ABSTRACT


Urban forests play a crucial role in the sustainability of urban ecosystems as they provide important ecological services leading to social, economic, psychological, and environmental benefits. The influences of urban forest fragmentation on ecosystem health and human health have been widely studied while those on human health have received little research attention.

This study aims at constructing a conceptual model to illustrate the links between urban forest fragmentation and human health, while investigated at the community scale through their relationships with ecosystem health, while investigating the multi-scale linkage needs to be established to inform future planning and management decisions at the corresponding scales. This study aims at constructing a conceptual model to illustrate the links between urban forest fragmentation and human health, examining the relationships with a consideration of confounding factors such as socioeconomic status at different spatial resolutions. The relationships between urban forest fragmentation and human health are mostly studied while those on human health have received little research attention.

The major characteristics of urban forest fragmentation, such as the decreases of patch size and the increases of patch density, show a positive correlation with increased human health. Some of the characteristics of urban forest fragmentation, such as the increases of patch density, have effects on both ecosystem health and human health. Landscape metric values at different spatial resolutions vary a lot and those at the finer resolution have stronger correlations with the human health variables. The methodology and results of this study provide empirical examples that will stimulate further research that integrates landscape ecology and social sciences in understanding human health.
effects of urban forest fragmentation, including comparisons among ecoregions and the selection of spatial resolution of landscape data for different levels of urbanized areas.
Linking Urban Forest Fragmentation with Human Health: Conceptual Foundations and Methodological Issues

by
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This dissertation is dedicated to my mother, Ke Huang, for her infinite support and love.
BIOGRAPHY

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CHAPTER 1: General Introduction

One of the grand challenges in our lifetime is the global trend of urbanization and its environmental, social and cultural ramifications. Over half of the world population are currently living in urban areas (United Nation, 2012). The continuing process of urbanization results in rapid transformation of rural to urban landscape dominated by built features with remnants of forests and other natural land cover (Alberti, 2005; Biamonte et al., 2011; Carrete et al., 2009). While urban forests, or trees located in or nearby urban areas (Konijnendijk, 2005), are typically fragmented and spatially dispersed by roads and buildings, they still serve crucial ecological roles. Urban forests constitute the remaining natural habitats for wildlife, provide a variety of ecosystem services, and contribute to human well-being (Dwivedi et al., 2009; Konijnendijk, 2005; Nowak and Greenfield, 2012). As human activities drive the composition and configuration of urban landscapes, fragmented forests may carry different meanings for human health from those for ecosystem health.

The consequences of urban forest fragmentation on ecosystem health have been widely studied. Urban forest fragmentation is characterized by the decreases of patch size, the increases of patch number, the increases of patch isolation, and the increases of patch isolation (Birch et al., 1997; Di Giulio et al., 2009; Fahrig, 2003; Le Tortorec et al., 2013; Murcia, 1995; Peyras et al., 2013). However, these characteristics of urban forest fragmentation and their effects on human health are not well understood. It is unclear how the fragmentation of natural systems, or the homogenization of the urban matrix, is linked human health indicators such as physical activity, obesity and chronic diseases.
Landscape metrics or landscape indices are commonly used to characterize landscape structures and quantify characteristics of landscape fragmentation. Many studies have applied landscape pattern analysis and related metrics in urban areas, particularly urban forests (Freitas et al., 2011; Tian et al., 2011; Trammell and Carreiro, 2011). Landscape metrics that have been identified to measure the effects of urban forests fragmentation on ecosystem health are total area, percentage of landscape, number of patches, Euclidean nearest distance, and landscape diversity (Bolger et al., 2008; Boulet et al., 2000; De Chant et al., 2010; Taylor et al., 2011; Yeh and Huang, 2009). The relevance of these metrics to human health is still yet to be evaluated empirically.

The environmental settings, which refer to landscape patterns, are often linked with human health, but the relationships have been identified at small scales such as neighborhoods, communities and zip codes. Analyzing data at larger scales, such as the county or metropolitan level, can contribute to a more holistic understanding of the effects of landscape patterns on human health. In addition, some landscape metrics are sensitive to the change in spatial resolution (i.e. grain size) and the change in spatial extent (i.e. the area of the landscape). The effects of the changes in spatial resolution and spatial extent on ecological processes have been extensively studied; however, few of them have been linked to human health.

The overall goal is this research is to conceptually and empirically examine the linkage between forest fragmentation and human health, through an application of landscape indices and an evaluation of spatial resolution effects. Three specific objectives include: (1) constructing a conceptual model that addresses the direct and indirect links between urban
forest fragmentation and human health through multidisciplinary studies, (2) examining the empirical relationships between urban forest fragmentation and human health at county and city scales, and (3) investigating the effects of the change in spatial resolution on the relationship between landscape pattern and human health variables. Three specific questions are guiding this study:

(1) What is the nature of relationship between variables that describe urban forest fragmentation and those that explain human health?

(2) What are the landscape metrics that are mostly related to human health and their relationships?

(3) Do different resolutions of these landscape metrics influence the results on human health?

These questions are used to build up comprehensive knowledge of the effects of urban forest fragmentation on human health through this three-step framework: understanding the similarities and dissimilarities of the effects of urban forest fragmentation on ecosystem health and on human health, adapting quantitative methods from ecological studies to measure the relationship between urban forest fragmentation and human health variables, and examining the effects of the common issues in ecological studies on human health variables.

This dissertation is structured in the journal article format with 5 chapters. The three main research questions are addressed by three manuscripts (Chapters 2, 3 and 4) intended for journal submission. The dissertation will also include a general introduction (Chapter 1) that describes the overall purposes and research needs. A general conclusions chapter
(Chapter 5) will also be included to summarize the research findings and implications of future work.
References


CHAPTER 2: Conceptualizing the Linkage between Urban Forest Fragmentation and Human Health: A Multidisciplinary Approach

Abstract

Urbanization is a major driving force of urban forest fragmentation which has resulted in altered environmental quality. While the effects of urban forest fragmentation are well recognized, research attention has been largely paid to ecological issues. Research has suggested that forests and greenspaces promote human health of urban residents through a range of ecosystem services. As urban forest fragmentation is largely driven by human needs, we consider whether the meanings and consequences of forest fragmentation are the same for the ecosystem and human health. We reviewed multidisciplinary literature relevant to landscape fragmentation in ecology, sociology, and recreation fields. We identified the major characteristics of urban forest fragmentation followed by a comparison of effects on ecosystem and human health. We also identified confounding factors that are not measurable directly from landscape characteristics. We constructed a conceptual model to offer an alternative view of urban forest fragmentation with its hypothesized relationships with ecosystem health and human health. Utilizing our conceptual model we illustrate potential direct and indirect relationships among different urban forest characteristics and human health. We concluded that some levels of urban forest fragmentation may benefit to human health as forests are closer and more accessible to humans. An improved understanding of these relationships will inform research in related disciplines and urban land use planning in the future.

Keywords: Urban forests, fragmentation, ecosystem health, human health
1. Introduction

Urbanization has rapidly increased globally over the past four decades. Almost half of the world’s population is now living in urban areas (United Nations, 2012; Zhang et al., 2014). One of the major consequences of urbanization is landscape change. The process of urbanization shifts rural landscapes dominated by forest cover and open space with low population densities, to urban landscapes occupied by artificial structures such as roads and buildings with high densities of human population (Medley et al., 1995; US Census Bureau, 2010). Along the rural-urban gradient, forests are increasingly fragmented as indicated by decreased size and increased edges of forest patches (Jim and Chen, 2003; McDonnell et al., 1997; Medley et al., 1995).

Despite their fragmented nature, urban forests, defined as trees or tree stands situated in or nearby the urban areas (Konijnendijk, 2005), still play a crucial role in determining the sustainability of urban ecosystems and in providing important ecological services to urban residents. These services generate a host of social, environmental, economic, psychological, and recreational benefits (Abraham et al., 2010; Bolund and Hunhammar, 1999; Dwivedi et al., 2009; McPherson et al., 1997; McPherson and Rowntree, 1993; Tzoulas et al., 2007). While the importance of urban forests is tied to both ecosystem and human health, much of the research attention about urban forest fragmentation has been focused on the effects of fragmentation on ecosystem health. The purpose of this paper is to fill this research gap by exploring the linkage between urban forest fragmentation and human health through a multidisciplinary literature synthesis and conceptual modeling.
1.1 Urban forests and ecosystem health

Urban areas are sometimes thought of as locations with low biodiversity that are dominated mainly by non-native species compared to natural landscapes (McKinney, 2002; Savard et al., 2000). Depending on the level of urbanization and the type of species (i.e. trees, birds, insects, etc.) being considered these results are not always clear (McKinney, 2002). In fact, within the built environment urban forests can possess relatively high biodiversity (Alvey, 2006; Miller, 2005; Pickett et al., 2008). As such, some of the better known benefits provided by urban forests are ecologically linked. Urban forests are primary habitats for wildlife living in the modified urban environment, and they form links to larger ecological networks that influence on ecosystem functions (Niemela et al., 2010; Tzoulas et al., 2007). A well-functioning urban ecosystem provides important services such as adjusting ambient temperature, removing air pollutants, noise abatement, and storm-water runoff reduction (Armson et al., 2012; Escobedo et al., 2008; McPherson et al., 1997; Nowak et al., 2006; Pauleit et al., 2005; Rapport et al., 2003; Tzoulas et al., 2007). Urban forests, in particular, can help improve air quality by removing the pollutants and allergy-related elements in the air (Beard and Green, 1994; Escobedo et al., 2008; McPherson et al., 1997).

Urban forests also help regulate hydrological systems in urban areas. The increase of impervious surfaces such as roads and buildings results in more storm-water runoff that brings pollutants into water systems (Legret and Pagotto, 1999). Unlike forested surfaces, where water can enter the surfaces and be evaporated through tree leaves, impervious surfaces do not provide a good penetration rate for water moving into the water cycle (Arnold and Gibbons, 1996). Inkiläinen et al. (2013) found that urban forests in residential
areas can intercept almost as much precipitation in storm events as rural forests. Furthermore, urban forests mitigate temperature in urban areas. The urban heat island (UHI) effect is caused by the increase of impervious surfaces such as roads and buildings that catch the heat and have high thermal storage. The presence of trees in urban areas can reduce the temperature and mitigate the UHI effect (Botkin and Beveridge, 1997; Bowler et al., 2010).

1.2 Urban forests and human health

Urban forests serve not only ecosystem functions but also provide ecosystem services for human health and well-being by providing comfortable living environment. For instance, urban forests are known to relieve stress on respiratory system by removing pollutants in the air (Armson et al., 2012; Bowler et al., 2010; Nowak et al., 2006; Whitford et al., 2001), though this benefit can be partly offset by forests’ disservices, such as inducing pollen allergy, the overabundance of given species acting as key pollen sources, the presence of invasive species, and the interactions between pollen and air pollutants (Carinanos and Casares-Porcel, 2011; Garcia et al., 1997; Hidalgo et al., 1999).

Urban forests also promote good physical, mental, and social health through their ecological, aesthetic and economic values. Urban forests provide daily access for urban residents and places for people engaging in physical activity (Mitchell and Popham, 2007; Roux et al., 2007; Seaman et al., 2010). They also provide scenic landscapes that help release work pressure, and increase positive emotions or feelings; additionally, they provide enjoyment of nature, facilitate recovery from surgery and illness (Alberti, 2005; Bedimo-Rung et al., 2005; Dwyer et al., 1992; Hull IV, 1992; Jackson, 2003; Millward and Sabir,
The biodiversity of urban forests provide educational opportunities on natural science for urban residents (Birch et al., 1997). Other social functions of urban forests include increased environmental safety by lowering crime rate (Kuo and Sullivan, 2001) and contribution to economic development (Grant et al., 1996; Joye et al., 2010; Tyrväinen and Miettinen, 2000; Wolf, 2005).

1.3 Urban forest fragmentation

The term ‘urban forest fragmentation’ has been used to describe the change in forest composition and configuration through the process of urbanization, and it has become a major issue in environmental sustainability (Carinanos and Casares-Porcel, 2011; Jongman et al., 2004b; Schipperijn et al., 2010). Current studies of the effects of urban forest fragmentation are mostly focused on ecosystem health, whereas the direct links between urban forest fragmentation and human health are seldom explored (Alvey, 2006; Fahrig, 2003). However, the meanings and consequences of urban forest fragmentation on human health may be different from those on ecosystem health. For example, one main reason of urban forest fragmentation is the construction of transportation infrastructure for human connectivity (Abdullah and Nakagoshi, 2007). Consequently, while urban forest fragmentation decreases the connectivity for wildlife as research has shown, it may actually increase the landscape connectivity for human inhabitants.

Recent research on the effects of urban forest fragmentation has begun to expand its focus to include both ecosystem and human health. Di Giulio et al. (2009) reviewed the
effects of habitat and landscape fragmentation on biodiversity and humans in areas with high population density. The authors addressed the effects of landscape fragmentation on humans from the perspective of landscape perceptions. In general, landscapes serve as ‘places’ for performing ecological processes. However, for people landscapes not only serve as ‘places’ to engage in activities but also as ‘scenes’ which have a profound psychological effect on their viewers. Consequently, urban forest fragmentation and human health should not only be linked ecologically but also socially, and the linkage goes beyond human perceptions of landscape.

This paper presents a comprehensive, multi-disciplinary literature review with the three specific objectives: (i) to identify characteristics of urban forest fragmentation that are not only linked to ecosystem health but also potentially tied to human health, (ii) to identify confounding factors of the relationships between urban forest fragmentation and human health, and (iii) to propose a urban forest fragmentation-human health conceptual model to guide future research.

2. Literature review

The scope of this study centered on the fragmentation effects on ecosystem health and human health, and the factors that may cause urban forest fragmentation but also have effects on human health. In order to broadly understand the landscape – health relationship, two sets of keywords, landscape- and health-related keywords, were firstly defined. Landscape-related keywords were firstly included broad definition of landscape such as landscape, environment, nature, scenery, and places. Secondly, we included forest-related keywords
such as parks, forests, green elements, green infrastructure, and greenspaces. Thirdly, we emphasized on the fragmentation effects, and therefore fragmentation-related keywords such as landscape fragmentation, forest fragmentation, and landscape metrics or indices. Health-related keywords included ecosystem health such as biodiversity, species richness, and mortality, and human health, such as physical health, mental health, and social health based on the definition of human health by World Health Organization (WHO, 1946).

We searched the literatures by a pair of the combinations of the landscape- and health-related keywords via major digital reference databases, including Web of Science and PubMed. We included studies of ecosystem functions and services, human physical, mental, and social health, human preferences of landscape, and quantitative methods of landscape in urban studies. The exclusions were studies of environmental toxins, river or ocean ecosystem, and water, soil or air pollutions induced by chemicals. The major journals identified here on the basis of the literature search were *American Journal of Preventive Medicine, American Journal of Public Health, Ecological Indicators, Ecosystems, Environmental Management, Landscape Ecology, Landscape and Urban Planning, Urban Ecosystems,* and *Urban Forestry & Urban Greening.*

Many of the search results by using the combinations of human health and landscape- or forest-related were published in the *American Journal of Preventive Medicine and American Journal of Public Health.* The intended focus here was on the concepts of how humans use landscapes or human preferences on landscape. The search results by using the combinations of ecosystem health and landscape- or forest-related keywords were mostly published in the *Ecosystems, Environmental Management, Landscape Ecology, Landscape*
and Urban Planning, Urban Ecosystems, and Urban Forestry & Urban Greening. The focus here was more emphasized on the effects of landscape features or changes on ecological processes. The search results by using the combinations of ecosystem health and fragmentation-related keywords were mostly published in the Ecological Indicators and Landscape Ecology. The focus here was mainly the effects of landscape change on ecosystem health and the methodological issues. However, the search results by using the combinations of human health and fragmentation-related keywords were mostly overlapped with the search results discussed before.

In addition to gaining a better understanding of the relationships between urban forest fragmentation (i.e., especially the characteristics of measurable landscape features) and health (i.e., especially human health), some advanced searches using measurable landscape terms such as park/greenspaces/forests size or distance as keywords were implemented in the major identified journals. We summarized the findings and categorized them into three groups, which were (1) landscape factors, (2) human factors and (3) moderators. The links of landscape and human factor, and moderator were built based on multidisciplinary studies such as landscape ecology and landscape architecture afterwards.

2.1 Characteristics of landscape fragmentation

We used both landscape fragmentation and urban forest fragmentation to discuss the findings, since many studies used “landscape fragmentation” to discuss ”forest fragmentation”. (Hepcan, 2013; Ren et al., 2013; Tian et al., 2011). A landscape can be regarded as a mosaic of different land covers within a landscape, and patches can be regarded
as the basic units of this mosaic based on the field of landscape ecology (Forman, 1995). A patch describes nonlinear features of landscape and differs widely in size, shape, and edge characteristics (Forman, 1986). As the relationships between landscape and ecosystem are based on landscape ecology, most of the studies characterized the effects of landscape fragmentation through the physical changes in the size, edge, and isolation of patches (Birch et al., 1997; Di Giulio et al., 2009; Fahrig, 2003; Le Tortorec et al., 2013; Murcia, 1995; Peyras et al., 2013). Fragmentation commonly involves in reduction of patch size, increase of patch number, increase of edge density, and increase of patch isolation.

As human activities are the major causes of forest fragmentation, the common characteristics of urban forest fragmentation seem to affect ecosystem health and human health in contrasting ways (Figure 1). For example, urban forest fragmentation decreases habitat areas but results in more human activity areas such as residential areas. Urban forest fragmentation interrupts habitat connectivity and creates gaps, but increases human landscape connectivity by creating transportation infrastructure and residential areas. Furthermore, urban forest fragmentation increases the distance between habitat patches, but human activity areas converted from urban forests are mosaicked into the landscape, which decrease the distance between human activity areas and forests. Lastly, urban forest fragmentation increases forest edges that contribute negatively to ecosystem health, but the increase of forest edges implies more accessible edges for humans to contact with natural areas. Therefore, the same factors of urban forest fragmentation may have opposite effects on ecosystem health and human health as forests are the primary habitat for wildlife but not the
primary areas for human living. The following sections provide more details of specific fragmentation characteristics.

**With the Increase of Landscape Transformation from Forests to Urban Infrastructure**

![Diagram showing the relationship between human health, ecosystem health, and urban forest fragmentation]

Figure 1 Influences of urban forest fragmentation on ecosystem health and human health. The reduction and increased fragmentation of urban forests brings mostly negative effects on ecosystem health but some positive effects on human health. For examples, the loss of habitat connectivity may be induced by transportation infrastructure, which increases human landscape connectivity. The loss of habitat areas may be induced by the establishment of residential areas, which increases human living areas. The increase of forest edges brings mostly negative effects on ecosystem health but increases opportunities for humans to contact with natural areas. Lastly, urban forest fragmentation brings negative effects on ecosystem health by increasing the distance between habitat patches but reducing the distance from residential areas to natural areas.
2.2 Effects of urban forest fragmentation on ecosystem health and human health

Landscape characteristics determine the movement of species and the availability of habitats. Human-induced landscapes, that convert habitats to other land use, increase the distance between habitats, and create more edges for habitat patches, are primarily barriers for species movement. For example, roads interrupt the connectivity of habitats and therefore decrease species accessibility to other habitats. Moreover, the existence of roads can be huge barriers for wildlife and increase the mortality by car collisions (Jaeger and Fahrig, 2004; Trombulak and Frissell, 2000). Although diverse landscape may contribute positively to biodiversity, it has to be gradual change between habitats such as forests versus grasslands. Human-made landscapes are abiotic environments for wildlife. Therefore, urban forest fragmentation and the effects of urban forest characteristics are particularly important to understand the responses of ecological processes and to reach sustainable environments.

The relationships between urban forest fragmentation and ecosystems have been explored in the field of landscape ecology, which deals with the potential relationships between spatial patterns and ecological processes (Collinge, 2009; Forman, 1995). The relationships between landscape and humans have been explored in the field of landscape architecture. Landscape architecture, which deals with design and planning of environment, has been developed over a long period of time, but it had not been merged with the concepts of landscape ecology until 1960s (Makhzoumi, 2000). Landscape architecture focuses more on planning the proper uses for human benefits, whereas landscape ecology considers more about the functioning of resources (Leitão and Ahern, 2002). With the revolution of landscape architecture, there has been an increasing awareness of the importance of natural
elements in designing human preferable environments. By accepting humans as a part of the ecosystem, humans should have intuitive needs of natural elements. Studies on human perceptions of landscape suggest that humans generally prefer to have natural components in the surroundings and believe that natural elements are healthy and restorative, especially in urban settings (Parsons, 1991; Ulrich, 1986). Subsequently, the characteristics of urban forest fragmentation and their effects on ecosystem health and human health are elaborated in the following section.

2.2.1 Size effects

Many studies discussed the effects of size change on biodiversity as an indicator of ecosystem health (Rapport, 1995). The relationships are mainly constructed based on the theory of island biogeography, which describes the relations between area size and species richness (MacArthur and Wilson, 1967). In general, the reduction of size contributes negatively to species richness, and therefore the reduction of the size of urban forests mostly causes negative effects on the surrounding ecosystem health. Fahrig (2003) reviewed the effects of forest fragmentation on biodiversity and indicated that patch size is still one of the major measurements for habitat fragmentation. Bickford et al. (2010) compared the species richness of frogs in three different sizes of forest areas, which are large fragments (>140 ha), middle-sized fragments (50 – 140 ha), and small fragments (<50 ha). The results showed that the mean species richness is the highest in the large fragments of forests, and additionally some species can only be found in large fragments. Other studies found that larger parks had higher species richness and birds’ nestedness than smaller parks (Fernandez-Juricic, 2000;
Fernandez-Juricic and Jokimaki, 2001; Godefroid and Koedam, 2003b). Fujita et al. (2008) also found that forest fragmentation in urban areas negatively impacted the species richness for ground beetles, and the total area of forests was markedly correlated to the richness of ground beetles. However, the relationships between area size and species richness are dependent on the species in question (Martensen et al., 2012).

The size effects of urban forest fragmentation on human health are different from those on ecosystem health. As design helps humans build the preferred environments, design of urban greenspaces is important in utilizing the limited space for parks in urban areas. Urban parks or greenspaces are relatively small but are more accessible for humans (Forsyth and Musacchio, 2005; Hofmann et al., 2012; Niemela et al., 2010). Forsyth and Musacchio (2005) recognized that urban parks may not be good for wildlife but benefit humans by improving the connections between natural areas and residential areas. In urban areas, even small greenspaces can have restorative value (Nordh et al., 2009). Unlike ecological studies, landscape-human health studies rarely discuss the relationships between the comparative size of urban parks and human preference of park use. Arnberger (2006) compared the recreation uses of an urban park and a peri-urban park in Vienna, Austria. The results showed that even the urban park was smaller than the peri-urban park, the frequency of visitor use of the urban park was higher than the peri-urban park. The reasons being (i) the urban park is encircled by residential areas, (ii) the urban park is more accessible for public, and (iii) the urban park is an intermediate neighborhood between school or business areas and home. Therefore, the determining factors of human park use depend more on the distance and accessibility to parks in their findings. Schipperijn et al. (2010) indicated that larger sized urban greenspaces had
higher use frequency than smaller ones while only considering the urban greenspaces with a distance less than 1.2 km. As urban spaces are limited, small urban parks may provide more opportunities for humans interacting with nature and utilizing the space.

2.2.2 Edge effects

Edges are the borders of patches connecting two habitat types. In other words they are the transitional zone between two or more distinct habitats or land covers (Murcia, 1995; Peyras et al., 2013). Consequently, edges are the places where species can interact with or be influenced by the surroundings. Edge effect has been recognized as a key influence of ecological processes (Alberti, 2005; Godefroid and Koedam, 2003a). Most of the natural edges are curvilinear and soft where the transition of different habitat/land cover types is gradual, but human-induced edges tend to be straight, distinct and abrupt (Collinge, 2009; Di Giulio et al., 2009; Dramstad et al., 1996; Lindenmayer and Fischer, 2006). Hard edges tend to have more species movement along them, whereas soft edges usually have species movement across them.

Moreover, edges involve both biotic and abiotic movement that influence species compositions such as the increase of invasive species population, and microenvironments such as altered humidity, wind speed, and air temperature (Collinge, 2009; Di Giulio et al., 2009; Lindenmayer and Fischer, 2006; Murcia, 1995; Yates et al., 2004). Edge effects resulting from landscape fragmentation may bring higher species richness. For example, Godefroid and Koedam (2003a) found that the appearance of rare species was about four times more in the edges than in the interior. Suarez et al. (1998) discussed the effects of
urban edges on Argentine ant activity, and the results showed that Argentine ant activity was negatively correlated to the distance to the nearest urban edge but positively to the exotic vegetation. If only viewing a patch, edges provide opportunities for native species moving out to other habitats and for non-native species moving into the habitat. The ecological processes in the edges may contribute positively to biodiversity at a larger spatial scale but may threaten the native species at a local scale.

The increase of edge in a patch not only provides more accessibility to wildlife but also to humans. Edges may be a problem from ecological perspective but are an important element in an environment that provides places for social connections (Forsyth and Musacchio, 2005). Edge effects are preferred by recreationists since edges are not only important for physical settings of recreation areas but also for sightseeing experiences in recreation areas. Studies pointed out that humans prefer to stay by the edges of an area. Edges fulfill the human psychological needs for the feelings of safety, refuge, and visual access (Edwards et al., 2012; Kaplan, 1998; Mumcu et al., 2010; Ruddell and Hammitt, 1987). Prospect-refuge theory describes the importance of seeing without being seen to meet early human’s survival needs and therefore edges become sources of aesthetic satisfaction and preference for seclusion. Ruddell and Hammitt (1987) applied the prospect-refuge theory to recreation settings for examining the edge effects on this human preference. The results showed that the most preferred scenes consisted of edge environments with viewing adjacent to the forest edge. In two of the most preferred settings, the viewers were located in a meadow but with accessible distance to forest edges. Unlike ecological processes, even hard edges can provide more connections and movements for humans to contact with the nature.
2.2.3 Isolation effects

Fragmentation also increases the isolation of habitats which causes the reduction of habitat amount in a landscape and consequently influences species abundance and persistence (Fahrig, 2003; Fahrig and Merriam, 1994). Patch isolation is primarily based on the theory of island biogeography, which treats the landscape as binary mosaics, habitat patches and non-habitat patches or uniform matrix (McGarigal et al., 2012). Patch isolation most likely can be regarded as spatial inaccessibility to move from other patches. Isolated patches have few or no immigrants to colonize them or to compensate for potential population decline (Bender et al., 2003). In a landscape, species movement is not only within patches but also among patches, and therefore the isolation of patches is a key factor for species migration.

The isolation of forest patches may provide more accessibility for human to natural areas. Distance between habitat patches is important to wildlife, but distance to recreation areas (i.e. parks, forests, greenspaces, and openspaces) is an important factor of the people’s use frequency of recreation areas and type of usage (Arnberger, 2006; Giles-Corti et al., 2005; Schipperijn et al., 2010). Urban forest fragmentation increases more human landscape connectivity to and therefore may decrease the distance for human reaching to the natural areas in cities. Arnberger (2006) indicated that people use the urban parks with relatively close distance to residential areas as daily commute. Schipperijn et al. (2010) conducted a study to compare the use frequency of nearest urban greenspaces by distance in Odense, Denmark and found that the use frequency of nearest urban greenspaces was inversely related to the distance to the urban greenspaces. Comparing to the daily use frequency of
15.4% for the urban greenspaces within 100 meters, the use frequency dropped by 7.8% while the estimated distance to the urban greenspaces was more than 100 meters. Therefore, distance is an important factor for recreation decisions, but the importance of the distance for humans is the distance ‘to’ urban forests while distance ‘between’ urban forests is a crucial factor for ecological processes.

2.3 Confounding factors of the relationship between urban forest fragmentation and human health

A confounding factor is a variable that is associated with the exposure and the outcome (Howards et al., 2012). The key confounding factors in this study are socio-economic factors that have potential effects on both urban forest fragmentation and human health, including population density, housing density, and socioeconomic status (SES).

Economic development, as well as pressure on the increases of urbanization, is the major cause of urban forest fragmentation (Abdullah and Nakagoshi, 2007; Henderson, 2003). The importance of green elements such as forests in urban areas has been proven by several studies. Incorporating green elements such as trees in built environments benefits mental health, such as relieving from mental fatigue of work (Kaplan, 1993; Kaplan, 1995a), improving recovery from a surgery (Ulrich et al., 1991), improving productivity and work efficiency (Bringslimark et al., 2009; Lohr et al., 1996), and helping children build cognitive and intellectual development, creative imagination, and social relationships (Min and Lee, 2006; Taylor et al., 2002). However, some other factors that also influence human health may be the driving forces of urban forest fragmentation. For example, economic development
greatly tied in with urbanization and results in rural migration to cities (Fox, 1981; Kornhauser, 1958; Sato and Yamamoto, 2005). Consequently, income can be one of the confounding factors. The population and housing growth are inevitably accompanied with the process of urbanization (Jones et al., 2008).

Moreover, mental health is not only influenced by environmental factors but also socio-economic factors as it is involved in psychological well-being. Socioeconomic status, including income, education, and employment dimensions, have positive relationships with urban development and is thought to be one of the factors affecting human health (Reynolds et al., 2005). Many studies mentioned that socioeconomic status is one of the factors that are accompanied by urban development has impact on ecological processes as well as human society (Alberti and Marzluff, 2004; Grimm et al., 2008). In addition, socioeconomic status has a positive association with tree cover across many different urban systems (Hope et al., 2003; McHale et al., 2013; Troy et al., 2007). Studies pointed out that childhood socioeconomic status had significant relationship on mental health outcomes in their adulthood (McLaughlin et al., 2011), lower employment rate reduced mental health (Bringslimark et al., 2009), and lower income caused higher rate of mental disorder (Miech et al., 1999). Therefore, the SES is a confounding factor that positively relates to urban forest fragmentation and human health.

However, the relationship between human health and the confounding factors may be more complicated. For example, people with higher income may have more opportunities to access greenspaces (Black and Macinko, 2008; Mitchell and Popham, 2008), but their dietary habits may not be healthy (Drewnowski, 2003). Besides the SES-related confounding factors,
human-built environmental factors may also have associations with urban forest fragmentation and human health. Therefore, availability of healthy or unhealthy food sources can be considered as confounding factors as well. In addition, some landscapes may be considered as human-made infrastructure but can contribute positively to human health such as greenways, sidewalks, and bike lanes. Therefore, transportation networks can be considered as advanced level of human landscape connectivity and as confounding factors as well.

3. Linking urban forest fragmentation and human health: A conceptual model

A growing body of research is dedicating to construct models to link the relationships of environment with human society. Collins et al. (2010) indicated that integrative studies that bridge environmental and social sciences are needed to understand the long-term relationships of this social-ecological system. They proposed an iterative framework, “Press-Pulse Dynamics” (PPD), to illustrate how human behaviors alter ecosystem processes. The presses of the social domain included climate change, nutrient loading, sea-level rise, and increased human resource consumption, and the pulses included fire, drought, storms, dust events, pulse nutrient inputs, and fertilization. They linked the relationship between social domain and biophysical domain by the PPD and ecosystem services. Their model provided direction to guide the social-ecological studies.

Many of the models specifically focused on the relationships between environments, especially natural landscapes, and human health. Most of these models described the relationships between natural landscape and human health through their links with ecosystem
health. Tzoulas et al. (2007) constructed a conceptual framework to integrate the connections among natural landscape (i.e., labeled green infrastructure in the study), ecosystem, and human health. The core concept of the framework was that green infrastructure and its associated melioration in ecosystem health create environmental settings for human health. They defined seven main components in the framework, including green infrastructure, ecosystem functions and services, ecosystem health, socio-economic health, community health, physical health, and psychological health. Any pair of the components can have interactions with each other. For example, green infrastructure improves ecosystem health, and ecosystem provides good feedback to maintain green infrastructure. In their model, the relationships between green infrastructure and human health were linked through its relationships with ecosystem health.

Abraham et al. (2010) constructed a heuristic framework to describe the relationships between landscapes (i.e., including natural and built environments) and human health. They described landscapes as different roles to promote different aspects of human health. Landscapes were described as restorative environments when promoting mental health, as walkable environments when promoting physical health, and as bonding structures when promoting social health. They mentioned that landscapes have to have certain characteristics such as being natural, aesthetic, or safe to influence human health directly or indirectly. Landscapes can help stress reduction when people perceive that the landscapes are beautiful and enjoy them. In addition, landscapes can help social integration when people perceive that the landscapes are safe and are willing to use them. In their model, the relationships between landscapes and human health were linked mainly by human perceptions of the landscapes.
Lachowycz and Jones (2013) created a socio-ecological framework to link the relationship between greenspace access and human health. The core concept of their model relied on that how the features within the physical environments change in health outcomes. They linked the relationships between the access of greenspace and human health by defining four moderating factors: demographic, living context, characteristics of greenspace, and climate, and three mediators: improved perceptions of living environment, aesthetic pleasure and relaxation from viewing greenspace, and use of greenspace. In their model, they also explained the mechanisms of moderation and identified the intra- and inter-relationships of the mechanisms and the mediators. The relationships between the access of greenspace and human health were linked mostly by social causes and social-induced interactions with the environments.

Although those models were constructed to indicate the importance of natural landscape, especially for urban areas, none of them indicated the potential effects of urban forest fragmentation. Furthermore, the direct links between natural landscape and human health are rarely discussed in the existing models. Based on the above literature review, we adopted the framework constructed by Collins et al. (2010) and added our specific interests, fragmentation and human health, and present a conceptual model (Figure 2) here to illustrate the nature of the relationship between urban forest fragmentation and human health.

Landscape factors and human factors were first identified to link the relationships. Secondly, moderators were identified to indicate the linkages that cannot be measured directly from landscape or human factors. The conceptual model was constructed based on multidisciplinary studies. Landscape physical features in landscape factors were mainly
based on landscape ecology and the theory of island biogeography. Landscape quality was mainly based on landscape architecture. Environmental preference and motivation in human factors were identified mainly based on leisure study. Ecosystem service was identified mainly based on urban ecology, and lastly the social-economic factors in the confounding factors were identified based mainly on urban planning, and built-environment factors were identified mainly based on urban park design and urban planning.

Landscape factors here focus on the measurements of landscape including physical features which refer to landscape composition and configuration, and landscape quality which refers to aesthetic assessments of individual trees or tree stands. Human factors here focus on the human connection with the nature including environmental preferences which refer to choices of the living environment or recreational activities, and motivations which refer to intentions for engaging in activities that promote health conditions. Moderators here focus on the relationships between ecosystem health and human health including ecosystem services which refers to the living comfort and environmental health and the variables that may have effects both on urban forest fragmentation and human health, such as socioeconomic status which refers to the development of an area and built environment which refers to the environmental settings by land management.
Figure 2 A conceptual model of the relationship between urban forest fragmentation and human health. L1 – L6 refer to the hypothesized links based on multidisciplinary studies, IL refers to the indirect link between landscape and human health, and DL refers to the direct link between landscape and human health.

The relationships between the factors are indicated by directional or bi-directional arrows. They can have positive or negative effects on each domain. L1 – L6 refer to the hypothesized links based on multidisciplinary studies, IL refers to the indirect link between landscape and human health.
landscape and human health, and DL refers to the direct link between landscape and human health. L1 indicated that landscape physical feature, which is related to the ecological and aesthetic values of urban forests, can have effects on the appearance of urban forests (i.e., landscape quality). L2 indicated that human preference on living or recreation can have effects on the motivations of recreation activity and vice versa (Kyle et al., 2004; Virden and Schreyer, 1988), and therefore the engagement of recreational activities or the contact with the nature influence on health outcomes (Abraham et al., 2010; Bratman et al., 2012; Kaplan, 1995b). L3 indicated that ecosystem service can have effects on social-economic development as ecosystem services can be regarded as goods (Bateman et al., 2011). Socio-economic development can influence on ecosystem services as well.

L4 indicated that Socio-economic development can determine the policy directions of the settings of built-environment (Jongman et al., 2004a; Liu et al., 2008; Turner and Daily, 2008). L5 indicated that landscape factors influence on ecosystem health or on economic development and policy by the effects of the characteristics on ecological processes and by the aesthetic values, and ecosystem or human activities provide feedbacks that may cause the changes of landscape characteristics. L6 indicated that human intentions of approaching the landscapes influence on the functions of ecosystem services and the policy of land management, and subsequently the feedbacks from moderators can change human intentions of landscape uses. IL indicated that landscape can influence on human behaviors and consequently on health outcomes through its link with moderators, and vice versa. Lastly, DL indicated that landscape factors can directly influence on how human decide to use or
approach the landscape and also influence on health outcome. Human factors can alter landscape features and quality as well.

4. Future directions and conclusions

The characteristics of urban forest fragmentation have effects on both ecosystem and human health. In this paper we identified the characteristics of urban forest fragmentation and their links with ecosystem and human health, identified the confounding factors that may influence on urban forest fragmentation and human health, and constructed an urban forest fragmentation-human health conceptual model that can guide future research. The effects of urban forest fragmentation on ecosystem health are more obvious and better recognized since forests are the primary habitats for sustaining ecosystem functions. In contrast, the effects of urban forest fragmentation on human health are not as straightforward as the effects on ecosystem since people tend to fragment forests to establish activity areas for human living. We started with the point that humans are part of the ecosystem, and humans therefore have an intrinsic need for contacting with it. However, humans act differently than other life forms in the ecosystem.

Humans play an active role on urban forest fragmentation. Based on our review and conceptualization, we suggest that, in the urban context, some level of forest fragmentation may provide more benefits to human health than one contiguous forest as a combination of forest fragments’ ecosystem services and their accessibility for human interactions. Further research is much needed for empirical examinations of this hypothesized non-linear relationship between the characteristics of urban forest fragmentation and human health and
the identification of threshold levels of fragmentation from the ecosystem health and human wealth perspectives. For example, the characteristics of urban forest fragmentation can be quantified by its spatial patterns by landscape metrics or spatial statistics, and their relationships with human health can be examined by regression. Results of this further analysis will have significant implications for urban development, planning and conservation policies.

Our literature review identified the major characteristics of urban forest fragmentation and illustrated the effects of same characteristics on ecosystem health and human health. Comparing the effects on ecosystem health and human health using the same factors provides parallel concepts for constructing relationships among urban forest fragmentation, ecosystem health and human health. However, the effects of those factors on ecosystem health and human health were also explored in different ways. Many of the ecological studies have discussed about them through physical measurements of landscape changes. In contrast, past studies rarely measured the effects on human health through physical measurements of landscape changes. Thus, physical measurements of landscape changes, and how these changes effect human perceptions and use of the landscapes can be created and examined by landscape simulations and visualizations to measure the potential effects of the characteristics of urban forest fragmentation on human health in the future.

We also described the confounding factors that may be important in shaping the relationships between urban forest fragmentation and human health. Our conceptual model identifies the factors having the most direct relationships with human health. Controlling the
model by the confounding factors helps to clarify the relationships between human health and urban forest fragmentation.

In addition to exploring the relationships between urban forest fragmentation and human health, studies at different spatial scales are needed. Most of the current studies on human health in the fields of recreation or preventive health are at the local scale. However, many studies consider ecosystem services as an important factor for human health. Thus large scale studies on human health should be conducted to find the relationships with human health at this same larger scale that most ecological studies are conducted at. The same factors may have different effects at different scales. Future research should identify the most crucial factors of the relationships between urban forest fragmentation and human health for different scales to provide hierarchical management plans for future land management.

Due to natural and social systems being inseparable, more research on the integration of ecology and social science, such as coupled human and natural systems (CHANS) is needed. Besides, landscape fragmentation is increasingly being considered as one of important factors in the CHANS study (Lindenmayer et al., 2008; Monticino et al., 2007; Zurlini et al., 2006). The issues of landscape fragmentation will need to be investigated more in future studies.
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CHAPTER 3: Examining the Association between Urban Forest Fragmentation and Human Health at National and Regional Scales

Abstract

Green landcovers, such as forests and shrublands, are crucial in supporting ecological and human health in urban landscapes. It is conceivable that the location, size, edge and other characteristics of green landcover may be associated with human health directly through opportunities for recreation and physical activity participation, and indirectly through ecosystem services. The relationship between landscape characteristics and ecosystem health has been studied extensively, but limited research has examined the linkage between landscape characteristics and human health, especially at scales beyond neighborhoods and communities. This study aims to understand the association between urban green landcovers and human health at national and regional scales across the United States. We integrated public accessible datasets to conduct the analyses, including landcover data from US Geological Survey’s National Land Cover Dataset (NLCD) and Center for Disease Control’s Behavioral Risk Factor Surveillance System Dataset (BRFSS). Landscape variables generated from landcover data included patch area, percent landcover, patch density, edge density, edge contrast index, Euclidean distance, and patch cohesion index of the green landcovers, and human health variables included physical activity, body mass index (BMI), asthma, and mental health. Furthermore, socio-economic status (U.S. Census Bureau) was included as a confounding variable. Spearman’s rank correlation and stepwise regression models were applied to quantify the bivariate and multivariate relationships between landscape variables and human health variables, respectively. Results show that physical
activity has strong and positive relationships with green landcovers at both nationwide and regional scales, especially the edge density and patch density. The regression model of physical activity also shows stronger relationships with the landscape metrics, with stronger relationships revealed in the regional analysis. The edge density of green landcovers exhibits the relative strong influence in the human health models. The large scale studies of landscape-human health can help land use planners and policy makers understand the potential impacts of their decisions on urban forest fragments and associated human health outcomes.

**Keywords:** green landcovers, forest fragmentation, urban areas, landscape metrics, human health
1. Introduction

Urbanization has increased rapidly during the past four decades (United Nations, 2012) and continues to exert tremendous pressure on natural resources by fragmenting landscapes and altering environmental quality (Alberti, 2005; Biamonte et al., 2011; Carrete et al., 2009). Urbanization is a major cause of forest fragmentation, a process of breaking up intact landscapes into smaller patches that result in increased landscape heterogeneity and differential ecological responses to internal and external threats (Fahrig et al., 2011; Lovett, 2005).

Urban forests play a crucial role in determining the sustainability of urban ecosystems and providing important ecological services with social, environmental, economic, psychological, and recreational benefits (Bolund and Hunhammar, 1999; Dwivedi et al., 2009; McPherson et al., 1997; McPherson and Rowntree, 1993). Studies have shown that urban forest fragmentation has negative consequences for ecosystem functions and health, including species endangerment, native species elimination, and biodiversity loss (Alvey, 2006; McKinney, 2002; Miyashita et al., 1998). In addition, urban forests can have impacts on human health not only through ecosystem services, such as adjusting ambient temperature and removing air pollutants, but also through such landscape functions such as providing scenic landscapes for work, leisure and homes (Arnberger, 2006; Brander and Koetse, 2011; Konijnendijk, 2005; Roux et al., 2007; Tzoulas et al., 2007).

As urban forest fragmentation is primarily caused by urban development for human needs, the meaning and effects of urban forest fragmentation for human society may differ from those for ecosystem. For example, establishments of transportation infrastructure reduce
habitat connectivity but can increase human landscape connectivity. In addition, habitat homogeneity is important for ecological processes since wildlife tends to move between the same habitat types, whereas humans prefer to live in environments with heterogeneous settings for living convenience (Di Giulio et al., 2009). Urban forest fragmentation is characterized by reduction of patch size, increase of patch density, decrease of patch connectivity, increase of the distance between the same type patches, and increase of edge length in a patch. These changes in forest characteristics can influence both ecosystem health and human health, though the directions of influence may differ (Table 1). For example, edge effects are a key factor of ecological processes in terms of species’ movement and biodiversity (Alberti, 2005) and also a key factor for the settings of recreational areas (Ruddell and Hammit, 1987).
Table 1 Factors influencing on ecosystem health and human health.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Ecosystem health</th>
<th>Human health</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>Size is positively correlated to species richness (MacArthur and Wilson, 1967).</td>
<td>Small parks in urban areas increases the opportunities for people using them (Forsyth and Musacchio, 2005).</td>
</tr>
<tr>
<td>Density</td>
<td>Not directly linked to the ecological processes, but the decreases of patch size usually accompany with the increases of patch density.</td>
<td>Availability of parks influences use frequency of parks (Cohen et al., 2007).</td>
</tr>
<tr>
<td>Connectivity</td>
<td>Habitat connectivity is important for species’ movement (Fahrig, 2003).</td>
<td>Accessibility to parks is a crucial factor for people engaging physical activity (Brownson et al., 2009; Cohen et al., 2007).</td>
</tr>
<tr>
<td>Distance</td>
<td>Further distance between same habitat types may compensate for population decline (Bender et al., 2003).</td>
<td>Parks with closer distance provide have higher use frequency (Arnberger, 2006; Kaczynski et al., 2008).</td>
</tr>
<tr>
<td>Edge</td>
<td>Edge effect is a key factor influencing ecological processes (Alberti, 2005).</td>
<td>People prefer to stay at edge of an area while doing recreation activity (Ruddell and Hammit, 1987).</td>
</tr>
</tbody>
</table>

Physical inactivity in built environments is one of the major issues in the world (Brownson et al., 2009). Natural features such as forests and grassland in urban areas are important for people’s engagement in physical or recreational activities (Seaman et al., 2010). Availability of green landcovers such as forests and greenspaces influences the opportunities for people connecting to these natural areas (Cohen et al., 2007); therefore, density of green landcovers, which implies the chance of people engaging in activities associated with health, is important. Accessibility between built environments and natural features influences the opportunities for people engaging in physical activities (Brownson et al., 2009; Cohen et al., 2007); therefore, the edges connecting green landcovers and built environments can be one of the determinants for people to participate in recreational
activities. Distance to parks influences the frequency of park use (Arnberger, 2006; Kaczynski et al., 2008); therefore, edges between human activity areas and natural features can be regarded as the indicator of the natural elements close to human activity areas. Besides, edges play an important role in the settings of recreational environments. Edges fulfill the human psychological needs of the feelings of safety, hiding, and visual access during recreational activities (Edwards et al., 2012; Kaplan, 1998; Mumcu et al., 2010; Ruddell and Hammitt, 1987).

There is a need for a better understanding of urban forest fragmentation effects on human health. Much of past research that explored the relationship between environments and human health was conducted at the community or local scale, while larger scales are more commonly adopted in ecological studies. Exploring the relationship between forest fragmentation and human health at scales beyond the local level may provide insights on the social significance of urban forest fragmentation. Increasing public availability of large-scale datasets from the U.S. Census Bureau (socio-economic), the Center for Disease Control and Prevention (CDC) (public health), and U.S. Geological Survey (USGS) (landcovers) provide opportunities to perform analyses at a larger scale to advance our understanding of the forest-health relationship. Utilizing the existing datasets is important for revealing their values in advancing research in the coupled ecological and social systems. In this study we aimed to explore the relationships between human health and landscape with a focus on urban forest fragmentation using large-scale datasets.
2. Study area

The urbanized areas in the study were the metropolitan statistical area (MSA) with a population over one million based on the definition of U.S. Census Bureau (U.S. Census Bureau, 1994). We analyzed the relationships at the unit of county. Based on the population of year 2008 from the U.S. Census, fifty-two MSAs met the criterion. Since one MSA can consist of more than one county, these MSAs consist of 416 counties. However, considering the availability of human health data, only 135 counties were included for the nationwide analysis in this study (Figure 1).

In addition, we considered the regional differences across the conterminous United States. Particularly, landcover classification involves satellite scenes, so partitioning into different regions can help capture the differences of landscape biogeographic features. In order to be consistent with the landcover data, the regions of National Land Cover Dataset (NLCD) 2001 Mapping Zones was used to partition the selected MSAs into five regions: Arid West, Bottomland East, Mountain West, Plains Midwest, and Upland East. The NLCD 2001 Mapping Zones were determined through considering not only landscape biophysical features but also spectral characteristics of satellite imagery. The landforms, soils, vegetation, spectral reflectance, and image footprints are relatively homogeneous in each zone (Homer et al., 2004). However, thirteen MSAs among the 52 MSAs are located between two regions. We only used the MSAs which are completely located in a region. As a result, the Arid West region contains 10 counties, the Bottomland East region contains 30 counties, the Mountain West region contains 7 counties, and the Upland East region contains 32 counties for the regional analysis.
3. Materials and methods

3.1 Human health data

The human health data of selected counties were collected from a project using Behavioral Risk Factor Surveillance system (BRFSS) data conducted by the CDC. The BRFSS is a state-based system of health survey that collects data monthly on health risk behaviors, preventive health practices, and health care access, primarily related to chronic disease, and injury of the population over 18 years old in all 50 states. Derived from the BRFSS, Selected Metropolitan/Micropolitan Area Risk Trends (SMART) produces local area
estimates annually for filling the critical needs locally. The SMART project analyzes the data of selected metropolitan areas, micropolitan statistical areas, and metropolitan divisions (MMSAs) with 500 or more respondents. The MMSAs were chosen as the criteria for this project since they can represent geographic areas that are used by the U.S. Census Bureau and other federal, state, and local governments. The estimates were calculated at MSA and county level; however, not all the counties included in MMSAs can be estimated due to the small sample size.

We considered that health status may take one to two years to respond to the environment and therefore chose the year of 2008 for the analysis. The health variables chosen in this study were physical activity, Body Mass Index, asthma, and mental health. The health variables were surveyed through a series of questions related the health variables, and many of them are binary answers (i.e., yes or no). For example, the AST was surveyed through asking if the participant has ever told by health professionals that they have asthma, and the PA was surveyed through asking if the participant engaged in any physical activities other than regular work in the past month. The BMI is a calculated variable derived from body weight and height, and the values were categorized into three classes: obese, overweight, and neither obese nor overweight. The MH was surveyed through asking the participant that how many days in the past month the mental health status is not good, and the answer was number of the days.

All the health variables were converted into percentage in the SMART report. We only chose the percentage of the answers with positive outcomes as human health variables. For example, we used percentage of respondents who answered yes for representing physical
activity (PA), percentage of neither obese nor overweight for representing good BMI (BMI), percentage of respondents who answered no for representing no asthma (No_AST), and percentage of days that people didn’t report as mental illness in a month for representing good mental health (MH).

3.2 Landcover data

The landcover data used in this study were National Land Cover Dataset (NLCD) conducted by a cooperative project by Multi-resolution Land Characteristics (MRLC) Consortium. The MRLC is a partnership of several federal agencies (Homer et al., 2012). The current available NLCD datasets are the years of 1992, 2001, and 2006. The NLCD 2006 was developed to identify land patterns for the conterminous United States at medium spatial resolution of 30-m using Landsat Thematic Mapper I data. The NLCD 2006, which is a two-level classification with a total of sixteen landcover classes, applied consistently across the United States. The accuracies of Level II classification (16 classes) and Level I classification (8 classes) are 78% and 84%, respectively (Wickham et al., 2013). Based on the consideration of the accuracy improvement of NLCD classes and the data size for applying analyses to the entire United States, Level I classification was selected. The types included in Level I classification are forest, shrubland, herbaceous, planted/cultivated, barren, developed area, water, and wetland. The landcover for each county was extracted by GIS batch processing (see Appendix A). The primary interests of the landcovers in this study are green landcovers, which include forest, shrubland, and herbaceous type.
3.3 Landscape metrics

The selected landscape metrics were generated in FRAGSTATS, a spatial pattern analysis program designed to compute a variety of landscape metrics for categorical maps (McGarigal et al., 2012). In FRAGSTATS, landscape metrics are categorized into six domains, and the landscape metrics selected in this study were generated at class level from the domains of area-edge, contrast, and aggregation. The landscape metrics in area-edge domain primarily measure for the composition and configuration of a landscape. The selected metrics from area-edge domain were patch area (AREA), percentage of landscape (PLAND), and edge density (ED). The AREA of the selected landcover types reflects the size effects of urban forests, as the patch size of green landcovers should be relatively small in urban areas. The PLAND reflects the abundance of green landcovers in an area, as the percentage of green landcovers in a county is fewer in a highly developed county. The ED reflects the accessibility of green landcovers, as edges are the places that connect two landcover types and where people can enter the green landcovers nearby their activity areas.

The landscape metrics in contrast domain primarily measure for the relative difference among patch types. The selected metric from contrast domain was edge contrast index (ECON). The ECON reflects the possibility of people moving from developed areas (e.g. residential area or business area) to green landcovers, as edge contrast index measures the degree of the contrasts between a patch and its neighborhood. The higher values of edge contrast index mean that there is higher contrasts between two target landcover types (McGarigal et al., 2012). The contrast can be set up from 0 (i.e., no contrast) to 1 (i.e., maximum contrast). We set the edges between the types of developed area and green
landcovers as the maximum contrast and the edges between any other two types of landcovers as the minimum contrast. As a result, we can only get the percentage of edge length between developed areas and green landcovers.

The landscape metrics in aggregation domain primarily measure for the degree of aggregation or clumping of patch types. The selected metrics from the aggregation domain were patch density (PD), Euclidean distance (ENN), and patch cohesion index (COHESION). The PD reflects the chances for people to contact with green landcovers, as urban forest fragmentation breaks up patches into many small patches and results in more patches. The ENN reflects the distance between two patches of the same landcover type. In urbanized areas, the green landcover patches are dispersed by other landcover types, and therefore it results in longer distances between two patches with the same type. The COHESION reflects the physical connectedness of the same landcover type, as the physical connectedness indicates the landcover type is more aggregated or clumped in an area. These seven selected landscape metrics were used to generate metrics for each type of green landcovers (i.e., forest, shrubland, and herbaceous), and therefore twenty-one landscape metrics in total were used in the analysis.

3.4 Confounding factors

The confounding factors considered in this study were population density, housing density, median household income, and race (i.e., we used percentage of Black\African American to represent race effect) through the American FactFinder at the U.S. Census Bureau website. The American FactFinder is an interactive inquiry that provides statistical
data from three main sources: the Economic Census, the American Community Survey, and the 2010 Census. We collected total population, total housing units, median household income, and percentage of Black/African American with a geographic type of county. The population and housing density were calculated using the total population and housing units divided by the total land area of the county, respectively. The unit of the density is per square kilometers to be consistent with the unit of landcover data (i.e. meter).

3.5 Analytical procedures

We explored the relationships by Spearman’s rho correlations and regression models. The bivariate relationship between each human health variable (i.e., 4 human health variables) and each landscape variable (i.e., 21 landscape variables) was tested using non-parametric Spearman’s rho correlation. Similar to the Pearson correlation, Spearman’s rho correlation coefficients range from -1 to 1.

Regression models were used to test the multivariate relationship between each human health variable (i.e., dependent variable) and all landscape variables (i.e., independent variables). We firstly used stepwise regression with bidirectional elimination using Akaike Information Criterion (AIC) as the criterion. Afterwards, hierarchical regression was used to test the best-fit models with controls for confounding factors. Hierarchical models are appropriate for research with more than one level (e.g., landcover and socioeconomic factors in this study) and allow us to estimate the associations between given independent variables (i.e., human health variables) and the outcomes while holding all of the other variables constant.
4. Results

4.1 Landcovers

The landcover was classified into eight categories: forest, shrubland, herbaceous, planted/cultivated, barren, developed, water, and wetland (Figure 2). The green landcovers for the national scale accounted for 42.79% (i.e., 24.23% of forest, 13.72% of shrubland, and 4.84% of herbaceous type). The type of developed area, the highest percentage among all the landcover types, accounted for 30.47%.

The landcover compositions show regional differences among the five regions. The Arid West and Mountain West regions consisted of a high percentage of green landcovers, 72.32% (5.58% of forest, 61.04% of shrubland, and 5.70% of herbaceous type) and 61.96% (49.09% of forest, 9.70% of shrubland, and 3.17% of herbaceous type), respectively. The green landcovers in the Arid West and Mountain West regions are dominated by shrubland (61.04%) and forest (49.09%), respectively; the herbaceous type in both regions only takes a small proportion in green landcovers. These two regions are relatively less developed, as the percentages of developed area are both below 20%. In the Bottomland East and Upland East regions, the compositions of green landcovers are 25.09% (21.50% of forest, 2.29% of shrubland, and 1.31% of herbaceous type) and 28.92% (27.44% of forest, 0.66% of shrubland, and 0.83% of herbaceous type), respectively. In contrast, these two regions are highly developed. The percentages of developed areas are both above 30%. In the Plains Midwest region, the percentage of green landcovers accounts for 38.28% (20.99% of forest, 5.08% of shrubland, and 12.21% of herbaceous type). The herbaceous type in this region is relatively high, whereas herbaceous only accounts for less than 5% for most of the regions.
4.2 Landscape patterns

Landscape patterns were characterized by landscape metrics (Table 2). For the nationwide analysis, the mean patch area for forest type is 17.46 m$^2$ (SD=18.79), for shrubland type is 11.64 m$^2$ (SD=42.87), and for herbaceous type is 3.50 m$^2$ (SD= 5.44). The mean patch density for forest type is 1.53 per 100 ha (SD= 1.03), for shrubland type is 0.97 per 100 ha (SD= 1.06), and for herbaceous type is 0.77 per 100 ha (SD= 0.90). The mean edge density for forest type is 41.62 m/ha (SD= 25.52), for shrubland type is 13.44 m/ha (SD= 17.56), and for herbaceous type is 10.53 m/ha (SD= 15.22).

The mean edge contrast index for forest type is 44.41% (SD= 24.52), for shrubland type is 20.32% (SD= 13.08), and for herbaceous type is 25.62% (SD= 14.98). The mean
Euclidean distance for forest type is 211.62 m (SD= 466.52), for shrubland type is 657.99 m (SD= 1,366.76), and for herbaceous type is 673.50 m (SD= 1,834.48). The mean patch cohesion index for forest type is 95.91% (SD= 5.43), for shrubland type is 81.79% (SD= 8.97), and for herbaceous type is 83.96% (SD= 8.73).

For the regional analysis (Table 2), the mean patch area for forest type ranges from 10.42 m² to 63.66 m², for shrubland type ranges from 1.43 m² to 125.86 m², and for herbaceous type ranges from 1.67 m² to 4.95 m². The mean patch density for forest type ranges 0.53 per 100 ha to 1.98 per 100 ha, for shrubland type ranges from 0.50 per 100 ha to 2.08 per 100 ha, and for herbaceous type ranges from 0.40 per 100 ha to 2.01 per 100 ha. The mean edge density for forest type ranges from 11.30 m/ha to 51.66 m/ha, for shrubland type ranges from 3.95 m/ha to 38.00 m/ha, and for herbaceous type ranges from 3.86 m/ha to 35.57 m/ha.

The mean edge contrast index for forest type ranges from 9.03% to 51.19%, for shrubland type ranges from 9.43% to 30.35%, and for herbaceous type ranges from 14.73% to 27.51%. The mean Euclidean distance for forest type ranges from 109.49 m to 431.12 m, for shrubland ranges from 102.55 m to 1,904.70 m, and for herbaceous type ranges from 175.26 m to 725.06 m. The mean patch cohesion index for forest type ranges from 96.01% to 99.82%, for shrubland type ranges from 76.26% to 99.85%, and for herbaceous type ranges from 80.04% to 96.12%.
Table 2 The mean of the landscape metrics for the nationwide analysis, and the lowest and highest means of the landscape metrics for the regional analysis.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Nationwide</th>
<th>Regional</th>
<th>Region</th>
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<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
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<td>10.42</td>
<td>Arid West</td>
</tr>
<tr>
<td>Shrubland</td>
<td>11.64</td>
<td>1.43</td>
<td>Mountain West</td>
</tr>
<tr>
<td>Herbaceous</td>
<td>3.50</td>
<td>1.67</td>
<td>Bottomland East</td>
</tr>
<tr>
<td>PD</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.53</td>
<td>Arid West</td>
</tr>
<tr>
<td>Shrubland</td>
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<td>0.50</td>
<td>Plains Midwest</td>
</tr>
<tr>
<td>Herbaceous</td>
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<td>0.40</td>
<td>Upland East</td>
</tr>
<tr>
<td>ED</td>
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<tr>
<td>Forest</td>
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<td>11.30</td>
<td>Arid West</td>
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<tr>
<td>Shrubland</td>
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<td>3.95</td>
<td>Mountain West</td>
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<tr>
<td>Herbaceous</td>
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<td>3.86</td>
<td>Upland East</td>
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<td>ECON</td>
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<td>9.03</td>
<td>Arid West</td>
</tr>
<tr>
<td>Shrubland</td>
<td>20.32</td>
<td>9.43</td>
<td>Mountain West</td>
</tr>
<tr>
<td>Herbaceous</td>
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<td>14.73</td>
<td>Mountain West</td>
</tr>
<tr>
<td>ENN</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
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<td>109.49</td>
<td>Mountain West</td>
</tr>
<tr>
<td>Shrubland</td>
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<td>102.55</td>
<td>Arid West</td>
</tr>
<tr>
<td>Herbaceous</td>
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<td>175.26</td>
<td>Arid West</td>
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<tr>
<td>Herbaceous</td>
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<td>80.04</td>
<td>Bottomland East</td>
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</table>


4.3 Human health variables

For the nationwide analysis, the mean physical activity for the nationwide analysis is 77.06% (SD= 4.92), the mean BMI is 38.02% (SD= 5.42), the mean no asthma is 86.62% (SD= 2.63), and the mean good mental health is 66.77% (SD= 4.57).

For the regional analysis, the mean physical activity ranges from 73.41% in the Plains Midwest region (SD=5.13) to 76.79% in the Upland East region (SD=4.13), the mean BMI ranges from 35.27% in the Bottomland East region (SD=4.14) to 39.30% in the Mountain West region (SD=4.38), the mean no asthma ranges from 84.89% in the Mountain West region(SD=1.08) to 87.63% in the Bottomland East region (SD=2.98), and the mean good mental health ranges from 65.05% in the Upland East region (SD=5.04) to 67.30% in the Mountain West region (SD=3.61).

4.4 Confounding factors

For the nationwide analysis, the mean population density is 1,087.70 per km² (SD= 2,751.05), the mean housing density is 482.55 km² (SD=1,373.29), the mean median household income is USD$63,035.12 (SD=15,900.59), and the mean race is 15.89% (SD=14.15).

For the regional analysis, the mean population density ranges from 278.24 per km² in the Arid West region (SD=480.87) to 745.58 km² in the Upland East region (SD=858.53), the mean housing density ranges from 118.17 in the Mountain West region (SD=86.81) to 326.99 km² in the Upland East region (SD=375.98), the mean median household income ranges from USD$51,879.14 in the Mountain West region (SD=11,406.87) to
USD$62,078.43 in the Upland East region (SD=6,571.47), and the mean race ranges from 6.21% in the Arid West region (SD=3.05) to 22.30% in the Bottomland East region (SD=15.06).

4.5 Bivariate correlation

The bivariate correlations reported by Spearman’s rho correlations showed that the percentage of green landcovers are only significantly associated with the engagement of physical activity. Most of the other six landscape metrics of green landcovers are also only significantly associated with the engagement of physical activity for the nationwide analysis (Table 3). Physical activity and patch density of herbaceous type has the highest correlation coefficient, 0.350 (p < 0.01).

Table 3 Significant Spearman’s Rho correlation coefficients and p-values between human health variables and percent green landcovers, and other landscape metrics for the nationwide.

<table>
<thead>
<tr>
<th>Physical Activity</th>
<th>Rho</th>
<th>p</th>
<th>Physical Activity</th>
<th>Rho</th>
<th>p</th>
<th>Good Mental Health Rho</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Forest</td>
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<td>&lt;.01</td>
<td>Forest_AREA</td>
<td>.202</td>
<td>.02</td>
<td>Herbaceous_PD</td>
<td>.179</td>
</tr>
<tr>
<td>% Shrubland</td>
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<td>.01</td>
<td>Forest_ED</td>
<td>.253</td>
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<td>Forest_ENN</td>
<td>-.216</td>
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<tr>
<td>% Herbaceous</td>
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<td>Forest_COHESION</td>
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<td>Herbaceous_ENN</td>
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<td>&lt;.01</td>
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</table>

However, not all of the percentage of green landcovers has a significant correlation with the engagement of physical activity for the regional analysis (Table 4). Only percentage of forest and herbaceous type in the Bottomland East region, and percentage of herbaceous type in the Mountain West and the Upland East regions are significantly associated with the
engagement of physical activity. The correlation coefficients for those regions are higher than those for the nationwide analysis.

The absolute values of the significant correlations of physical activity are all above 0.40 for the regional analysis, especially for those in the Mountain West region, which are all above 0.78. The highest correlation of physical activity for the regional analysis is edge density of herbaceous type in Mountain West regions (Rho=-0.857, p=0.01). Good BMI has more correlations with the landscape metrics of shrubland and herbaceous types in the Arid West region. The absolute values of the significant correlations of good BMI are all above 0.37, especially for those in the Arid West region, which are all above 0.64. The highest correlation of the good BMI for the regional analysis is patch density of herbaceous type in the Arid West region (Rho=0.77, p<0.01).

The absolute values of the significant correlations of no asthma are all above 0.36, especially for those in the Mountain West region, which are all above 0.78. The highest correlation of no asthma is Euclidean distance of shrubland type in the Mountain West region (Rho=0.96, p<0.01). The absolute values of the significant correlations of good mental health are all above 0.41, especially for those in the Plains Midwest region, which are above 0.76. The three highest correlations of good mental health are all in the Plains Midwest region, which are patch density of herbaceous type (Rho=-0.76, p=0.05), edge density of herbaceous type (Rho=-0.76, p=0.05), and Euclidean distance of herbaceous type (Rho=0.76, p=0.05).
Table 4 Significant Spearman’s Rho correlation coefficients and p-values between human health variables and percent green landcovers, and other landscape metrics for the five regions.

<table>
<thead>
<tr>
<th>% Green Landcovers</th>
<th>Physical Activity</th>
<th>Rho</th>
<th>p</th>
<th>Good BMI</th>
<th>Rho</th>
<th>p</th>
<th>Good Mental Health</th>
<th>Rho</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BE % Forest</td>
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<td>AW % Shrubland</td>
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<td>PM % Herbaceous</td>
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<td>.05</td>
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<tr>
<td></td>
<td>BE % Herbaceous</td>
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<td>AW % Herbaceous</td>
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<td>UE % Shrubland</td>
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<td>MW % Herbaceous</td>
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<td></td>
<td>UE % Herbaceous</td>
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Other landscape metrics

<table>
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<th>Good BMI</th>
<th>Rho</th>
<th>p</th>
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No Asthma

<table>
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<th>Good Mental Health</th>
<th>Rho</th>
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</tbody>
</table>

AW = Arid West; BE = Bottomland East; MW = Mountain West; PM = Plains Midwest; UE = Upland East
4.6 Regression models

Due to the sample size, the regression models were only applied to the nationwide scale (N=135) and two regions for the regional scale: the Bottomland East (N=30) and the Upland East (N=32) regions. The results are reported using standardized coefficients (Table 5), since the independent variables (i.e., landscape metrics and confounding factors) are mostly in different units.

The regression models for the nationwide analysis showed that the model of physical activity can explain the most variance compared to other human health models (Table 5). The value of AIC for the best-fit models of physical activity, good BMI and good mental health are around 400, and the value for the best-fit model of no asthma is around 200. The best-fit model of physical activity explained 21.4% of variance and explained up to 47.2% with the controls of confounding factors. The most three significant influential metrics in the physical activity model with the considerations of confounding factors are: the percentage of forest type with a beta coefficient of -0.779 ($p<0.05$), the edge density of forest type with a beta coefficient of 0.774 ($p<0.001$), and the patch area of forest type with a beta coefficient of 0.443 ($p<0.05$). The best-fit model of good BMI explained 20.6% of variance and explained up to 38.6% of variance with the controls of confounding factors. The most three significant influential metrics in the good BMI model with the considerations of confounding factors are: the edge density of shrubland type with a beta coefficient of 1.080 ($p<0.001$), the patch density of shrubland type with a beta coefficient of -0.76 ($p<0.001$), and the percentage of shrubland type with a beta coefficient of -0.616 ($p<0.05$).
The best-fit model of no asthma explained 11.6% of variance and explained up to 16% of variance with the controls of confounding factors. The most three significant influential metrics in the good mental health model with the considerations of confounding factors are: the percentage of herbaceous type with a beta coefficient of -0.505 \( (p<0.01) \), the edge density of herbaceous type with a beta coefficient of 0.472 \( (p<0.01) \), and the Euclidean distance of herbaceous type with a beta coefficient of 0.356 \( (p<0.001) \). The best-fit model of good mental health explained 11.5% of variance and explained up to 24.2% of variance with the controls of confounding factors. The most three significant influential metrics in the good mental health model are: the Euclidean distance of shrubland type with a beta coefficient of -0.277 \( (p<0.01) \), the patch density of shrubland type with a beta coefficient of -0.255 \( (p<0.05) \), and the patch density of forest type with a beta coefficient of 0.193 \( (p<0.05) \).
Table 5 The best-fit models of physical activity, good BMI, no asthma, and good mental health, and the full models (i.e., best-fit models with confounding factors) for nationwide analysis. The coefficients are reported using standardized coefficients.

<table>
<thead>
<tr>
<th>Nationwide (N=135)</th>
<th>Physical Activity (AIC = 389.49)</th>
<th>Good BMI (AIC = 412.39)</th>
<th>No Asthma (AIC = 243.65)</th>
<th>Good Mental Health (AIC = 377.84)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjusted R-Squared</td>
<td>Best-fit model</td>
<td>Full model</td>
<td>Best-fit model</td>
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<tr>
<td></td>
<td></td>
<td>.214</td>
<td>.472</td>
<td>.206</td>
</tr>
<tr>
<td>Forest AREA</td>
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<td>.443*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest PLAND</td>
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<td>-.779*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest PD</td>
<td>.828**</td>
<td>.774***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest ED</td>
<td>.337**</td>
<td>.291**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest ECON</td>
<td>.366</td>
<td>.439</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest COHESION</td>
<td>.398*</td>
<td>.382*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd AREA</td>
<td>-.319</td>
<td>-.367*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd PLAND</td>
<td>-.557</td>
<td>-.616*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd PD</td>
<td>-.319</td>
<td>-.367*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd ED</td>
<td>.398*</td>
<td>.382*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd ECON</td>
<td>-.120</td>
<td>-.049</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubalnd COHESION</td>
<td>.415***</td>
<td>.288**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herbaceous AREA</td>
<td>.366</td>
<td>.439</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herbaceous PLAND</td>
<td>-.319</td>
<td>-.367*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herbaceous PD</td>
<td>.398*</td>
<td>.382*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herbaceous ED</td>
<td>-.120</td>
<td>-.049</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herbaceous ECON</td>
<td>.366</td>
<td>.439</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density</td>
<td>-3.231***</td>
<td>-3.252**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing Density</td>
<td>3.362***</td>
<td>2.346**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Household Income</td>
<td>.479***</td>
<td>.391***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>.18*5</td>
<td>.109</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance level: ***: <0.001; **: <0.01; *: <0.05
In the Bottomland East region, the model of physical activity explained the most variance compared to other human health models (Table 6). The values of AIC for all the human health models are much smaller than the values for nationwide analysis. The AIC value of physical activity model is 58.62, the value of good mental health model is 79.86, and the values of AIC of good BMI and no asthma models are around 40.

The best-fit model of physical activity explained 75.5% of variance and explained up to 77.9% of variance with the controls of confounding factors. The most three significant influential metrics in the physical activity model are: the Euclidean distance of herbaceous type with a beta coefficient of 14.82 ($p<0.05$), the Euclidean distance of forest type with a beta coefficient of 1.751 ($p<0.05$), and the edge contrast index of forest type with a beta coefficient of -1.498 ($p<0.01$). The best-fit model of good BMI explained 82.3% of variance and explained lower to 75.8% of variance with the controls of confounding factors. The most three significant influential metrics in the good BMI model are: the patch area of herbaceous type with a beta coefficient of 1.21 ($p<0.05$), the Euclidean distance of herbaceous type with a beta coefficient of -1.196 ($p<0.05$), and the patch cohesion index of herbaceous type with a beta coefficient of -0.586 ($p<0.05$).

The best-fit of no asthma explained 64.4% of variance and explained up to 65.8% of variance with the controls of confounding factors. The most three significant influential metrics in the no asthma model are: the edge contrast index of shrubland type with a beta coefficient of -1.707 ($p<0.01$), the edge contrast index of herbaceous type with a beta coefficient of 1.540 ($p<0.05$), and the patch area of shrubland type with a beta coefficient of 1.219 ($p<0.001$). The best-fit of good mental health explained 41.5% of variance and
explained up to 58.5% of variance with the controls of confounding factors. The most three significant influential metrics in the good mental health model are: the patch density of herbaceous type with a beta coefficient of 3.476 ($p<0.05$), the edge density of forest type with a beta coefficient of 3.386 ($p<0.05$), and the patch density of forest type with a beta coefficient of -2.79 ($p<0.01$).
Table 6 The best-fit models of physical activity, good BMI, no asthma, and good mental health, and the full models (i.e., best-fit models with confounding factors) for the Bottomland East region. The coefficients are reported using standardized coefficients.

<table>
<thead>
<tr>
<th>Bottomland East (N=30)</th>
<th>Physical Activity (AIC = 58.62)</th>
<th>Good BMI (AIC = 40.71)</th>
<th>No Asthma (AIC = 41.95)</th>
<th>Good Mental Health (AIC = 79.86)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted R-Squared</td>
<td>Best-fit</td>
<td>Full model</td>
<td>Best-fit</td>
<td>Full model</td>
</tr>
<tr>
<td>Forest_AREA</td>
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<td>-1.120</td>
<td>-1.019*</td>
<td>-.567</td>
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<tr>
<td>Forest_PLAND</td>
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<td>.755</td>
<td>.704</td>
<td>.567</td>
</tr>
<tr>
<td>Forest_PD</td>
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<td>-1.402*</td>
<td>-.810**</td>
<td>-.706</td>
</tr>
<tr>
<td>Forest_ED</td>
<td>2.372*</td>
<td>-.122</td>
<td>.494**</td>
<td>.346</td>
</tr>
<tr>
<td>Forest_ECON</td>
<td>-.487</td>
<td>-1.498**</td>
<td>-.497**</td>
<td>-.561</td>
</tr>
<tr>
<td>Forest_ENN</td>
<td>-.804*</td>
<td>1.751*</td>
<td>.626*</td>
<td>.496</td>
</tr>
<tr>
<td>Shrubalnd_AREA</td>
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<td>-2.604</td>
<td>1.070</td>
<td>1.219***</td>
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<tr>
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<td>-4.016</td>
</tr>
<tr>
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<td>.437</td>
<td>-1.612***</td>
<td>-1.707**</td>
</tr>
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<td>.982*</td>
<td>.622</td>
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</tr>
<tr>
<td>Herbaceous_PLAND</td>
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<td>-.072</td>
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<td>1.210*</td>
</tr>
<tr>
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<td>.580</td>
<td>-.1786*</td>
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<td>.788</td>
<td>1.711*</td>
<td>1.725</td>
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<tr>
<td>Herbaceous_ECON</td>
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<td>-.691</td>
<td>1.136*</td>
<td>1.540*</td>
</tr>
<tr>
<td>Herbaceous_ENN</td>
<td>-1.163**</td>
<td>14.820*</td>
<td>-1.096***</td>
<td>-1.196*</td>
</tr>
<tr>
<td>Herbaceous_COHES</td>
<td>-.561**</td>
<td>-.586*</td>
<td>-.295*</td>
<td>-.260</td>
</tr>
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<td>Population Density</td>
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<td>-.066</td>
<td>.158</td>
<td>1.201</td>
</tr>
<tr>
<td>Housing Density</td>
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<td>.213</td>
<td>-.304</td>
<td>-1.275</td>
</tr>
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<td>Median Household</td>
<td>1.005*</td>
<td>.120</td>
<td>.500</td>
<td>.531</td>
</tr>
<tr>
<td>Race</td>
<td>.447</td>
<td>.078</td>
<td>.239</td>
<td>.931*</td>
</tr>
</tbody>
</table>

Significance level: ***: <0.001; **: <0.01; *: <0.05
In the Upland East region, the model of physical activity also explained the most variance compared to other human health models (Table 7). The best-fit model of physical activity explained 65.2% of variance and explained up to 73.1% of variance with the controls of confounding factors. The most three significant influential metrics in the physical activity model are: the edge density of shrubland type with a beta coefficient of 10.279 \( (p<0.05) \), the percentage of shrubland type with a beta coefficient of -6.869 \( (p<0.05) \), and the percentage of forest type with a beta coefficient of -1.135 \( (p<0.05) \). The best-fit model of good BMI explained 46.5% of variance and explained lower to 33.7% of variance with the controls of confounding factors. The most three significant influential metrics in the good BMI model are: the patch density of shrubland type with a beta coefficient of 9.393 \( (p<0.05) \), the edge density of shrubland type with a beta coefficient of -8.221 \( (p<0.05) \), and the percentage of forest type with a beta coefficient of -5.554 \( (p<0.05) \).

The best-fit model of no asthma explained 13.3% of variance and explained lower to -0.01% of variance with the controls of confounding factors. The most three significant influential metrics in the no asthma model are: the edge density of shrubland type with a beta coefficient of -33.525 \( (p<0.05) \), the patch density of shrubland type with a beta coefficient of 17.404 \( (p<0.05) \), and the percentage of shrubland type with a beta coefficient of 16.594 \( (p<0.05) \). The best-fit model of good mental health explained 61.9% of variance and explained up to 72.7% of variance with the controls of confounding factors. The most three significant influential metrics in the good mental health model are: the patch area of herbaceous type with a beta coefficient of -1.489 \( (p<0.01) \), the percentage of herbaceous type
with a beta coefficient of 1.371 ($p<0.05$), and the patch area of forest type with a beta
coefficient of -0.58 ($p<0.05$).
Table 7 The best-fit models of physical activity, good BMI, no asthma, and good mental health, and the full models (i.e., best-fit models with confounding factors) for the Upland East region. The coefficients are reported using standardized coefficients.

<table>
<thead>
<tr>
<th>Upland (N=32)</th>
<th>Physical Activity (AIC = 64.68)</th>
<th>Good BMI (AIC = 87.92)</th>
<th>No Asthma (AIC = 43.43)</th>
<th>Good Mental Health (AIC = 77.78)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjusted R-Squared</td>
<td>Best-fit</td>
<td>Full model</td>
<td>Best-fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>.652</td>
<td>.731</td>
<td>.465</td>
</tr>
<tr>
<td>AREA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLAND</td>
<td>-1.736***</td>
<td>-1.135*</td>
<td>-5.280**</td>
<td>-5.554*</td>
</tr>
<tr>
<td>PD</td>
<td></td>
<td>2.175**</td>
<td>2.122**</td>
<td>1.444</td>
</tr>
<tr>
<td>ED</td>
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<td>1.520</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECON</td>
<td>-.367</td>
<td>-.147</td>
<td>.504*</td>
<td>.651</td>
</tr>
<tr>
<td>ENN</td>
<td>.802*</td>
<td>.701*</td>
<td>.498</td>
<td>.693</td>
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<td></td>
</tr>
<tr>
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<td>.656</td>
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<td>.508</td>
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<td>.547</td>
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<td>.039</td>
<td>-.189</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td>-.060</td>
<td>-.235</td>
<td>-.431</td>
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</table>

Significance level: ***: <0.001; **: <0.01; *: <0.05
5. Discussion

Urban green landcovers are characterized by fragmented landscape such as smaller size of patch area, and higher patch and edge density (Di Giulio et al., 2009; Fahrig, 2003; Peyras et al., 2013). Despite of the fragmentation characteristics, studies have shown that green landcovers in urban areas have a multitude of positive effects on human health and well-beings (Abraham et al., 2010; Roux et al., 2007; Tzoulas et al., 2007; Wickham et al., 2010). Alternatively, fragmentation of urban forests and natural ecosystems has been shown to have negative impacts on ecosystem structure and function (Bender et al., 2003; Collinge, 2009; Fahrig, 2003; Rapport, 1995). Our results show that there is a positive association between vegetation cover and human health variables at multiple scales; however, a fragmented natural landscape in urban areas may be more beneficial to human health and well-beings because it provides more access and opportunities for people to contact with the nature. Other research also supports the results that patch density is positively associated with human health variables at the national scale and most of the regions based on the bivariate relationships as the availability of green landcovers influences the frequency of park use (Cohen et al., 2007)

Moreover, edge density is positively associated with human health variables (i.e., physical activity, good BMI, and good mental health) as edges play an important role on environmental settings of a recreational area and fulfilling the psychological needs (Edwards et al., 2012; Kaplan, 1998; Mumcu et al., 2010; Ruddell and Hammitt, 1987); patch size is negatively associated with human health variables (i.e., physical activity, good BMI, and good mental health) in the east region as improving the connections between natural areas
and residential areas (Forsyth and Mussacchio, 2005); and connectivity between herbaceous and human activity areas are positively associated with human health variables (i.e., good BMI, no asthma, and good mental health) in most of the regions as distance to recreation areas (i.e. parks, forests, greenspaces, and openspaces) is an influential factor for people’s use frequency of recreation areas (Arnberger, 2006; Giles-Corti et al., 2005; Schipperijn et al., 2010).

In terms of the multivariate relationships, research also supports our results that patch density and edge density were proved as one of the important factors for human health (Cohen et al., 2007; Mumcu et al., 2010; Ruddell and Hammitt, 1987). These two metrics were selected into and play as one of the most positive influential factors in most of the human health models for the nationwide and regional scales. Edge density is mostly selected into the best-fit models of physical activity and good BMI in the nation, and most of the human health models in the Bottomland East region. In the Upland East region, only the edge density of forest and shrubland types has positive effects on physical activity; and the edge density of shrubland and herbaceous types has negative effects on good BMI and no asthma.

In addition, patch density has positive effects on human health models for the nationwide and regional scales as well, but the effects are more restricted to the types of green landcovers. For example, only patch density of forest type has positive effects on human health models (i.e., no asthma and good mental health) for the nationwide scale; only patch density of herbaceous type has positive effects on human health models for the Bottomland East region; but patch density of all the types of green landcovers has positive
effects on human health models (i.e., physical activity, good BMI, and no asthma) for the Upland East region.

However, these fragmented features of green landcovers have different impacts on ecosystem health and human health, managing urban landscapes for sustaining both ecosystem health and human health may have conflicts. As urban areas consist of complex dynamic interactions among socioeconomic and biophysical components (Alberti et al., 2003; Childers et al., 2014), challenges we may meet to manage for both ecosystem and human approaches include (i) how to understand and quantify the landscape services at both approaches, (ii) how to communicate ecosystem and human society by landscape, and (iii) how to determine the fragmentation level to benefit both ecosystem and human society (de Groot et al., 2010). For example, edge effect is important for ecological processes (Alberti, 2005) and as well as for human needs in terms of psychological and recreational aspects (Edwards et al., 2012; Mumcu et al., 2010; Ruddell and Hammitt, 1987). Edge density influences on the dynamics of native habitats (Ewers and Didham, 2006) and may result in the loss of the native species by introducing predators or invasive species (Rand et al., 2006). However, our results showed that edge density is highly associated with good human health outcomes. To conquer with the issues, the integration of social and natural science is needed for balancing the needs of ecosystem and human society (Liu and Taylor, 2002). Instead of considering the ecology “in” the cities, considering ecology “of” the cities is indeed to recognize the complexity of urban systems to approach both ecosystem and human needs from the landscapes (Cadenasso et al., 2006).
In addition, scales may matter in the relationships of landscape with ecosystem health and human health as well. Landscape-ecosystem studies mostly analyze data at large spatial scales in order to understand structure and function (O'Neill et al., 1999). However, many of landscape-human health studies were implemented in community or park levels (Floyd et al., 2008; Kaczynski et al., 2008; Sugiyama et al., 2008). As landscape structure interpreted from remote sensing data can be varied a lot by different scales and resolutions, and the effects may cause different relationships between landscape patterns and ecological process (Corry, 2005; Lawler and Edwards, 2002; O'Neill et al., 1996; Wu, 2004). This study tested the landscape-human health relationships at large spatial scale, county. As landscape patterns can vary in different regions (Wickham and Norton, 1994), the landscape-human health relationships can have regional differences (Bowden et al., 2011). Our results also showed that the landscape-human health relationships are stronger for the regional scale than the nationwide scale in terms of both bivariate and multivariate relationships.

The landscape-human health relationships can be altered after considering socioeconomic status (SES). The SES is one of the major considerations in many landscape-ecosystem health studies (Collins et al., 2010; Grimm et al., 2008a; McHale et al., 2013; Pickett et al., 2011). Research also supports our results that the landscape-human health relationships can be changed after considering the confounding factors (i.e., population density, housing density, median household income, and race in this study) (Hartig et al., 2014; Redman et al., 2004). The strength of most of the variables became weaker when considering confounding factors into model. It indicates that these factors can have effects on
both urban fragmented landscape and human health (Black and Macinko, 2008; Mitchell and Popham, 2008; Sato and Yamamoto, 2005).

It is important to note that our analyses were correlational in nature. Our results reveal statistical association, not causality. We cannot determine, for instance, if certain characteristics of green landcovers cause improved human health, or if healthier people tend to move to places with those same green landcover characteristics. The reasons for choosing a neighborhood (neighborhood selection factors) or neighbors that are preferred (preferences) influence on neighborhood selection and behavior (Frank et al., 2007). This issue, known as self-selection, makes it difficult to evaluate the causations among the landscape, behavior, and associated health outcomes in this study. For example, if fragmented urban green landcovers create more accessibility, the accessible environments may result in higher levels of the engagement of physical activity and in lower obesity prevalence for those people who prefer the accessibility. Both self-selection and environmental settings can impact on the landscape-human health relationships (Frank et al., 2007; Handy et al., 2005). Moreover, the issue of self-selection cannot exclusively account for the relationship between the availability of park and physical activity (Kaczynski and Mowen, 2011). The results of this study derive from cross-sectional data and measures and were not be able to the causations of landscape and human health outcomes (Hartig et al., 2014). The correlations analysis is commonly used in the landscape-human health relationships and can provide understandings of the potential relationships. Further research can take the findings of correlational analysis to examine the causations with temporal data.
6. Implications and Conclusions

Green landcovers in urban areas benefit human health and well-beings through providing a range of ecosystem services (James et al., 2009; Tzoulas et al., 2007). Urban green landcovers provide green infrastructure essential for parks, greenspaces, openspaces, and greenways that support recreational and physical activity (Wickham et al., 2010). The importance of urban green landcovers to the contributions of human health through the use of parks and greenspaces is increasingly recognized. Many studies employed associations between built environments and human health at park or neighborhood levels (Floyd et al., 2008; Kaczynski et al., 2008; Sugiyama et al., 2008). Few of them have examined the relationships at large spatial scale (e.g., county). Moreover, studies have not applied landscape metrics to explore their implications for human health.

This study contributes to integrate the ecological concepts with social science. We applied the concepts and methodologies of “landscape fragmentation” to the relationships with human health. We explored the empirical relationships between human health and landscape at large scale (county) by landscape metrics through utilizing the existing annually- or periodically-surveyed datasets. Furthermore, we explored the relationships at nationwide and regional scales and were able to explain the needs of landscape characteristics that may benefit human health at different spatial scales.

The results of this study showed that physical activity is related the most with green landcovers based on both bivariate and multivariate relationships. In addition, human health variables have stronger relationships with landscape variables at regional scale than those at nationwide scale. These results brought more advanced values for the current existing and
free public accessible datasets (see Appendix B). To advance the understandings of the effects of landscape human health relationships, studies across multiple gradients are needed (Grimm et al., 2008b). We examined the relationships at nationwide and regional scales. Not only the different trends of the landscape-human health relationships can be observed, but also we have more understandings of landscape characteristics that can benefit human health at different scales.

Limitations in this study include that: (1) the analysis was cross-sectional and thus unable to explain the causation between landscape and human health outcomes; (2) the health data was based on self-report from survey respondents so the objective measures were missing; and (3) the quality of landscape data (30-m resolution) may not be enough to interpret the complexity of urban landscapes. Future research should advance the analysis by using time series data to examine the temporal effects and consider the adequate resolution for interpreting urban landscape at different spatial scales.

This study provided some insight into the relationships between urban green landcovers and human health. The analysis was implemented by the measures of landscape fragmentation that allow land manager or policy makers to better understand the specific correlations of urban green landcovers with human health. This study provided an example of how to integrate free and public accessible datasets to understand the landscape-human health relationships. The results provided a reference for land manager or city planner to develop a hierarchical framework for creating health-beneficial landscapes at different scales. Future research is needed to improve data sources and measures, identify the more specific landscape metrics for linking with human health outcomes at different scales, recognize the
spatial resolution effects on the relationships of landscape and human health, and increase understandings of the policy processes that can be applied to achieve a better environmental settings for human health in urban areas.
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CHAPTER 4: Exploring Spatial Resolution Effects on the Relationships between Urban Landcover and Human Health

Abstract

Landscape patterns affect ecological processes and human society. Landscape studies that examine these patterns and processes rely heavily on spatial data, which are resolution-dependent. Landscape structure can vary at different resolutions and result in different interpretations of the relationships of landscape patterns with ecological and human health. The effects of resolution changes on the relationships with ecosystem health have been widely studied, but few of them have worked on the relationships with human health. We aimed to explore these relationships between urban green landcovers and human health with landscape metrics generated by three different resolutions. The Neighborhood Health Profiles of the Baltimore City from the Baltimore City Health Department were used as health data, and the National Land Cover Dataset (NLCD) at 30-m, the National Agriculture Imagery Program (NAIP) at 10-m, and Baltimore Ecosystem Study, Long Term Ecological Research (BES LTER) at 3-m, were used as landcover datasets. Landscape variables examined include percentage of landcover, edge density and patch density, and human health variables include life expectancy and birth rate. Furthermore, socioeconomic factors obtained from U.S. Census Bureau were used as confounding factors. Spearman’s rank correlation and stepwise and hierarchical regression models were applied to examine the effects of spatial resolution changes on landscape variables and their associations with human health. The results show that landscape metrics can vary substantially with resolution change, and the relationships between spatial patterns of urban green landcovers and human health variables are weaker.
with increasing resolution. In addition, different resolutions of landscape metrics can result in a complete change in direction of correlations with human health variables. To understand the acceptable resolutions of landcover data for urban areas, future examinations on resolution dependence of the relationships between different degrees of urbanization and human health are needed.

**Keywords:** spatial resolution, landscape metrics, human health
1. Introduction

Landscape patterns influence ecological processes, and they influence how humans interact with the environment and derive benefits from it. The linkage between landscape patterns and ecosystem functions and processes has been examined extensively, but the relationships between landscape patterns and human health is not as well established. Past research has suggested that green landcovers play an important role in promoting human health through a range of ecosystem services (Arnberger, 2006; Roux et al., 2007). For example, green landcovers was found to have independent salutogenic effects -- factors that support human health and well-being (Mitchell and Popham, 2008). Besides providing opportunities for physical activity, green landcovers are also associated with improved psychological and physiological status, such as reducing stress, and increasing healing speed after surgical interventions (Bratman et al., 2012; Chang et al., 2008; Kaplan, 1993; Kaplan, 1995).

Landscape and landcover patterns have been mostly identified using remote sensing data. Consequently, changes of spatial resolution and extent can result in different interpretations of the relationships between landscape patterns and ecological processes (Corry, 2005; Lawler and Edwards, 2002; O'Neill et al., 1996; Wu, 2004). Due to the heterogeneous patterns in fine scales, landcover classifications in urban areas may be more prone to the effects of spatial resolution, even more so than that of spectral information (Myint et al., 2011). It is conceivable that the relationships between landscape patterns and human health may also be subject to spatial resolution effects.
Landscape patterns are widely analyzed by landscape metrics (Uuemaa et al., 2009). Some of the landscape metrics are sensitive to resolution change. For example, the values of patch density vary a lot at different resolutions. It is greatly dependent on the identifications of the cells from remote sensing data. Adjacent cells with the same type will be identified as one unit, and therefore patch density will be less when more adjacent cells are the same type (McGarigal et al., 2012). Since each cell of satellite imagery can only be assigned to one landcover type while classifying landcovers, a 10-m resolution data can have eight more landcover identifications for the same cell of a 30-m resolution data.

Studies have examined the effects of spatial resolution on landscape metrics (Wickham and Riitters, 1995) and identified three categories of metrics: simple, unpredictable, and staircase functions. For example, number of patches, edge density, and patch size belong to the category of simple metrics, which follows a linear trend, contagions and shape index belong to the category of unpredictable metrics, which cannot be predicted simply by one trend, and patch richness and Shannon’s diversity index belong to the category of staircase metrics, which the changes follow within a series of intervals (Peng et al., 2007; Wu, 2004; Wu and Hobbs, 2007).

As the relationships between landscape patterns and human society can differ directly from the interactions of landscape and indirectly from ecological services while exploring by data at different resolutions, the landscape patterns at different resolutions can result in different interpretations of the relationships with human society as well. In particular, landscape patterns such as size, distance, and density, can have influence on the outcomes of human health through the opportunities for people to contact with the nature. For example,
patch density of the greenlandcovers can influence the availability of parks (Cohen et al., 2007). Besides the physical contacts with the park, edges in an area are important for fulfilling the human psychological needs of the feelings of safety, hiding, and visual access during recreation activities (Edwards et al., 2012; Kaplan, 1998; Mumcu et al., 2010; Ruddell and Hammitt, 1987).

This study examines the effects of resolution change on the relationships between landscape patterns and human health. Our research question is: does the resolution dependency of landscape metrics have effects on their relationships with human health? We first selected potential landscape metrics based on the links of landscape patterns with human health, generated them at three different resolutions, and performed statistical analyses to discover the relationships with human health variables at different resolutions. We also included confounding factors such as demographic and socio-economic variables to determine how they influence the relationships between landscape patterns and human health.

2. Materials and methods

2.1 Study area

We analyzed the relationships between green landcovers and human health in Baltimore City, Maryland, belonging to Piedmont Upland region on the basis of US Environmental Protection Agency Ecoregion Levels (Kemp, 2014). In this region, the temperature ranges from -12°C in winter and 30°C in summer. Annual precipitation ranges from 1,000 to 1,500 mm with relatively even distribution of amount throughout the year,
creating ideal conditions for tall broadleaf, deciduous trees and needle-leaf conifers with a diversity of shrubland and herbaceous layers (CEC, 1997).

Baltimore City is one of the top 50 cities in the United States. The total area of Baltimore City is about 209.63 km\(^2\) in land area and 28.8 km\(^2\) in water (US Census Bureau, 2012). The city was built around World War II and had its peak population in the 1950s. At that time, the population was about one million and the population density approached to 4,000 persons/km\(^2\) (Bigsby et al., 2013). However, the population has been reduced by 15.58% from 1990s, the current population density is now 2,962 persons/km\(^2\) (US Census Bureau, 2012). Despite the current population decline, its historical development still retains the patterns of high densely residential neighborhoods in high proximity to industrial buildings, gridded street networks, and less development intensity further from the city center.

Besides the urban development in the city, Baltimore City has abundant natural settings. It has approximately 24,280 hectares of parks and public spaces, and over 300,000 street trees are located within the city border. In addition, Baltimore City continues to promote green living environments through several programs, such as the TreeBaltimore program which aims to increase tree canopy cover, and TreeNeighborhood program which provides free trees for designated healthy neighborhoods and half price trees to all neighborhoods.

Many monitoring programs and studies in Baltimore City are reported by a geographic unit of Community Statistical Areas (CSAs), which are clusters of neighborhoods with integrations of census tract developed by Baltimore City Planning Department. The
CSAs consist of one to eight census tracts with ranges of total population from 5,000 to 20,000. The demographic characteristics in CSAs are relatively homogeneous. The Baltimore City consists of fifty-five CSAs (Figure 1).
2.2 Data

The datasets included in the analysis were human health data, landcover data, and socioeconomic data. These datasets were acquired from free and public accessible sources in order to utilize the existing datasets and also make other researchers easy to duplicate the methods.

2.2.1 Human health data

Human health variables included in this study are life expectancy and birth rate from the reports of Neighborhood Health Profiles (NHP), conducted by the Health Department in Baltimore City. The primary data sources for NHP reports include U.S. Census Bureau, Baltimore Neighborhood Indicators Alliance (BNIA), Maryland Department of the Environment, Maryland Vital Statistics Administration at the Department of Hygiene and Mental Health, Mayor’s Office of Information Technology (MOIT), and Johns Hopkins Center for a Livable Future; Baltimore City Public Schools. However, some limitations exist within these data sets, including small numbers and data availability. The neighborhoods with small population sizes in certain age groups can skew the differences in rates. At the time of this study they had released the reports for years 2008 and 2011.

The reports primarily include seven sections – demographic, socioeconomic characteristics, education, community built and social environment, housing, food environment, and health outcomes, and two sections for summaries of social determinants of health and health outcomes. The health variables used in this study, life expectancy and birth rate, are both in the section of health outcomes. The life expectancy is a measure of health
over the entire life span, and the birth rate can represent the health of mothers and babies, which is one the most sensitive indicators of a community’s health. The life expectancy used in this study is the life expectancy at birth, which is the average number of years a newborn expect to live, and the birth rate is number of live births per 1,000 persons.

2.2.2 Landcover data

Landcover datasets included three spatial resolutions: 3-m resolution obtained from Baltimore Ecosystem Study, Long Term Ecological Research (BES LTER), 10-m resolution classified by National Agriculture Imagery Program (NAIP) of the year 2006, and 30-m resolution obtained from National Land Cover Datasets 2006. The classifications in these three datasets are different, we finally used five classes in the study: coarse vegetation (i.e., trees and shrublands), fine vegetation (i.e., herbaceous), barren, developed area, and water, in order to make the classifications in these three datasets the same.

The 3-m resolution landcover dataset was classified using NAIP 2007 with a combination of the use of Light Detecting and Ranging Data (LiDAR) from 2006. The ancillary data if building footprints, roads, and water was also used to improve the classification results. The overall classification accuracy of 3-m resolution is 92.5% with a kappa statistic of 0.91. The coarse vegetation has a producer’s accuracy of 97.8% and user’s accuracy of 90%, and the fine vegetation has a producer’s and user’s accuracy of both 86%.

The 10-m resolution landcover dataset was classified by Jenks Natural Breaks using NAIP 2009. The Jenks Natural Breaks is a method that seeks to minimize variation within the classes but maximize the variation between classes (Brewer and Pickle, 2002). We
classified them into 10 classes and identified them into five classes of landcover. Ancillary data of building footprints, roads, and water were used to improve the classification results. The overall classification accuracy is 89% with a kappa statistic of 0.86. The coarse vegetation has a producer’s accuracy of 94% and user’s accuracy of 78%, and the fine vegetation has a producer’s of 85.3% and user’s accuracy of 93%.

The 30-m resolution landcover dataset was classified using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 5 Thematic Mapper (TM) imagery (Fry et al., 2011). Ancillary data of Digital Elevation Model (DEM) and nighttime stable-light satellite imagery was used to aid the classification results. The overall classification accuracy for the conterminous United States is 84% (Wickham et al., 2013). However, the overall classification accuracy of the Baltimore City is only 65% with a kappa statistic of 0.56. The coarse vegetation has a producer’s accuracy of 60% and user’s accuracy of 81%, and fine vegetation has a producer’s accuracy of 61% and user’s accuracy of 72%.

2.2.3 Landscape metrics

Landscape metrics were generated by FRAGSTATS, a spatial pattern analysis program designed to compute a variety of landscape metrics for categorical maps (McGarigal et al., 2012). We selected seven landscape metrics at class level from three domains. Patch area (AREA) and edge density (ED) are in the domain of Area and Edge metrics, mainly for measuring landscape composition and configuration; edge contrast index (ECON) is in the domain of Contrast metrics, mainly for measuring the relative difference among patch types; and patch density (PD), Euclidean distance (ENN), and patch cohesion index (COHESION)
are in the domain of Aggregation metrics, mainly for measuring the degree of aggregation or clumping of patch types.

The patch area was used to represent the size effects on urban green landcovers, percentage of landscape and patch density were used to represent the density effects on urban green landcovers, the edge density was used to represent the edge effects on human recreational preference, the Euclidean distance and patch cohesion index were used to represent the connectivity effects on the accessibility of parks, and the edge contrast index was used to represent the distance between residential area and green landcovers.

Among these seven metrics, the average of patch area is the mean of the total area for its corresponding type in square meters. The percentage of landscape is the proportional abundance of each type in the landscape with a unit of percent, and the value of percentage of landscape must be greater than zero and equal to or less than one hundred if the corresponding exists. The edge density is the sum of the lengths of all edge segments involving the corresponding patch type with a unit of meters per hectare, and its value must be equal to or greater than zero.

The edge contrast index is the sum of the patch perimeter segment lengths multiplied by their corresponding contrast weights divided by total patch perimeter with a unit of percent, and the value of edge contrast index must be equal to or greater than zero and equal to or less than one hundred. The patch density is the total number of patches of the corresponding patch type per 100 hectares with a unit of number per 100 hectares, and the value of patch density much be greater than zero if the corresponding type exists. The Euclidean distance is the distance to the nearest neighbor patch of same type based on the
shortest edge to edge distance with a unit of meters, and the value of the Euclidean distance must be greater than zero if the corresponding type exists. Lastly, the patch cohesion index measures the physical connectedness of the corresponding patch type without a unit, and the value of patch cohesion index must be between zero and one hundred.

We only focused on the landscape metrics of coarse vegetation and fine vegetation, with seven metrics generated for each at 3-m and 10-m resolution. Since coarse vegetation and fine vegetation did not exist in most of the communities for the landcover classification at 30-m resolution, we only kept the metrics to which a value of zero was relevant to the analysis (i.e. coarse vegetation having a value of zero thereby suggesting its absence from the area in question). Therefore, only patch area, percentage of landscape, patch density, and edge density were used for analysis at 30-m resolution. The landscape metrics for coarse vegetation and fine vegetation were prefixed by CV and FV, respectively.

2.2.4 Confounding factors

Confounding factors included population density, housing density, median household income, and race. We acquired the data of confounding factors from the NHP and the U.S. Census Bureau. The population density was calculated using the total population divided by total land area in a community, which were acquired from NHP and calculated using the geometry tools in ArcMap, respectively. The unit of land area is square kilometers in order to be consistent to the metric unit of landcover data. The housing density was calculated by total housing units divided by total land area in a community, the housing units were acquired from the U.S. Census Bureau. The units of population density and housing density are both
number per square kilometer. The median household income was collected from the NHP, and race was presented by percentage of Black\African American in a community also collected from the NHP.

2.3 Analytical Procedures

The bivariate correlations of human health and landscape health variables were examined by Spearman’s rho correlation, as it is computed on ranks and depicts the monotonic relationships. The range of Spearman’s rho correlation is from -1 to +1, which indicates the perfectly negative and positive correlation between two variables, respectively. Regression models were used to explore the relationships of each human health variables with the considerations of all the landscape variables in the model. Firstly, the stepwise regression with bidirectional elimination was used to find the best-fit model for human health variables. The bidirectional elimination is a combination of forward selection and backward elimination, and the Akaike Information Criterion (AIC) was the criterion used in the study. After finding the best-fit models of human health variables with landscape metrics, hierarchical regression was used to examine the effects of confounding factors. Hierarchical models are appropriate for research with more than one level (i.e., landcover and other descriptive data) to estimate the associations between given independent variables (i.e. human health variables) and the outcome with holding all other variables constant (HOX, 1994). We first put confounding variables into the model to see the relationships with human health variables, and then added selected landscape metrics of the best-fit model to see the model changes.
3. Results

3.1 Landcover composition at different resolutions

Result show that landcover composition at 30-resolution is misclassified around 40% of the green landcovers (i.e., coarse vegetation and fine vegetation) as developed area (Figure 2). Landcover composition at 3-m resolution show that the coarse vegetation and fine vegetation totally account for 43.3%, barren accounts for 0.98%, developed area accounts for 50.55%, and water accounts for 4.97%. At the 10-m resolution level, the composition showed that the coarse vegetation and fine vegetation totally account for 50.6%, barren accounts for 0.98%, developed area accounts for 43.43%, and water accounts for 4.98%. The results are only slightly different from the composition at 3-m resolution.

Landcover composition at 30-m resolution show that the coarse vegetation and fine vegetation only account for 6.51%, barren accounts for 0.08%, developed area accounts for 88.68%, and water accounts for 4.74%. These results are greatly different from the compositions at 3-m or 10-m resolutions. One major difference was with fine and coarse vegetation cover, which decreased by over 43% from 10-m to 30-m resolution.
Figure 2 Landcover compositions at 3-m, 10-m, and 30-m resolution in Baltimore City.

3.2 Confounding variables

We classified the confounding variables into five categories based on the total percentage of green landcovers at 3-m resolution. The five categories are less than 15%, 15 – 30%, 30 – 45%, 45 – 60%, and greater than 60% (Figure 3). Population density ranges from 356.60 to 10,793.66 per km² with a mean of 3,763.32 per km², and the housing density ranges from 244.46 to 4,883.25 per km² with a mean of 1,943.60 per km². Population density and housing density have the same trend which is opposite to the direction of total percentage of green landcovers.

The median household income ranges from USD$13,388 to 90,492 with a mean of USD$40,058.27. The trend of median household income in these five categories is V-shaped,
where the two highest values of median household income are in the categories of the least percentage and the most percentage of green landcovers, and the lowest household income is in the category of 30 – 45% of green landcovers.

The race ranges from 2.7 to 97.1% with a mean of 62.55%. The average percentage of race in these five categories shows that places with less percentage of green landcovers have lower percentages of Black/African American; however, the places with medium percentage of green landcovers have the largest percentage of Black/African American.

Figure 3 Average of confounding variables in each category of total green landcovers. The confounding variables are population density, housing density, median household income, and race (i.e., percentage of Black/African American). The total green landcovers, which is the total percentage of coarse vegetation and fine vegetation, are classified into five categories: <15%, 15 -30%, 30-45%, 45-60%, and >60%.
3.3 Landscape metrics

There are fourteen landscape metrics in total at 3-m and 10-m resolution, and eight landscape metrics in total at 30-m resolution. Among the landscape metrics at all resolutions, the percentage of landscape has the same meaning as the landcover compositions.

The ranges of the selected landscape metrics vary substantially among different spatial resolutions. The ranges of the selected landscape metrics vary substantially among different spatial resolutions. The mean coarse vegetation patch area at 3-m resolution is 0.69 m² (SD=0.82), at 10-m resolution is 0.20 m² (SD=0.26), and at 30-m resolution is 1.96 m² (SD=2.97). The mean fine vegetation patch area at 3-m resolution is 0.29 m² (SD=0.14), at 10-m resolution is 0.07 m² (SD=0.04), and at 30-m resolution is 0.3 m² (SD=0.58). The mean coarse vegetation patch density at 3-m resolution is 45.57 per 100ha (SD=16.32), at 10-m resolution is 239.63 per 100ha (SD=94.68), and at 30-m resolution is 1.85 per 100 ha (SD=1.97). The mean fine vegetation patch density at 3-m resolution is 70.48 per 100 ha (SD=29.35), at 10-m resolution is 290.24 per 100 ha (SD=300.85), and at 30-m resolution is 0.05 per 100 ha (SD=0.11). The mean coarse vegetation edge density at 3-m resolution is 140.18 m/ha (SD=55.84), at 10-m resolution is 469.85 m/ha (SD=114.27), and at 30-m resolution is 20.43 m/ha (SD=28.99). The mean fine vegetation edge density at 3-m resolution is 176.09 m/ha (SD=79.97), at 10-m resolution is 364.10 m/ha (SD=168.04), and at 30-m resolution is 0.4 m/ha (SD=0.89).

Three of the seven selected landscape metrics, edge contrast index, Euclidean distance, and patch cohesion index, were only generated by 3-m and 10-m resolution. The mean coarse vegetation edge contrast index at 3-m resolution is 60.19% (SD=14.19), and at
10-m resolution is 69.84% (SD=12.10). The mean fine vegetation edge contrast index at 3-m resolution is 66.55% (SD=11.5), and at 10-m resolution is 55.49% (SD=9.77). The mean coarse vegetation Euclidean distance at 3-m resolution is 27.47 m (SD=6.35), and at 10-m resolution is 22.58 m (SD=1.33). The mean fine vegetation Euclidean distance at 3-m resolution is 24.95 m (SD=8.58), and at 10-m resolution is 25.56 m (SD=5.64). The mean coarse vegetation patch cohesion index at 3-m resolution is 97.72% (SD=2.04), and at 10-m resolution is 89.54% (SD=8.29). The mean fine vegetation patch cohesion index at 3-m resolution is 97.05% (SD=1.35), and at 10-m resolution is 79.99% (SD=11.52).

3.4 Human health variables

The human health variables are shown by the averages in five categories of total green landcovers (Figure 4). The range of life expectancy is from 62.90 to 83.10 year with a mean of 71.49, and the range of birth rate is from 6.30 to 25.80 per thousand persons with a mean of 15.41. The averages of life expectancy reach minimum values when moving towards the center, leading to a trend is slightly V-shaped. The two highest values of life expectancy are in the categories of the two highest percentages of total green landcovers. However, the birth rate has a trend opposite to that of life expectancy. The two lowest values of birth rate are in the categories of the two largest percentages of total green landcovers, while the two highest birth rates are in the categories 15 – 30% and 30 – 45%.
Figure 4 Mean values of health variables in each category of total green landcovers. The health variables selected in this study are life expectancy and birth rate. The five categories of total green landcovers are less than 15%, 15 – 30%, 30 – 45%, 45 – 60%, and greater than 60%.
3.5 Bivariate relationships

The two human health variables are only significantly correlated with the landscape metrics at 3-m and 10-m resolutions (Table 1). The correlations of life expectancy with the landscape metrics at 3-m resolution are generally stronger than those at 10-m resolution. The edge density of coarse vegetation at 3-m resolution has the most positive correlation with the life expectancy with a value of 0.417 ($p<0.01$), whereas the edge contrast index of fine vegetation at 3-m resolution has the most negative correlation with life expectancy with a value of -0.528 ($p<0.01$).

The significant correlations of birth rate with the landscape metrics at 3-m resolution are also stronger than those at 10-m resolution. The Euclidean distance between the patches of coarse vegetation at 3-m resolution has the most positive correlation with the birth rate with a value of 0.544 ($p<0.01$). The edge density of coarse vegetation at 3-m resolution has the most negative correlation with a value of -4.62 ($p<0.01$).
Table 1 Significant Spearman’s Rho correlation coefficients and p-values between human health variables and landscape metrics

<table>
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<th>Rho</th>
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<th>10-m</th>
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3.6 Multivariate relationships

The results of the best-fit regression models at different resolution levels show that selected landscape metrics are more associated with life expectancy than birth rate at the resolutions of 3-m and 10-m. However, the selected landscape metrics are barely associated with life expectancy and birth rate at the resolution at 30-m (Table 2). The best-fit model of life expectancy at 3-m, 10-m, and 30-m resolutions can explain 61.1%, 42.3%, and 2.3% of the variance, respectively. The explanation of the variance for the life expectancy model at 3-m, 10-m, and 30-m resolutions can increase to 75.5%, 73.5%, and 60.6% of the variance, respectively, after taking confounding variables into account. The best-fit model of birth rate at 3-m, 10-m, and 30-m resolutions can explain 38.3%, 18.1%, and 3.8% of the variance,
respectively. The explanation of the variance for the birth rate model at 3-m, 10-m, and 30-m resolutions can increase to 37.6%, 28.6%, and 22.7% of the variance, respectively, after taking confounding variables into account.
Table 2 The best-fit models of life expectancy and birth rate and the full model (i.e., the best-fit models with confounding factors) at different resolutions with the considerations of confounding variables. The coefficients are reported by standardized coefficients.

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Significance level: ***: <0.001; **: <0.01; *: <0.05
The models of life expectancy with the landscape variables at 3-m and 10-m resolutions show that they have some same metrics selected into model; however, not all of them have the same direction. The variables that have different directions are patch density or edge density, since their values are much different at 3-m and 10-m resolution. For example, the edge density of coarse vegetation contributes positively to life expectancy with the landscape metrics at 3-m resolution but contributes negatively to life expectancy at 10-m resolution. The model of life expectancy with the landscape metrics at 30-m only includes the patch density of fine vegetation into model, and the coefficient is less than 0.1.

The model of birth rate with the landscape variables at 3-m resolutions is more correlated than the 10-m and 30-m resolution models. The selected landscape variables at 3-m resolution in the model of birth rate are also in the model of life expectancy; however, they have totally opposite effects on birth rate and life expectancy. For example, the Euclidean distance of fine vegetation in the life expectancy model has a coefficient of 0.643 but its value in the birth rate model is -0.67.

4. Discussion

The goal of this study is to explore the effects of spatial resolution change on relationships between green landcovers and human health by three resolution data (i.e., 3-m, 10-m, and 30-m). Green landcovers in urban areas have been recognized as important sources for human health through providing a range of ecosystem services (James et al., 2009; Tzoulas et al., 2007). Even urban green landcovers are characterized as more fragmented landscapes (Di Giulio et al., 2009; Peyras et al., 2013), urban green landcovers
have independent salutogenic effects - factors that support human health and well-being (Mitchell and Popham, 2008). They also provide green infrastructure important to benefit human health outcomes by several dimensions, such as physical activity, recreational activity, social connections, psychological well-being, and even life expectancy and birth outcomes (Bedimo-Rung et al., 2005; Burgess et al., 1988; Seaman et al., 2010).

Research supports our results that vegetation covers (i.e., percentage of coarse vegetation or fine vegetation) are positively associated with life expectancy at different spatial resolutions (Correia et al., 2013; Keuken et al., 2012; Takano et al., 2002). However, vegetation covers were negatively associated with birth rate based on the bivariate relationships. Though the fragmented features of green landcovers may impact negatively on ecosystem (Alberti, 2005; Fahrig, 2003; Forsyth and Musacchio, 2005), the fragmented features of urban green landcovers showed to have positive associations with life expectancy and birth rate. Edge density has a positive association with life expectancy, and the edges connecting between green landcovers and human activity areas have a positive association with birth rate. In terms of the multivariate relationships, patch area shows contributes negatively, and edge density and the edges connecting between green landcovers and human activity areas contribute positively in the human health model at finer resolution (3-m resolution).

Moreover, the relationships between green landcovers and human health variables vary by using different resolution of landcover data. As landcover data is relied heavily on satellite imagery, each pixel can be only assigned to one landcover type. Studies have shown that changes of spatial resolution can result in different interpretation of the relationships
between landscape and ecological processes (Corry, 2005; O'Neill et al., 1996; Wu, 2004). Urban landscapes are more complex and fragmented than rural landscapes, and therefore the spatial resolution is more important than the spectral information for landcover classification in urban areas (Myint et al., 2011). Research indicated that many of small features cannot be identified by coarse resolution data (Corry, 2005).

We found that many of the coarse vegetation and fine vegetation areas were misclassified as developed area by using 30-m resolution data. In addition, the selected landscape metrics vary by different resolution data. Even though the landscape compositions at 3-m and 10-m resolutions are similar, some of the landscape metrics are very different in these two resolutions. Research supports our results that mean patch size has a positive relationship with the decrease of spatial resolution (i.e., from 3-m to 30-m resolution in this study) (Buyantuyev et al., 2010). As the resolution determines the types of each cell, and the adjacent cells with the same type will be aggregated as the same parcel. Our results also showed that patch density and edge density are more sensitive to the changes of spatial resolution (McGarigal et al., 2012).

In addition, the inferences of the landscape-ecological relationships can differ by the changes of spatial resolution (O'Neill et al., 1996; Wu, 2004), as well as the landscape-human health relationships. Our results showed that the relationships between green landcovers and life expectancy or birth rate have a positive relationship with the increase of spatial resolution (i.e., from 30-m to 3-m resolution in this study). The results indicated that the relationships between landscape and ecosystem health or human health may share some similarities, and therefore the concepts of landscape ecology can be applied to the human
society as well. However, the finer resolution data usually costs more in terms of data expense, labor, and time consumption. Future research is needed to explore the adequate resolution for different levels of urbanized area for a better efficiency investigation of the landscape-human health relationships.

The landscape-human health relationships can be influenced by socioeconomic factors as they may have effects on both landscape change and human health outcomes (Alberti and Marzluff, 2004; Grimm et al., 2008). The Baltimore City is one of the fastest-growing cities in the U.S., and its growth started from the Inner Harbor and moved to the outside of the urban cores (Sexton et al., 2013). Our results also showed that the total population and housing density have a positive relationship with the distance to the Inner Harbor. On the other hand, the total percentage of green landcovers has an inverse relationship with the population and housing density. The median household income and race did not show totally a positive or an inverse relationship with the distance to the Inner Harbor. Instead, the two highest values of median household income are distributed in the lowest and highest percentage of total green landcovers.

The results indicated that highly developed areas provide more opportunities of employment (Gerald et al., 2001), but wealthier people are more attractive by natural amenities for their living quality (Hansen et al., 2002). In terms of the distribution of race, our results showed that the highest percentage of Black/African American is distributed in the middle percentage of total green landcovers. The result was corresponded to the history of the distribution of the Black/African American in the Baltimore City. The Black/African American was originally in the northeast and northwest areas of downtown but expanded into
previously white neighborhoods later (Moore, 2004). Consequently, the distributions of these socioeconomic factors may be influenced by the history and the development of the city. To better understand the landscape-human health relationships, these socioeconomic factors and history of the area have to be taken account in the future research.

Although we found that some of the characteristics of green landcovers are associated with human health variables, the causality of what contributes positively to human health outcomes cannot be explained by our results. On the other hand, we cannot explain that if this certain settings or characteristics of landscape make people healthy or healthy people prefer a certain settings or characteristics of landscape. Self-selection, including neighborhood selection factors and preferences, makes our research difficult to assess the causation among landscape, human behavior, and associated health outcomes (Frank et al., 2007; Hartig et al., 2014). Studies have mentioned that the issue of self-selection has to be accounted for the relationships between environment and human health (Handy et al., 2005; Kaczynski and Mowen, 2011). In our case, for example, wealthier people prefer to have natural settings in their living environment (Hansen et al., 2002), and they also tend to have longer life expectancy (Wilkinson, 1992). Besides, this analysis is cross-sectional that the causation cannot be explained by cross-sectional analysis. Therefore, future research is needed to explore the self-selection issue and use time series data to better understand the relationships between landscape and human health outcomes.

We employed ecological concepts and methodologies to social science by exploring the relationships between green landcovers and human health variables using landscape metrics. One of the common seen methodological issues of landscape metrics, the effects of
changes of spatial resolution on the associated ecological processes, was applied to examine the relationships between landscape and human health. The results demonstrated that the need to take into account varying spatial resolution when examining the landscape-human health relationships.

5. Implications and conclusions

Green landcovers in urban area can benefit human health and well-beings, such as life expectancy and birth outcomes through providing green infrastructure that essential for physical activity and ecosystem services that improving air quality (Correia et al., 2013; Keuken et al., 2012; Wickham et al., 2010). The results of this study show that certain characteristics of green landcovers have positive associations with life expectancy and birth rate. However, the characteristics of green landcovers in urban areas are more difficult to be correctly interpreted due to the complexity of urban landscapes (Corry, 2005). Therefore, spatial resolution is crucial for landcover classification in urban areas (Myint et al., 2011). Many studies have examined the effects of spatial resolution changes on the relationships between landscape patterns and ecological processes (Buyantuyev et al., 2010; Huang et al., 2006; O'Neill et al., 1996), but few of them have explore their effects on the relationships with human health.

The results of this study demonstrated that the spatial resolution may have influences on the relationships between green landcovers and human health variables. Finer resolution data has better interpretation of the relationships between landscape and human health variables. However, finer resolution data costs more in terms of several aspects, such as
expenses on data collection, labor, and time consumption. Future research is needed to develop a system to identify the proper resolutions for urban studies based on the levels of urbanization with the consideration of all the costs. In addition, a hierarchical framework for exploring the effects of the changes of both spatial resolution and extent on the relationships with human health is needed.

Some limitations in this study has to be mentioned. The self-selection issue is not considered, and the analysis is cross-sectional. Future research should take advantage of the use of temporal data to explore the “cause and effects” of the landscape-human health relationships. Despite the limitations, this study brought out the needs of proper spatial resolution for urban areas and provided an example of how to integrate landscape and human health data to reveal the values of these existing datasets. Land managers or policy makers should review the resources in the area, and apply the findings or multiply the methodologies to maximize the functions of urban land areas based on different approaches.

6. Acknowledgement

We would like to thank Mr. Kevin Bigsby for providing us the information of landcover classification at 3-m resolution of Baltimore City.
7. References


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CHAPTER 5: General Conclusions

Urban green landcovers such as trees and greenspaces, through a variety of ecosystem service, provide social, environmental, economic, psychological and recreational benefits (Abraham et al., 2010; Dwivedi et al., 2009; McPherson and Rowntree, 1993; Nowak et al., 2006) that can lead to enhanced human health and well-being (Lachowycz and Jones, 2013; Tzoulas et al., 2007). The importance of urban green landcovers has been increasingly recognized by researchers since the rapid increase of urbanization fragments natural landscapes. This dissertation aimed at understanding the relationships between urban forest fragmentation and human health through constructing the linkages between them conceptually, examining the relationships empirically, and investigating the effects of spatial resolution in ecological studies on human health variables methodologically.

While most of the studies discussed the relationships between urban green landcover and human health through the importance of their existence in an area, we applied the concept of fragmentation in landscape ecology to explore the landscape-human health relationships. The conceptual model not only provided the linkages of landscape-human relationships through the ecological services but provided an insightful perspective of the nature relationships between landscape and human beings. The effects of urban forest fragmentation on human health can be quite different from those on ecosystem health, though some effects may be similar (Lindenmayer and Fischer, 2006). For example, decrease of habitat connectivity typically results in biodiversity loss, but it tends to increase human landscape connectivity (Fahrig, 2003; Lindenmayer and Fischer, 2006). On the other hand, more patch edges can increase the biodiversity and fulfill human’s psychological needs.
simultaneously (Fahrig, 2003; Mumcu et al., 2010; Ruddell and Hammitt, 1987). The findings show that the major characteristics of urban forest fragmentation do have effects on both ecosystem health and human health.

Many studies examined the relationships between urban green landcovers and human health at the park or neighborhood level (Floyd et al., 2008; Kaczynski et al., 2008; Sugiyama et al., 2008). Few have explored the relationships at large geographic scales. We provided an understanding of the effects of green landcover on human health at large scale by exploring their empirical relationships with a consideration of socioeconomic factors at a geographic entity of county. The results show that green landcovers are associated with the engagement of physical activity, good BMI, never having asthma, and good mental health. We also examined the nationwide and regional differences. The associations of the human health variables and landscape variables are stronger for the regional analysis than for the nationwide analysis at county scale. The results at regional analysis show that patch area contributes negatively and patch density contributes positively to most human health variables in the Bottomland East and the Upland East regions. It suggests that fragmented green landcovers can help improve human health. Considering confounding factors into model mostly helped improve the relationships between human health and landscape variables. It indicates that the confounding factors identified in the study have effects on human health and landscape patterns. The results help researchers or policy makers refine the directions of land management and health promotion.

Landscape patterns can have different interpretations at different spatial resolutions as well as the interpretation of their relationships with ecological processes (Corry, 2005;
Lawler and Edwards, 2002; O'Neill et al., 1996; Wu, 2004). We provided an understanding of the effects of the resolution change on the relationships of landscape metrics associated human health. The results show that landscape variables at the finer resolution have stronger relationships with life expectancy and birth rate. Furthermore, the positive contributions of urban forest fragmentation to human health are more obvious at city scale than county scale. For example, patch and edge density of coarse vegetation (i.e., trees and shrublands) in the regression model are positively correlated to life expectancy at 3-m resolution. The findings reveal that the importance of spatial resolution for urban areas is not only in identifying urban complex landscape but also the interpretations of their relationships with human health.

Some limitations existed in this study. Firstly, the health data used for the analysis at county level were self-reported data that were inevitably more subjective than direct health measures. Secondly, our analysis is correlational and cross-sectional. Therefore, the causation of the landscape-human health relationships cannot be established in this study, though it helped identify priority for future research that addresses causality. Thirdly, health data were missing for some counties due to the small sample size. Therefore, the relationships between urban green landcovers and human health may change when having different sample size. Fourthly, the human health data is not available for finer scale. We didn’t compare the scale and resolution effects of landscape patterns on human health using the same variables. Lastly, the landcover data are at med-resolution. The complexity of urban landscape cannot be captured based on our findings of the analysis at city scale.
We also provided an example of how to integrate massive and free accessible datasets such as landcover, health surveillance, and census data, and to generate more advanced information from them. This dissertation built the knowledge of the relationships between urban forest fragmentation and human health that helps achieve a healthy environment for ecosystem and human societies through providing useful information and valuable evidence for proper management plans or designs.

For future research, a special focus on the integration of ecological and social science is a fruitful direction to advance our understanding of the interactions between the natural environment and human society. Based on the integration of ecological and social science, hierarchical frameworks are needed to conduct analyses at different scales for achieving sustainable relationships between the nature and human, and for the evaluations of the adequate datasets with the practical considerations of all the costs. Furthermore, the use of time series data has to be considered to examine the temporal effect and the causations. Developing more advanced knowledge of the landscape-human health relationships will undoubtedly inform the future planning and management of urban forests and greenspaces with both human and ecosystem health as beneficial outcomes.
References


APPENDICES
Appendix A: Python scripts for GIS batch processing

Description: The python script was used for extracting the landcover data for each county from National Land Cover Dataset (NLCD) 2006 and for reclassifying the landcover types into eight classes afterwards in the CHAPTER 3: Examining the Association between Urban Forest Fragmentation and Human Health at National and Regional Scales. This script was also applied to extract the landcover data at three different resolutions for each community in CHAPTER 4: Exploring Spatial Resolution Effects on the Relationships between Urban Landcover and Human Health.

```python
# Import system modules
import sys, arcpy

from arcpy import env
from arcpy.sa import *

#Check extension
arcpy.CheckOutExtension("Spatial")

workspace = "F:/StudyArea/CountySplit"
arcpy.env.workspace = workspace

#List shapefile in workspace
shpData = arcpy.ListFeatureClasses("*.shp")

#NLCD data
rasterData = "F:/NLCD/Int_nlcd2006"
```
# Extract NLCD by counties

```python
for shp in shpData:
    # print shp
    outfolder = "F:/StudyArea/NLCDCounty"
    rasterData = "F:/NLCD/Int_nlcd2006"
    outExtractByMask = ExtractByMask(rasterData, shp)
    # arcpy.env.overwriteOutput = 1
    outRaster = outfolder + "/" + shp[:-4]
    # print outRaster
    outExtractByMask.save(outRaster)
    print outRaster

    outRastReclass = "F:/StudyArea/NLCDCounty8Class/" + "re8" + outRaster[24:]

    reclassField = "VALUE"
    remap = RemapValue([[11, 1], [12, 1], [21, 2],[22, 2],[23, 2],[24, 2],[31, 3], [41, 4], [42, 4], [43, 4], [51, 5], [52, 5], [71, 7],[72, 7],[73, 7],[74, 7],[81, 8], [82, 8], [90, 9], [95, 9]])

    # Execute Reclassify
    outReclassify = Reclassify(outRaster, reclassField, remap, "NODATA")
    # Save the output
    outReclassify.save(outRastReclass)
    print outRastReclass
```
Appendix B: List of data sources

Description: The sources of the free and public-accessible datasets used in the dissertation.

<table>
<thead>
<tr>
<th>Data</th>
<th>Chapter</th>
<th>Year</th>
<th>Source</th>
<th>Format</th>
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