics with already converted areas. Shoreline areas, especially in the North and the Middle, and areas along the regional and local transportation routes tend to have higher development potential. In the South, lands near the boundary of the existing urban areas and the major road intersections also tend to have higher developmental potential.
Figure 11: Probability map of exurban conversion from logistic regression model
**Classification Trees**

Table 17 summarizes the results from the zone-specific full grown classification trees and the pruned trees. As expected the full grown classification trees retained almost all variables in all three zones with a large number of terminal nodes and low misclassification rate. However, looking at the tree size verses misclassification graph it is evident that the greater tree sizes did not contribute substantially to reduce the misclassification rate. Thus, for the North, Middle, and South zones the full grown tree was pruned by 70, 82, and 93 respectively. Resulting models from the pruned trees retained only three variables in each zone without substantially compromising the misclassification rate.

**Table 17: Classification tree results for the full grown and the pruned trees**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Terminal Nodes</th>
<th>RMD</th>
<th>Misclassification</th>
<th>ROC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full tree</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>75</td>
<td>0.447</td>
<td>0.097</td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>87</td>
<td>0.537</td>
<td>0.114</td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>103</td>
<td>0.590</td>
<td>0.128</td>
<td></td>
</tr>
<tr>
<td><strong>Pruned tree</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North (70)</td>
<td>9</td>
<td>0.559</td>
<td>0.114</td>
<td>0.945</td>
</tr>
<tr>
<td>Middle (82)</td>
<td>16</td>
<td>0.619</td>
<td>0.131</td>
<td>0.939</td>
</tr>
<tr>
<td>South (93)</td>
<td>13</td>
<td>0.696</td>
<td>0.150</td>
<td>0.922</td>
</tr>
</tbody>
</table>
Like the logistic models, the classification trees models also reflect that exurban development’s location is explained mostly by local development density and distance to local roads. Though the classification trees resulted in simpler models, they clearly identified the expected difference in the explanatory variables for the natural amenity rich zones and more urbanized zone. In the North and the Middle zones, distance to water body was retained indicating importance of natural amenities in such areas, whereas retention of functional distance to Toronto reflects the more urbanized characteristic of the South.

The related potential future exurban development map shows most sites have a very low likelihood of converting (Figure 12). The overall pattern is similar to the logistic regression based map: the shoreline areas, especially in the North and the Middle, and areas along the regional and local transportation routes tend to have higher development potential and in the South the areas near the boundary of the existing urban areas and the major road intersections tend to have higher developmental potential.
Figure 12: Probability map of exurban conversion from classification tree model
Comparison of the two approaches

The ROC for the logistic regression and classification tree models (Table 15 and 17) indicate excellent agreement with the reference data in all three zones; Hosmer and Lemshow (2000) identify over 0.8 as excellent. Nevertheless, the classification trees method consistently performs better, with values above 0.9.

The overall level of agreement for the confusion matrix of the five different classes of exurban conversion probabilities resulting from the logistic and classification trees method is only 53%, and the K-hat statistics, which is a more conservative measure of agreement as it takes into account agreement due to chance, is only 26% (Table 18). For extreme probability classes or less than 10% and more than 75%, the logistic method showed high omission compared to the classification trees results.

Table 18: Confusion matrix for the probability classes from the logistic regression verses the classification tree method

<table>
<thead>
<tr>
<th>Logistic Pixels</th>
<th>0-10</th>
<th>10-25</th>
<th>25-50</th>
<th>50-75</th>
<th>75-100</th>
<th>Row</th>
<th>Omis</th>
<th>Comm</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-10</td>
<td>14,315,490</td>
<td>121,139</td>
<td>217,654</td>
<td>4,157</td>
<td>16,993</td>
<td>14,675,433</td>
<td>0.57</td>
<td>0.98</td>
</tr>
<tr>
<td>10-25</td>
<td>9,668,093</td>
<td>1,468,947</td>
<td>1,005,913</td>
<td>101,367</td>
<td>65,258</td>
<td>12,309,578</td>
<td>0.54</td>
<td>0.12</td>
</tr>
<tr>
<td>25-50</td>
<td>1,270,539</td>
<td>887,009</td>
<td>1,449,370</td>
<td>720,775</td>
<td>258,920</td>
<td>4,586,613</td>
<td>0.42</td>
<td>0.32</td>
</tr>
<tr>
<td>75-100</td>
<td>19,564</td>
<td>153,708</td>
<td>478,991</td>
<td>182,381</td>
<td>314,310</td>
<td>1,148,954</td>
<td>0.17</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Overall Agreement = 0.53
K-hat = 0.26
4.3.2 Future land conversion risk

Results indicate that in Peterborough County the total area under high exurban conversion risk is fairly low, as modeled by both logistic and classification tree methods (3% and 4% approximately; Table 19). Even when the second highest risk class is included, the total area under substantial exurban conversion risk does not exceed 7% of the total available area in Peterborough County. Most of the region (approximately 80% of Peterborough) seems to be facing a negligible amount of threat (less than 25%). When broken down at a zonal level the basic trend is similar, though classification trees shows slightly more location with high risk level (approximately 10%) for the South and higher estimations of very low risk areas in all zones (more than 70%).

Table 19: Future exurban conversion risk

<table>
<thead>
<tr>
<th></th>
<th>Tot. Area sq. km</th>
<th>Very high sq. km (%)</th>
<th>High sq. km (%)</th>
<th>Medium sq. km (%)</th>
<th>Low sq. km (%)</th>
<th>Very low sq. km (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Logistic</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>3373</td>
<td>101 (3)</td>
<td>115 (3)</td>
<td>459 (14)</td>
<td>1231 (36)</td>
<td>1468 (44)</td>
</tr>
<tr>
<td>N</td>
<td>1495</td>
<td>50 (3)</td>
<td>47 (3)</td>
<td>135 (9)</td>
<td>616 (41)</td>
<td>648 (43)</td>
</tr>
<tr>
<td>M</td>
<td>783</td>
<td>26 (3)</td>
<td>35 (4)</td>
<td>100 (13)</td>
<td>303 (39)</td>
<td>319 (41)</td>
</tr>
<tr>
<td>S</td>
<td>1095</td>
<td>24 (2)</td>
<td>33 (3)</td>
<td>224 (20)</td>
<td>313 (29)</td>
<td>501 (46)</td>
</tr>
<tr>
<td><strong>Classification trees</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>3373</td>
<td>119 (4)</td>
<td>110 (3)</td>
<td>345 (10)</td>
<td>271 (8)</td>
<td>2528 (75)</td>
</tr>
<tr>
<td>N</td>
<td>1495</td>
<td>51 (3)</td>
<td>17 (1)</td>
<td>145 (10)</td>
<td>161 (11)</td>
<td>1121 (75)</td>
</tr>
<tr>
<td>M</td>
<td>783</td>
<td>17 (2)</td>
<td>36 (5)</td>
<td>98 (13)</td>
<td>78 (10)</td>
<td>553 (71)</td>
</tr>
<tr>
<td>S</td>
<td>1095</td>
<td>50 (5)</td>
<td>57 (5)</td>
<td>102 (9)</td>
<td>32 (3)</td>
<td>853 (78)</td>
</tr>
</tbody>
</table>
4.3.3 Conflict with biodiversity conservation

The areas identified as having a high risk of exurban conversion from the method with higher ROC values, the classification trees method, were compared against the high value areas for biodiversity and the greenlands protection status data.

Of all high value areas for conservation, based on the Great Lakes Conservation Blueprint for Biodiversity (GLCBB), only about 55% is public lands while the rest are all in private lands whose status is largely unknown (Table 20). Out of those public areas, about 20% are fully protected, 28% have limited protection, and 6% have no protection at all. Thus, a large portion of GLCBB within Peterborough has limited or no protection from developmental threats.

Table 20: Great Lakes Conservation Blueprint for Biodiversity and greenlands protection status overlap

<table>
<thead>
<tr>
<th>GLCBB &amp; Protection status</th>
<th>Hectares</th>
<th>% of GLCB in PB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>43226</td>
<td>55*</td>
</tr>
<tr>
<td>L1 – Fully protected</td>
<td>15890</td>
<td>20</td>
</tr>
<tr>
<td>L2 – Somewhat</td>
<td>8131</td>
<td>10</td>
</tr>
<tr>
<td>L3 – Partially</td>
<td>14112</td>
<td>18</td>
</tr>
<tr>
<td>L4 – Unprotected</td>
<td>5093</td>
<td>6</td>
</tr>
</tbody>
</table>

* Remaining 45% of the GLCBB is in private lands thus not covered by the protection status data

The overlap between the high value areas within Peterborough and the exurban risk map created (Table 21) indicate that approximately 84% of the high value areas overlap with lands available for exurban conversion. Only a small proportion (3%) of the high value areas is high risk, while three fourth is predicted to be under very low risk from exurban conversion. Finally, only about half a percentage of the high value area that is at high risk is unprotected or has very limited protection (Table 22). These limited areas that have been identified as the potential conflict areas
between conservation and development interests can be managed for proactive conservation planning.

**Table 21: Great Lakes Conservation Blueprint for Biodiversity and exurban conversion risk overlap**

<table>
<thead>
<tr>
<th>GLCBB &amp; Risk overlap</th>
<th>Hectares</th>
<th>% of GLCB in PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low</td>
<td>57879</td>
<td>73</td>
</tr>
<tr>
<td>Low</td>
<td>2824</td>
<td>4</td>
</tr>
<tr>
<td>Medium</td>
<td>4129</td>
<td>5</td>
</tr>
<tr>
<td>High</td>
<td>660</td>
<td>1</td>
</tr>
<tr>
<td>Very high</td>
<td>1196</td>
<td>2</td>
</tr>
</tbody>
</table>

* Remaining 16% of GLCBB were included in the masked areas

**Table 22: Percent of Great Lakes Conservation Blueprint for Biodiversity area within Peterborough with different levels of protection status and exurban conversion risk**

<table>
<thead>
<tr>
<th>Protection status</th>
<th>L1 Full</th>
<th>L2 Somewhat</th>
<th>L3 Partial</th>
<th>L4 Unprotected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low</td>
<td>15.2</td>
<td>5.0</td>
<td>13.5</td>
<td>4.8</td>
</tr>
<tr>
<td>Low</td>
<td>0.5</td>
<td>0.3</td>
<td>0.5</td>
<td>0.2</td>
</tr>
<tr>
<td>Medium</td>
<td>1.5</td>
<td>0.3</td>
<td>1.0</td>
<td>0.2</td>
</tr>
<tr>
<td>High</td>
<td>0.4</td>
<td>0.2</td>
<td>0.3</td>
<td>0.0</td>
</tr>
<tr>
<td>Very high</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

### 4.4 DISCUSSION

This research sought to identify the location of potential future exurban development in the study area based on the existing location of such development and correlated locating factors. Potential risk maps for exurban conversion in the study area using two different modeling techniques were created. The comparison of the logistic regression and the classification tree methods indicate that though the two models were different in predicting the amount of very high or low exurban conversion risk the general trends were similar.
Examination of the eight different logistic regression models indicated that the worst performing models in all three zones were those where the distance variables were excluded, indicating the general importance of accessibility measures. Interestingly, the model using only three biophysical variables performed reasonably well, likely due to two reasons: (1) biophysical conditions of a site are important and (2) these conditions are not randomly distributed throughout the region. Every equation explained the location of exurban development better in the northern zone than in the other two zones. This could be because locating factors not included in the analysis play a larger role in the Middle and the South and/or because there is less variation in the locating factors in these zones.

The classification tree models also indicated that exurban development location is explained mostly by local development density and distance to local roads. Though the classification trees resulted in simpler models, they clearly highlighted the expected difference in the explanatory variables for the natural amenity rich zones and the more urbanized zone by retaining access to water and to Toronto, respectively.

The exurban conversion probability maps align with the general North American-wide trend of increased affinity towards living in “natural” settings, like shoreline development, or close to socio-economic amenities. Also, the specific relationship between exurban development locations and significant variables highlights some common trends in exurban landscapes: (1) low density residential development tends to be highly clustered, when examined across a landscape and (2) buildings tend to be located away from the local access road, within a specific parcel, yet built on parcels located relative close to major roads and highways. Thus, any future
road creation would likely have a major impact on exurban conversion, potentially opening new areas to such threats.

Given the difference in the nature of the two models, with the classification trees having more discrete boundaries, as it creates a number of if-then statements and the logistic regression applying a curvilinear model, the predicted locations of the exurban conversion risks were not exactly the same. Since the classification trees is a data mining technique that does not make any assumptions about the data and is capable of revealing non-monotonic relationships, it is preferred in cases where no substantial assumptions can be made about the relationships among the variables. In this study, the classification trees predicted more locations to be in the extreme categories (very high or very low), indicating that it is a bold predictor. The final models retaining only three variables indicate that the classification trees results in much simpler models than the logistic regression. But logistic regression provided more detailed insight into the ways the variables could be influencing exurban locations. The related predictions were mostly in the moderate risk classes, indicating that in this case it was a more conservative predictor.

Based on the conflict assessment, most of the high value areas for conservation in the study area face limited threat from exurban conversion. However, about 3% of the high value areas are under high risk from exurban conversion, out of which about one-sixth have limited or no protection. Proactive conservation planning should focus on these areas.

As with any other studies there are limitations with the methods used. First, while the exurban data, whose methods were described in detail in Chapter 3, was able to achieve accuracy levels
that are generally accepted, no map is ever 100% accurate. This should not be a significant problem if a random selection of exurban development sites were miss-classified. However, it is possible that some forms of exurban development were systematically excluded, potentially impacting the results of the locating factor analysis. Likewise, there were also wrongly classified exurban pixels in the exurban map, which will also bias the locating factors analysis. Second, the regression process used to identify characteristics of sites with a greater likelihood of converting is based on the assumptions that the potential locating factors included in the analysis are meaningful in the study area and that the process locating exurban development in the past will remain stable into the future. The first assumption appears to be met, given the strong goodness-of-fit measures. However, it is not only possible but likely that the process of land conversion will change in the future— for economic, social, demographic or other reasons— since land-use change is a result of many complex driving forces (Meyer and Turner 1994) and locating factors (Verburg et al. 2004). Finally, the map does not indicate the rate or timing of conversions, it only illuminates the sites that are most suitable for conversion. There is the potential that the ‘best’ sites will not develop first, due to particularities of the landowner or conditions in the broader market (i.e. waiting for a future time when a property may be worth more money). Thus, the map should be used to evaluate broad patterns rather than what will happen at specific sites. Additionally, as new development occurs, the most likely sites may change in response to the new landscape conditions.
4.5 CONCLUSION

This study examined a number of potential locating factors for exurban development founded on biophysical, accessibility, and natural amenity based characteristics in a relatively large, heterogeneous landscape. While accessibility in general was a major factor, importance of access to the urban centers or the natural amenities differed depending upon the general nature of the area. Comparison between the two modeling approaches showed similar trends with the exception that classification trees resulted in much simpler models, though at the expense of the detailed inference. Results from the exurban conversion analysis showed that the probability maps align with the general North American-wide trend of increased affinity towards living in “natural” settings, like shoreline development, or close to socio-economic amenities. Lastly, the conflict assessment illustrated that most of the high value areas for conservation in the study area face limited threat from exurban conversion. Nonetheless, a substantial portion of areas that are at risk have limited or no protection, which can be the focus of proactive conservation planning efforts.
Chapter 5: Ecological impacts of exurban development: An assessment of barrier effects and landscape connectivity

ABSTRACT

In exurban landscapes, isolated buildings and associated roads can physically fragment the landscape through perforation, incision and dissection. In addition, they also pose functional constraints to wildlife movement through barrier effects that extend beyond their physical footprint. Usually fragmentation at large spatial extents are evident through moderate resolution land cover data, but the barrier effects of exurban development are often not fully captured due to its relatively small area and isolated nature. In this study, the functional effect of exurban built structures on the landscape was assessed by developing a spatially explicit model to estimate their overall barrier effect in different wildlife movement scenarios. In particular, using the case study of Blanding’s turtle in the study area, Peterborough County (Ontario, Canada), relative weights were given to exurban buildings and the associated road network, based on their characteristics and expected Blanding’s turtle’s response behavior. This information was then combined with land cover data to estimate the overall barrier effect and landscape connectivity measures using a circuit theoretic approach. The comparison of the results from using original and refined land cover data, land cover and weighted roads, and land cover, weighted roads, and weighted exurban development illustrated that there are substantial differences in the results. The exclusion of fine level information on exurban development and roads, as occurs often in ecological studies, result in omission of cumulative impacts of these anthropogenic disturbances in the landscape, thereby underestimating the actual ecological impacts.

5.1 INTRODUCTION

Anthropogenic disturbances such as residential development and roads impose distinct patterns on the landscape and influence a wide range of ecological processes (Forman and Alexander 1998). Habitat for wildlife is directly removed during construction and, once constructed, built surfaces create a physical and chemical environment different from that of surrounding areas.
These changes are mostly irreversible, and can stimulate further changes in the landscape. For example, expansion of a road network to serve new settlement, can lead to further development due to the increased accessibility. These interspersed development patches connected by linear infrastructures, like roads, result in landscape fragmentation, which has various ecological impacts for species distribution and persistence.

Exurban development, which is the low density residential development outside of designated urban areas, not only inflicts substantial changes in the landscape but is also expanding at unprecedented rates (Brown et al. 2005, Theobald 2005 a). Exurban development is often located near ecologically sensitive areas (e.g. protected areas or water bodies) resulting in a disproportionately large ecological impact relative to its physical footprint (Hansen et al. 2005). The direct and indirect effects include alteration of habitat (loss and/or fragmentation), ecological processes (fire regimes, flood regimes, nutrient cycles), and biotic interactions (predator-prey, invasive, infectious disease), along with the introduction of various forms of human disturbance (roads, pets, general land use) (for in depth review refer to Hansen et al. 2005). Though each of these ecological effects of exurban development is important, this study focuses on effects of habitat fragmentation, specifically in terms of barrier effects and landscape connectivity for wildlife movement.

Exurban development in the landscape perforates land cover types that provide refuge for wildlife, while the associated road network (and other linear infrastructure) dissect or incise patches resulting in compromised quality and quantity of habitat (Forman 1995, Jaeger 2000). This results in undesired ecological effects that are visible, such as structural and compositional
changes in species and vegetation communities, and others changes that are less noticeable, such as reduced landscape connectivity that compromises the long term persistence of wildlife. Specifically, reduced connectivity can subdivide the populations and reduce resource accessibility, in addition to lost habitat and human-wildlife conflict (e.g. road mortality), which can have substantial cumulative impacts on wildlife’s ability to persist in the landscape (Forman 1995, Jaeger et al. 2005).

In recent years a number of scientific studies have examined the impacts of exurban development on wildlife (Miller and Hobbs 2002, Hansen et al. 2005). Nevertheless, there is still paucity of studies that examine the ecological implications at a large spatial extent. Lack of spatially explicit data on exurban development has been the major hindrance to such studies (McCauley and Goetz 2004, Theobald 2005 a), although this is beginning to change (Cova et al. 2004, Shrestha and Conway 2011). Nevertheless, advances in road ecology over the past decade (Forman and Alexander 1998, Trombulak and Frissell 2000, Forman et al. 2002 b, Jaeger 2005) have provided a much needed conceptual and technical foundation for studying the anthropogenic barriers in the landscape that may be applicable to exurban development. Thus, this study builds upon the road ecology literature to quantify the barrier effects of exurban development and associated roads, and its implications on overall landscape connectivity.

Generally in ecological studies the barrier effects in a landscape are examined using commonly available land cover data that captures major land cover classes but often omits the finer level details such as the interspersed built areas like exurban and local road networks. This study specifically seeks to compare the estimates of barrier effects and landscape connectivity.
measures using (i) original land cover, (ii) refined land cover, (iii) land cover and weighted roads, and (iv) land cover, weighted roads, and weighted exurban development to determine if there are substantial differences in the results. This study also examines the applicability of a recently proposed tool, Circuitscape, which uses a circuit theoretic framework (McRae et al. 2008) for assessing landscape connectivity for wildlife with limited dispersal ability in an exurban context. The study area is the exurban portions of the Peterborough County, Ontario (Canada). A case study species, Blanding’s turtle, was used to ensure the barrier effects mapping and landscape connectivity assessment was ecologically relevant as measures of both are species dependent.

5.1.1 Barrier effect and landscape connectivity

Landscape connectivity is defined as ‘the degree to which the landscape facilitates or impedes movement among resource patches’ (Taylor et al. 1993). With et al. (1997) describes it as the functional relationship among the habitat patches attributing to their spatial configuration and the movement response of organisms. These definitions emphasize that landscape connectivity not only depends on the landscape structure (composition and configuration), but also on the response behavior of the organisms that moves across the landscape (Tischendorf and Fahrig 2000, Moilanen and Nieminen 2002, Adriaensen et al. 2003). Barriers in the landscape that restricts or completely prevents flow of movement (of organisms or matters) complement or impede landscape connectivity (Forman 1995). Barrier effects posed by various structures, both natural (e.g. mountains, rivers, gorges) and anthropogenic (e.g. buildings, roads, fences, power
lines) can be viewed as the part of the landscape structure that landscape connectivity depends upon and organisms respond to.

In conservation planning, connectivity among resource patches and population is considered crucial in maintaining general ecological processes such as metapopulation dynamics, gene flow, range expansion, invasion, population persistence and so on (Ricketts 2001, Moilanen and Nieminen 2002, Fagan and Calabrese 2006). In order to conserve and/or restore connectivity in a landscape it is important to quantify what connectivity exactly is and among what features connectivity is needed (Tischendorf and Fahrig 2000, Adriaensen et al. 2003, Marull and Mallarach 2005, McRae et al. 2008).

Landscape connectivity, in the scientific literature, has been used as a structural measure as well as a functional concept (for in depth review see Tischendorf and Fahrig 2000). Structural connectivity is mostly related to habitat configuration and is primarily quantified through various landscape indices that are relatively easy to derive (McGarigal and Marks 1995, Schumaker 1996, Tischendorf and Fahrig 2000). These indices, while making the idea of connectivity operational, may sometimes reflect a misplaced idea that connectivity is a generalized feature of a landscape that can be explained by one absolute number instead of recognizing that the same landscape may have different levels of connectivity for different wildlife (Tischendorf and Fahrig 2000, Moilanen and Nieminen 2002). It is possible that structurally connected habitat patches may not be functionally connected and vice versa depending on the species (With et al. 1997). Alternately, functional connectivity explicitly considers the response behavior of an
organism to the various landscape elements and characteristics that facilitates or impedes their movement (Tischendorf and Fahrig 2000).

Various methods have been used in the literature to measure the functional connectivity within a landscape (reviewed by Tischendorf and Fahrig 2000, Moilanen and Nieminen 2002, Calabrese and Fagan 2004). Common approaches include (i) individual movement simulation modeling based on dispersal success, search time, and immigration success (Doak et al. 1992, Demers et al. 1995, Schumaker 1996, Hargrove et al. 2005); (ii) geographic models, such as gravity models that take into account the distance between patches and related linkage strengths (Bossenbroek et al. 2001, Beaudry et al. 2008), and (iii) analytic measures, such as graph theory and least cost path models (Keitt et al. 1997, Urban and Keitt 2001, Adriaensen et al. 2003, Minor and Urban 2007, McRae et al. 2008, Dale and Fortin 2010, Galpern et al. 2011). Though models that simulate individual based movements can accommodate wildlife behavior and life history requirements, they are data demanding and have high computational requirements, thereby limiting their use in many applications (Minor and Urban 2007). As a result analytic models using graph-theory and least cost paths have become increasingly popular in landscape connectivity studies for conservation planning (Adriaensen et al. 2003, McRae et al. 2008).

5.1.2 Circuit theoretic approach to modeling landscape connectivity

McRae et al. (2008) proposed a connectivity model based on electrical circuit theory, which is expected to fill in the niche between powerful but data and computationally demanding simulation approaches and simpler analytic connectivity models based on Euclidean or least cost path analysis. Circuit theoretic model has a theoretical basis in electrical circuit theory, graph
theory and random walk theory, which makes it mathematically rigorous and ecologically relevant. This explicit relationship is a distinct advantage of circuit theoretic model as it lends the model to rigorous theoretical justification, thus the connectivity measures it generates can be considered to be process-based. Also, because of these relationships, circuit theoretic model is easy to parameterize, and the interpretations of parameters and outputs are clear in ecological terms (McRae et al. 2008).

In circuit theoretic model landscapes are represented as resistance (or conductive) surface with low resistance values assigned to habitats and other land cover that are most permeable to movement and high resistances are assigned to barriers to movement. Based on the well-developed theory of electrical circuits the concepts of resistance, current, and voltage are used to generate measures of connectivity across the landscape that can be related to the random walks of organisms on the analogous graphs. Figure 13 is used to illustrate these concepts via nine simple rasters (Figure 13 a, 1 to 9) of 1000 by 1000 cells with two habitat patches that are connected by different configuration of potential pathways with varying resistance values (McRae et al. 2008).

The first measure of connectivity that a circuit-theoretic model can compute is resistance distance. It is defined as a distance metric reflecting the effective resistance between a pair of nodes when all graph edges are replaced by analogous resistors. Resistance distance, unlike other functional distances, such as least cost distance, incorporates contributions of multiple pathways connecting nodes. The habitat patches connected by multiple pathways or wider pathways have lower resistance distance than by a single pathway, which unlike least cost path, is captured by
the circuit theoretic model (Figure 13 b). The second connectivity measure is current density that can be interpreted as movement probabilities of random walkers from one node to other on analogous graphs, which is directly proportional to its conductance. As with effective resistance, current density also incorporates contribution of multiple dispersal pathways such that it is higher when there is only one potential pathway than when there are multiple pathways available for a random walker to move across the landscape (Figure 13 c). The higher current density at any location also indicates that converting it will have a larger impact on overall landscape connectivity, thereby highlighting the potential bottleneck locations (E.g. Bright yellow locations in Figure 13 c: rasters 4-6). The third and last measure of connectivity from circuit-theoretic model is voltage, which reflects the probability of a random walker who starts at one particular node will successfully disperse to any other defined nodes. (McRae et al. 2008, Shah and McRae 2008)

Thus, unlike other analytic connectivity models (e.g. least cost path models) circuit theoretic model has an ability to evaluate contributions of multiple dispersal pathways in the landscape. This means that it accounts for the loss of one dispersal pathway by increasing the importance of the remaining pathways. This provides an important insight for identification of the critical areas for connectivity in the landscape. Also, the circuit theoretic model uses parameters and concepts such as resistance and current, which have wider intuitive appeal and are easily understood by scientists and practitioners alike, thereby increasing the chance of adoption for complex connectivity analysis in an understandable manner. Lastly, the data structures (patch based, network style, or raster) that are used in this model are similar to those already used by other
approaches, such as graph theory and least cost path analysis, thus making it easily applied in the
traditional graph-theoretic or GIS frameworks. (McRae et al. 2008)
Figure 13: Illustration of (a) nine simple rasters (1 – 9) representing landscapes with various configuration of habitat and resistance values, (b) resistance distance value for each raster compared to the least cost path, and (c) current density rasters reflecting the flow of current across the raster (bottlenecks are most obvious in 4, 5, and 6 as bright yellow color) (Source: McRae et al. 2008)
5.2 MATERIALS AND METHODS

5.2.1 Data

Spatially explicit raster data of exurban development for the County of Peterborough, based on remotely sensed SPOT / HRVIR imagery and other ancillary data, was used (Shrestha and Conway 2011). County road data (Peterborough County 2008), provincial road network data (OMNR 2010), and land cover data (OMNR 2000) were also used in the study to characterize the landscape. Urban area boundaries (Statistics Canada 2006) were used to mask out the obvious non-exurban areas from the analysis.

5.2.2 A case study: Blanding’s turtle (*Emydoidea blandingii*)

In this study, the barrier effect of exurban development and associated roads is quantified for one of the sixteen hypothetical wildlife response scenarios (Table 23). The scenarios were defined based on four major road characteristics (noise, surface width, traffic, and speed) and assumed wildlife response to them, in terms of avoidance behavior (Jaeger *et al.* 2005). The same concept was adapted and applied to exurban development as well, but due to lack of data on characteristics associated with dwelling types and level of use, only physical footprint information (surface area) was used.
Table 23: Potential modeling scenarios based on wildlife response behavior to the road characteristics

<table>
<thead>
<tr>
<th>Road Char.</th>
<th>Wildlife response behavior to road characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Noise</td>
<td>Low (L)</td>
</tr>
<tr>
<td></td>
<td>High (H)</td>
</tr>
<tr>
<td>Surface width/area</td>
<td>L</td>
</tr>
<tr>
<td>Traffic</td>
<td>L</td>
</tr>
<tr>
<td>Speed</td>
<td>L</td>
</tr>
<tr>
<td>Scenario</td>
<td>1111 1112 1121 1122 1211 1212 1221 1222 2111 2112 2121 2122 2211 2212 2221 2222</td>
</tr>
</tbody>
</table>

† Blanding’s Turtle is the selected representative species for modeling scenario 1111.

In this study the scenario that represents wildlife that show low avoidance behavior to all major characteristics of roads is modeled as a case study. These species are most likely to approach roads (and likely other built surfaces) to meet basic needs, thereby making them vulnerable to threats such as wildlife-vehicle collisions, road mortality, and other wildlife-human conflicts. This may not only reduce their population size but also threatens long term persistence of these species, especially if their habitat is already fragmented as in settled landscapes like the study area. Since amphibians are recognized as being most affected by roads and other built surfaces, Blanding’s turtle (*Emydoidea blandingii*) was selected as the target species for the case study. In Ontario, Blanding’s turtles are provincially recognized as Species at Risk (SAR) with road mortality identified as one of the major threats to its persistence in the landscape (OMNR 2011).

Blanding’s turtle is a medium sized turtle identified by its yellow throat, smooth spotted upper shell, and hinged lower shell. It begins to reproduce between the ages of 14 and 20 years and can live for more than 75 years. It fits the profile of the selected scenario by showing low avoidance of roads, thus being susceptible to the most direct impact of roads (i.e. road mortality). In
In addition, it is attracted to roadsides and other built surfaces as they often provide warm sandy substrate for nesting. Over the course of a year, Blanding’s turtles tend to make several overland movements between different wetlands for foraging, mating, nesting, estivation, and overwintering habitats. (Natural Heritage and Endangered Species Program 2007). A study in Maine found that Blanding’s turtles use an average of 6.7 different wetlands and moves across upland habitat on an average of 8.5 times a year (Beaudry et al. 2006). Their average and maximum home range lengths were approximately 1000 meters and over 3 kilometers, respectively (Piepgras et al. 1998, Grgurovic and Sievert 2005). Spring movements from permanent to ephemeral wetlands tend to be more extensive than summer and fall travel (Natural Heritage and Endangered Species Program 2007). The high vagility nature of Blanding’s turtle results in long distance movements and several overland trips making them highly susceptible to encountering multiple barriers, like roads, and places them at risk from direct and indirect barrier effects, such as road mortality and reduced accessibility to resources.

5.2.3 Barrier effect analysis

Based on Blanding’s turtle’s avoidance behavior, land cover, road and exurban data were weighted from one to ten to characterize the resistance posed by these landscape features from the organism’s perspective (Figure 14). This approach is commonly used in landscape resistance mapping using readily available data like land cover. As different land covers have different levels of permeability for wildlife, their response behavior is an important consideration while assigning relative weights. Also, the grain or resolution of data should be fine enough to
sufficiently capture the targeted phenomenon, which in the case here is the barrier effect of exurban development and roads for Blanding’s turtle.

Along with the original land cover data, a refined land cover dataset was created by combining exurban development footprints (Shrestha and Conway 2011) and the rasterized provincial road network to capture a finer-level of land cover. The two land cover maps were then reclassified into four simple groups based on Blanding’s turtle’s habitat preference: habitat, hospitable matrix, inhospitable matrix, and barriers, to be weighted numerically from value one to ten (Table 24, Figure 14 a, b, c and d).

The third variant incorporated weighted road data. Each cell of the rasterized road network data (10m) was weighted from one to ten using four major structural attributes: speed, traffic volume, surface width, and noise (Table 24). The speed limit data based on road type was part of the original provincial road data. Traffic volume data were harder to obtain as different municipalities and levels of government are responsible for different areas and types of roads. The Annual Average Daily Traffic (AADT) data was available for the county roads that were obtained from Peterborough County (2008) while the provincial and the federal highways from Ministry of Transportation (2006) were in a non-digital format, which was manually digitized into GIS. For the local roads, however, the traffic volume information is largely absent, thus exurban development density was used as a surrogate assuming that higher development density will result in higher traffic volume along local roads. Surface width estimates were provided by the County of Peterborough. Though they varied among different road types, a general criteria was defined based on the County’s road design guidelines that called for approximately 11 m for
two lane paved roads (3.5m each lane with 2 m shoulder in each direction) (County of Peterborough, personal communication). Lastly, noise level was derived as the function of the speed (limit) and the level of traffic volume assuming that higher levels of these two will result in higher noise level.

The total barrier effect of roads was then calculated by summing all four weighted road characteristic together. A modified Inverse Distance Weight (IDW) distance decay function was then used to extrapolate the barrier effects from the road segments to neighboring areas, recognizing that the zone of influence often extends beyond the physical footprint of the barrier. A moving window approach was used to estimate the sum of weights in all pixels within Blanding’s turtle’s average dispersal distance, 1 km, of each pixel. The sum of weights was then divided by the distance to estimate the weight for each pixel near the roads. This is to ensure that the areas closer to the roads with high barrier effects or high density of roads are distinguished from the areas with lower effects (Figure 14 e and f).

The last barrier effect map included weighted exurban development along with the land cover and the weighted road data. For exurban development, multiple characteristics like physical footprint, extent and time of use, presence of pets, chemical pollution, and light pollution will influence its level of ecological impacts; data on most of these characteristics are rarely available. Thus, only exurban development footprints were included to provide the surface area information. As with land cover and roads, exurban development pixels were also assigned a value of zero or ten based on exurban presence or absence (Table 24). The modified IDW
distance decay function was then applied to extrapolate exurban barrier effect weights beyond the physical footprint to the neighboring areas (Figure 14 g and h).

The four barrier effect maps [(i) original land cover, (ii) refined land cover, (iii) land cover and weighted roads, and (iv) land cover, weighted roads, and weighted exurban development] were then used to assess the influences of including roads and exurban development (along with their structural characteristics and zone of influence) in barrier effect analysis. In addition, these maps were also the input in the landscape connectivity analysis using Circuitscape (Shah and McRae 2008, McRae et al. 2008), which provided a more sophisticated and ecologically relevant approach to quantify connectivity from the perspective of Blanding’s turtle.
Table 24: Relative weights assigned to land cover, roads, and exurban development based on their characteristics and target species response behavior scenario.

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Relative weight</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Land cover (original and refined)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Habitat</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Hospitable matrix</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>In hospitable matrix</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Barriers</td>
<td>10</td>
<td></td>
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<tr>
<td><strong>Roads</strong></td>
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<tr>
<td>Speed</td>
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<tr>
<td>10</td>
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<tr>
<td>100</td>
<td>10</td>
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<tr>
<td>Traffic</td>
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<tr>
<td>&lt;500</td>
<td>1</td>
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<tr>
<td>1000</td>
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<tr>
<td>Trails</td>
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<tr>
<td>Local Road</td>
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<tr>
<td>County Road</td>
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<tr>
<td>Highway</td>
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<tr>
<td>Expressway</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td><strong>Noise</strong></td>
<td></td>
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<tr>
<td>f (Traffic + Speed)</td>
<td>1 – 10</td>
<td></td>
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<tr>
<td><strong>Exurban</strong></td>
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<tr>
<td>Present</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>0</td>
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</tbody>
</table>
Figure 14: Illustration of classified maps and relative weights with distance decay (where relevant) for original land cover (a and b), refined land cover (c and d), roads (e and f), and exurban development (g and h).
5.2.4 Landscape connectivity analysis

In this study a circuit-theoretic model Circuitscape (McRae et al. 2008, Shah and McRae 2008, McRae and Shah 2009), was used due to its ability to evaluate contributions of multiple dispersal pathways, which facilitates identification of critical areas for connectivity (described more previously in Section 5.1.2). In Circuitscape, habitat patches and the rest of the landscape (matrix) are represented as a resistance (or conductive) surface, with low resistance value assigned to habitat patches and other hospitable areas within the matrix and high resistance values assigned to features that restrict flow. In this study, the four barrier effect maps were used as the resistance surfaces in four separate runs of Circuitscape. Within Circuitscape every cell in the resistance raster with a value is represented as a node in a graph and is connected to its eight neighboring cells. Cells with infinite resistance or no data are dropped from the analysis. Cells with zero resistance values are considered habitat patches. Habitat patches containing a cluster of cells are collapsed into a single node (focal nodes) of the graph structure for the circuit analysis (McRae and Shah 2009). In this study, the habitat patches for Blanding’s turtle are defined as the wetlands that have at least 30% forest cover within 1 km, which is its average dispersal distance (Grgurovic and Sievert 2005).

Using the resistance and habitat maps, Circuitscape calculates connectivity measures that can be related to random walk theory and interpreted for connectivity conservation (McRae et al. 2008). In this study, current density was used as the measure of connectivity and Circuitscape was run in “all to one” mode, where each focal node is connected to the ground and the rest or the nodes are connected to an equal amount of current sources (1-amp) reflecting that these focal nodes or
habitat patches are assumed to have same level of connectivity. Theoretically, current dissipates as it leaves one focal node to cross a resistance surface. If the current reaches another focal node before it is exhausted, those two focal nodes are considered connected. High current density through a node indicates that modifying or removing it will have a relatively high impact on the overall landscape connectivity. As the availability of multiple dispersal pathways increases, current density tends to decrease indicating low probability of movement (McRae et al. 2008).

In this study the Circuitscape model was run using the four barrier effect maps for each of the three zone of the study area at two levels. The first level captured connectivity among every habitat patch, which includes patches that are distant from each other. Though long distance dispersal by the Blanding’s turtles is rare, it was deemed important to maintain connectivity beyond the maximum dispersal distance mainly because some individuals can recolonize the distant patches, potentially facilitating long term population persistence (D’eon et al. 2002). The second level of assessment captured the connectivity of habitat patches within the “habitat networks” in each zone. A habitat network is defined as a set of habitat patches that are located close enough to each other that a reasonable amount of inter-patch dispersal occurs (Verboom and Pouwels 2004, Van der Grift and Pouwels 2006). In this study all habitat patches within a one kilometer Euclidean distance of each other were included in the same habitat network. The output maps for the two levels of analysis were then used to identify “pinch points” (McRae et al. 2008) or bottleneck locations that delineate the critical areas for long term and immediate connectivity conservation.
5.3 RESULTS

5.3.1 Barrier effect analysis

Figure 15 presents the barrier effect maps created using the four sets of data: original land cover, refined land cover, land cover and weighted roads, and land cover, weighted roads, and weighted exurban development in the study area.

At the extent of Peterborough County, the highest predicted barrier effect is concentrated in the South, revealing the overall Peterborough county wide pattern but masking the finer level details within each zone. Examining each zone separately, spatial distribution of barrier effects within them is more visible (Figure 15). In the South, which has a well-developed grid-based road network, the highest predicted barrier effects are concentrated along major road networks and intersections. In the middle zone, where shoreline developments are prevalent, the highest barrier effects are seen following shorelines. In the North, which is least developed, the highest barrier effects are concentrated along the major highway running North-South, with some high values scattered around shorelines and elsewhere.

Not surprisingly, comparison among the four barrier effect maps indicates that original land cover data alone was too general to distinguish many of the barriers located in the study area (Figure 15 a). This is mainly because of the dominance of the coarse land cover classes (e.g. agriculture, forest) that describe the landscape at a broader level. Refining the land cover by adding the road and exurban footprint data illuminated variation in barrier effects, but it was not enough to infer about the overall trend (Figure 15 b). Nonetheless, using refined land cover and
roads data with structural attributes and zone of influence further defined the gradients in the barrier effect levels (Figure 15 c). Including details of exurban presence and zone of influence affected the barrier effect map only moderately, except in the South (Figure 15 d). Here roads are somewhat uniformly distributed, thus exurban data was useful in adding further details. However, overall, the results clearly indicate an increase in barrier effects in some areas of the landscape more than in the others as more details on the barriers such as roads and exurban development are incorporated in the analysis.
Figure 15: Barrier effect maps using (a) original land cover, (b) refined land cover, (c) land cover and weighted roads, and (d) land cover, weighted roads, and weighted exurban development (darkest magenta represents the ~20% of each zonal area with highest barrier effect)
5.3.2 Landscape connectivity analysis

Figure 16 presents cumulative current density maps created by including resistance values of original land cover and the combined land cover, weighted roads, and weighted exurban development data. Since these two cases represent the least and the most barrier effect information at zonal and habitat network level respectively, they are expected to capture the essential components of the discussion.

Within each of the three zones of Peterborough County the highest current, thus connectivity, areas are within the habitat patches or focal nodes (Figure 16). This is not surprising given that the Circuitscape tool assigns full current (1-amp) to all habitat patches and allows it to dissipate as it moves across the resistance surface during the Circuitscape run. The well connected habitat patches retain higher current density whereas the isolated patches lose most, revealing their low contribution to the landscape connectivity. Isolated habitat patches are primarily in the north-west section of the southern zone. Interestingly, the moderate current density areas, which reflect possible dispersal pathways for wildlife to move across the landscape, are not as distinct in the North and the Middle zones as compared to the South. This may be a result of presence of absolute barriers (i.e. large lakes) isolating the habitat patches such as in the Middle zone or it may be attributed to the relative homogeneity of the landscape. In the North the landscape is dominated by large tracts of forested lands, thus the uniform low resistance value associated with it may be suggesting that the probability of wildlife movement is pretty much similar across the landscape.
A comparison of the current density maps using original land cover information and the combined land cover, weighted roads, and weighted exurban information indicated that the added detailed information assisted in refining landscape connectivity analysis and produced current density maps that better delineated the critical linkage areas or bottleneck locations as shown in the insets of Figure 16. It is worth noting that this distinction was more visible in the South, where the landscape is more heterogeneous in terms of its resistance values, than in the North.

The habitat network level (Figure 17) analysis produced similar results to the zonal level analysis in that they showed a better delineation of critical linkage areas when finer level information was used. However, the location of these critical areas were different than at those indicated by the zonal level revealing that when the wildlife’s dispersal distance is taken into account the importance of pathways shift to reflect the important areas that are most relevant to the wildlife’s daily and seasonal movements. In the South, three habitat networks located towards the center of the zone have well defined critical linkage areas, especially evident in the connectivity maps produced using the combined land cover, weighted roads, and weighted exurban data. These can be interpreted as the priority habitat networks for Blanding’s turtle within the southern zone due to the availability of multiple bottleneck locations that can be mitigated to maintain a functioning habitat network. On the other hand, the habitat network in the north-west corner has one distinct pathway identified, which may indicate another level of priority as this may be the only crucial opportunity to maintain the functionality of that particular habitat network.
Figure 16: Cumulative current density maps from Circuitscape for zonal level analysis using resistance values from (a) original landcover, and (b) landcover, roads, and exurban data (darkest green represents top 10% areas with highest connectivity).
Figure 17: Cumulative current density maps from Circuitscape for habitat network level analysis using resistance values from (a) original landcover, and (b) landcover, roads, and exurban data (darkest green represents top 10% areas with highest connectivity).
5.4 DISCUSSION

Exurban development impacts ecological processes through a number of direct and indirect effects including habitat loss and fragmentation. In this study a closer look at habitat fragmentation was taken, specifically by first quantifying the barrier effects of exurban development and associated roads and then by assessing its implications on landscape connectivity. Building on the road ecology literature and limited exurban studies, the quantifiable structural characteristics of exurban and roads, wildlife’s response behavior, and the zone of influence were used to assess the contribution of exurban development information in such ecological analyses.

The barrier effect analysis for the case study species, Blanding’s turtle, included the structural and functional characteristics of the barriers (land cover, roads, and exurban development) and their zone of influence. Comparison of the results from the four barrier effect analyses highlighted that inclusion of finer information, such as exurban development and roads, substantially refined the outputs thereby having strong management implications. When exurban development is excluded in the landscape, the cumulative impact goes largely unnoticed, thereby underestimating the actual impact on the ground, and possibly misleading the conservation planning process. Though inclusion of the road networks provided the larger difference as compared to the original land cover data, only including roads still misses the variation in barrier effects in areas where roads are not strictly related to the level of residential development. For example, in the southern zone of the study area the uniformly laid gridded road network could not differentiate between areas with and without exurban dwellings. In such cases the direct
measure of residential development is needed for accurate estimations of the combined impacts.

The barrier effect analysis conducted in this study is simple in nature, providing quick yet powerful analytical tool for conservation planning. The most crucial step in this analysis, perhaps, is assigning the relative weights to each barrier type. Basing this step on the broad response behavior of wildlife associates the non-ecological GIS data with the ecologically relevant mobility information. Also, recognizing that the barrier effects extend beyond the physical structure of the barriers itself and incorporating it through a distance decay function extending up to the zone of influence of the barriers for the particular wildlife, allows for accurate representation of the impacts. This makes the barrier effect maps useful in highlighting areas with the highest combined barrier effects, which serve as the basis for prioritizing areas for landscape connectivity conservation.

The landscape connectivity analysis conducted in this study applied the recently proposed circuit theoretic modeling approach (McRae et al. 2008) to an exurban landscape context at two levels of analysis, capturing connectivity at two spatial scales. The first applied the model at the zonal level of the study area, which assesses connectivity among all habitat patches within each zone assuming that the wildlife may move across the entire landscape. This is an important management consideration because maintaining landscape connectivity over a longer time period is prudent in the face of uncertainties associated with large scale land and climate change. The second level of analysis is at the habitat network level, which restricts assessment to areas deemed “functioning” for the given wildlife based on its maximum dispersal ability. This is intended to capture the connectivity among the habitat patches most important for the wildlife’s
daily and seasonal requirements (e.g. breeding, foraging). Integration of results from both levels of analysis is expected to inform conservation planning at both regional and local spatial scales.

The zonal level results clearly indicate that the circuit theoretic approach delineated the critical linkage areas in the study area. In the North where the resistance values are relatively homogeneous, the current density values also seem to be relatively uniform reflecting equal probabilities of wildlife movement across the landscape. This suggests that there may not be critical linkage areas or bottleneck locations in this zone, suggesting the utility of circuit theoretic approach in landscapes with homogeneous conditions may be limited. The lack of critical linkage areas may also suggest that the data is not fine enough to capture the heterogeneity of the landscape. At the habitat network level the critical linkage areas are more distinct. This illustrates the applicability of the circuit theoretic approach at finer spatial scales, provided that the data captures the variability in landscape condition. Comparison of the current density maps resulting from the four different variants of barrier effect information indicate that using the most detailed information delineated the critical linkage areas more distinctively, though at the finer levels of analysis the difference were less visible.

Like any other study this one has a number of limitations. First, the model scenarios are heavily based on road characteristics and an understanding of road effects on Blanding’s turtle from the literature. This is mainly due to a lack of exurban literature, as well as data. Second the combined barrier effect map is not comprehensive. Other barriers in the landscape, both natural (i.e. mountains, rivers) and anthropogenic (i.e. powerlines) exist. For this study however it should not matter much as the target species is an amphibian species for which impervious surfaces like
roads and driveways pose a significant threat. Third, the sensitivity of the weighting technique is cautioned in the literature (Theobald 2005 b, Rayfield et al. 2010), but not examined in this study. To keep it simple, a relative weight between one and ten was used in this study. Fourth, Circuitscape, the circuit theoretic model used in this study, has its inherent limitations. Movements are assumed to be random walk so that each movement step of the target species is assumed to be independent of the previous step. Also, resistance is considered the same in both directions so that in some cases this method may be less suitable such as in higher elevation areas where movement downhill may be easier than uphill. Though these are important considerations, the goal of the study is not to involve fine-level detailed behavior of any single species, but rather to broadly highlight the extent of impacts associated with anthropogenic disturbances, like exurban development, can have on the landscape and wildlife. Lastly, the Circuitscape model, like other spatially explicit models, is computationally demanding, which forces the analysis to be conducted at a coarser resolution (100m in this study) for large spatial extents. This results in loss of fine level detail that is present in the landscape thereby masking the influence of such information. Nevertheless, examination of a smaller sample area at a finer resolution of 10m indicated that the overall spatial pattern of the current density map was similar, thereby not affecting the resulting identification of the critical linkage areas.

5.5 CONCLUSION

This study highlighted the importance of including exurban development and roads in studies examining barrier effects and landscape connectivity. A case study species, Blanding’s turtle was
used to ensure ecologically relevant information was included. The exclusion of fine level
information on exurban development and roads, as often occurs in ecological studies, resulted in
omission of impacts associated with these anthropogenic disturbances in the landscape, thereby
underestimating the actual ecological impacts. Though inclusion of the roads provided
substantial improvement over using the original land cover data alone, it still misses the variation
in barrier effects in areas where roads are not strictly related to the level of development. In such
cases the direct measure of development is needed for accurate estimations of impacts.
Additionally, this study also revealed the applicability of a recently proposed circuit theoretic
framework using Circuitscape tool to assess landscape connectivity in an exurban context at both
regional and local scales. Though circuit theoretic approach can provide useful information for
long and short term conservation planning, its utility may be limited in a relatively homogeneous
landscape or in cases where the data is not fine enough to capture the heterogeneity. Regardless,
the methods used in this study represent quick, flexible, and operational tools that are
ecologically relevant and can be integrated at both local and regional spatial scales for short and
long term conservation planning when applied appropriately.
Chapter 6: Conclusion

6.1 DISsertation Summary

Since the land use associated with residential development is a leading cause of species imperilment (Wilcove et al. 2000) and exurban development is the most rapidly growing form of residential development (Nelson 1992, Brown et al. 2005), it is crucial for both conservationists and land managers to have a better understanding of this phenomenon. This dissertation investigated exurban development in the County of Peterborough, Ontario. Here, exurban development is defined as the low density residential development that is outside incorporated urban areas in landscape dominated by either rural land uses or natural land cover. Quantitatively, the built areas within private property parcels up to eight hectares were defined as exurban development. This research is unique not only in a sense that it encapsulates different facets of exurban development in general, but also is one of the limited, if not only, study on exurban development in Canada as a whole.

Each chapter in this dissertation is aimed to improve our understanding of the exurban development dynamics through spatial analysis of its location, locating factors, and ecological impacts. The effect of scale and context is repeatedly considered throughout by examining each research question at multiple spatial extents that reflects the heterogeneity of the study area. The first chapter provides an overview of exurban development along with the dissertation context, problem statement, objectives, study area, and the outline of the dissertation. As spatially explicit data on exurban location are often unavailable, the following two chapters examine multiple
geomatic approaches to mapping exurban development. Specifically, the second chapter evaluates commonly used surrogates, such as roads and census data, for their ability to capture exurban development. The third chapter focuses on the utility of remote sensing imagery and techniques in exurban mapping. Utilizing the output from the previous chapter, the fourth chapter investigates a number of potential locating factors of exurban development to evaluate future land conversion risk and identify potential conflict with conservation goals. Lastly, the fifth chapter focuses on quantifying the ecological impacts of exurban development and associated road network, through an analysis of its barrier effects and landscape connectivity.

Recognizing that the paucity of data on exurban development had led to increased use of surrogates, mainly roads and census data, Chapter 2 of this dissertation examined the ability of these two data types to capture exurban development at large spatial extents. To date, there has been a lack of accuracy assessment associated with exurban mapping using surrogates. The mixed results obtained from the multi-scale correlation analysis of road density and dasymetric maps of census dwelling count data against reference data highlighted that at large spatial extents the heterogeneity contained within the study area can greatly obscure the overall relationships that may be evident at smaller spatial extents, where conditions are relatively more homogeneous. Also the geographical and historical context of the study area is important in determining the effectiveness of the methods. When surrogates are used, the distribution of the surrogate itself may be context dependent (e.g. roads being built to serve residences or regardless of settlements) thereby affecting the overall effectiveness of the mapping approach, thus caution should be taken while using these methods. Lastly, comparison of the two commonly used
methods indicated that dasymetric maps of dwelling counts performed better, but only when the census blocks were of relatively smaller size. These results raise concern regarding the validity of common surrogates used at large spatial extents for exurban development. Future research should consider these uncertainties and explicitly test the applicability of these surrogates before opting to adopt them.

Chapter 3 explored a more direct way to capture exurban development across large spatial extent through a remote sensing based method that utilizes Normalized Difference Vegetation Index (NDVI) recoding of moderate resolution (10 m) Système Pour l’Observation de la Terre / High Resolution Visible and Infrared (SPOT 5 / HRVIR) imagery. While an accuracy assessment of the initial NDVI recoding had a good producer’s accuracy of approximately 80%, reflecting low errors of exclusion, the user’s accuracy was extremely low, reflecting high errors of inclusion. To improve the latter, post-classification structural and contextual processing using readily available data were examined. The structural processing produced slight improvement, but the errors of exclusion were still mostly below acceptable levels. Contextual processing using water, roads, and a dasymetric map also showed only slight improvement. Alternatively, the inclusion of parcel boundary data proved to be the most effective method for exurban mapping in the study area, with user’s accuracy over 65% and producer’s accuracy over 80%. This chapter highlighted how the low density and dispersed nature of exurban development compounds the normal challenges associated with mapping built cover, making most traditional post-classification processing methods ineffective. An exception to this appears to be contextual processing based on private property parcel boundary data that provided size information. It is worth noting that
private property parcel data are often not easily accessible due to various reasons, including privacy laws and cost of data collection. Nevertheless the boundary files (without any associated attributes) are more often available for nominal fees or through data sharing agreements with responsible authorities. This study illustrated the utility of such data that provides a limited but useful contextual basis to interpret the land cover information derived from moderate resolution satellite data that are readily accessible. Application of the method used in this chapter provides a unique opportunity to expand the exurban research to other geographic areas and time period, which so far has been limited due to scarcity of spatially explicit data (McCaulley and Goetz 2004, Theobald 2005 a, Hansen et al. 2005).

With the availability of spatially explicit exurban data, Chapter 4 examined the relationship between current exurban development and multiple locating factors based on biophysical conditions, socio-economic accessibility, and natural amenity features to determine the factors influencing exurban developments' location. Future risk maps were then created based on these relationships. These maps were compared with previously identified conservation priority areas for biodiversity protection to begin to understand the extent of exurban threats to conservation goals in the study area. The analysis of potential locating factors using two methods, logistic regression and classification trees, both indicate that accessibility factors consistently play an important role in exurban development patterns. Many other factors had significant influence but only in certain zones of the study area depending on their geographical and historical context. Though this study included only one snapshot in time, mainly due to the lack of exurban data, the results provided a good understanding of the potential factors influencing these
developments. Creation of the risk maps suggested that based on existing conditions the study area is not under substantial threat of future exurban conversion, primarily due to a lack of suitable development areas. Nonetheless, the comparison of the conversion risk map with the pre-defined conservation priority areas indicates that though a substantial portion of the priority areas is not located in areas with a high risk of development, a large portion of the priority areas is unprotected, thus is vulnerable to any future changes in the landscape that may not have been captured in this study. Incorporating risk assessment framework and proactively identifying potential conflict areas have been repeatedly recommended as pivotal part of successful conservation planning (Wessels et al. 2003, Ma et al. 2009). This study applied this concept in the exurban context in its simplest form, which is expected to stimulate further research as more data becomes available.

Expanding on the theme of impacts of exurban development, Chapter 5 examined the influence of exurban development on the ecological function of the landscape by quantifying its overall barrier effects and impact on landscape connectivity for wildlife movement. Due to its relatively small area and isolated nature, the impacts of exurban development are often not fully captured in ecological studies. In this study, however, using the case study of Blanding’s turtle, exurban buildings and associated road network were explicitly included using their major quantifiable characteristics and expected response behavior of the case study species. This information was then combined with land cover data to estimate the overall barrier effect and landscape connectivity, measured using a circuit theoretic approach. A comparative of results based on original land cover, refined land cover, land cover and weighted roads, and land cover, weighted
roads and weighted exurban development clearly show that the exclusion of fine level details about exurban and roads results in an underestimation of the cumulative impacts of these anthropogenic disturbances in the landscape. This chapter not only emphasized the importance of exurban development in these ecological studies, but also successfully evaluated recently proposed analytical method using circuit theory to quantify landscape connectivity at two different scales. This research contributes to landscape management by providing operational and easy to use tools based on sound ecological principles for long and short-term connectivity conservation planning at both regional and local spatial scales.

6.2 RECOMMENDATIONS

6.2.1 Management recommendations

Several management recommendations emerge from this research. First and foremost the common practice of using surrogates to estimate the level of development intensity needs to be treated with caution. The validity of surrogates are highly dependent upon the scale and context of the study parameters as well as the study area, thus potential of surrogates should be explicitly evaluated for relevance. Second, though there are various direct ways to map urban cover using remote sensing, it can be very costly, if very high resolution imagery is being used across large spatial extents. Nonetheless compared to alternate data source, such as property parcel data, remote sensing imagery may still be less expensive. Aside from the cost, access to property parcel data is often restricted for a variety of reasons making its usage limited for land planning. The combination of moderate resolution remote sensing and readily available ancillary data, as
used in this research, may provide the operational solution to this problem. So far the use of remote sensing in urban planning was largely restricted by large data volume of high resolution imagery and intensive computational requirements, which practically made it prohibitively expensive (McCauley and Goetz 2005). In recent years this is changing and land managers should capitalize on this technology, especially since spatially explicit data on low density development is crucial for land management. This will increase data accessibility for research that in turn will contribute hugely to successful land management through a better understanding of phenomenon such as exurban development.

Third, to incorporate future threat of land conversion or to simply maintain or prevent further deterioration of the ecological integrity of a landscape, land managers and conservation planners need to heed attention to the influencing locating factors. This study emphasized accessibility measures as the most important influencing factor for exurban development, confirming findings of several other studies (Verburg et al. 2004, Conway 2005). This highlights a key point that limited accessibility may be the only way to restrict further anthropogenic disturbances such as exurban development in the landscape. This means that some areas may need to remain road-less or, if there already is existing road network, may need roads closures (Strittholt and Dellasala 2001). Another important consideration for land management that is highlighted by this study is that some exurban development is just an extension of suburban development, like in the southern zone of the study area where factors like school and other social amenities are more important influencing factors. With this in mind, land planning needs to proactively consider
plan designs and mitigation measures that minimize the impact of these developments in the future.

Last, but not the least, this study makes a strong recommendation that ecological impact assessments for regional land planning should strongly emphasize capturing the cumulative impacts of low density developments and the road network, including private roads where possible. In addition, recognizing that the effects of these structures extend beyond the physical footprint, thereby affecting much larger land area is crucial for conservation planning. This is especially true for exurban development that is often located near ecologically sensitive areas. Further consideration also needs to be given to other barriers (e.g., powerlines) in the landscape for other wildlife (e.g., birds). Utilizing the methods used in this study at several geographic and temporal scales (e.g., regional and local levels for long term and immediate connectivity conservation planning) land managers should operationalize the concept of integrating multi-scale impact analysis of anthropogenic disturbance into land use and conservation planning.

### 6.2.2 Research recommendations

For the mapping of low density development, such as exurban, much work is needed at research level. Additional studies that explicitly evaluate several variants of surrogates are needed to provide a better understanding of the appropriateness of surrogates in different situations. In terms of remote sensing, special attention should be given to capturing the rapid growth in exurban development at a regional scale. For urban remote sensing the commission error or error of inclusion continues to be a challenge, mainly due to the variety of substrate present in the urban setting (Goetz et al. 2004, Guindon et al. 2004, Dumas et al. 2008, Shrestha and Conway
An investigation of methods to minimize commission errors through mix of spectral, structural, contextual, and textural information, perhaps, in an object oriented setting should be undertaken (Stuckens et al. 2000, Sim 2004, Lackner and Conway 2008). Other sophisticated methods, such as spectral mixture analysis (Small 2001 and 2004), also need to be explored at multiple resolutions to examine the utility of these methods in exurban mapping. With advances in computing and remote sensing technologies, there may be increased ability to deal with the very high resolution imagery, which previously was prohibitively demanding to use over large spatial extents. Urban remote sensing should capitalize on these opportunities and examine their applicability over large spatial extents that allows for inferences to be made about regional patterns and processes.

In terms of conservation and ecological implications of exurban development, there is still paucity of studies that explicitly examine them. It is widely accepted over the past decade that exurban development have disproportionately large ecological impacts (Hansen et al. 2005, Gude et al. 2006), especially when the road network associated with it is taken into account (Forman and Alexander 1998, Trombulak and Frissell 2000). Exurban development is advancing at alarmingly rapid rates (Brown et al. 2005, Theobald 2005 a, Merenlender et al. 2010), yet it is repeatedly ignored in most impact assessment studies. More research that reveals the overall impact of exurban development, which accounts for its zone of influence and the various characteristics, in different landscapes needs to be conducted through spatially explicit studies that can contribute to the overall scientific knowledge on the anthropogenic disturbance.
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