EFFECTS OF GREENSPACE MORPHOLOGY ON POPULATION HEALTH

A Dissertation

by

HUAQING WANG

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Chair of Committee,	Louis G. Tassinary
Co-Chair of Committee,	Galen D. Newman
Committee Members,	Vani A. Mathur
	Gerard T. Kyle
Head of Department,	Shannon S. Van Zandt

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ABSTRACT

The association between urban greenspace and health is well known, but less is known about how the spatial arrangement of greenspace affects population health. The relationships between urban greenspace distribution, mortality, and morbidity risk were investigated via cross-sectional studies of major cities in the US, based on accepted landscape metrics (i.e., greenness, fragmentation, connectedness, aggregation, and shape), using geographical spatial pattern analysis programs. Study 1, utilized negative binomial regression, focused specifically on all-cause and cause-specific mortality (related to heart disease, chronic lower respiratory diseases, and neoplasms) recorded in the city of Philadelphia. Study 2 adopted spatial regression models, focusing specifically on morbidity risk related to poor mental health, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and physical inactivity in five major cities in the US (i.e., Seattle, Los Angeles, San Antonio, Miami, and New York). Overall, census tracts with more connected, aggregated, coherent, and complex shape greenspaces had a lower mortality and morbidity risk, although the magnitude of these effects varied across health outcomes and cities. The results support the proposition that environment-based health planning should consider the shape, form, and function of greenspace. Study 3, based on the results of the prior two studies, explored a novel health evaluation tool using machine learning and spatial gaussian process models. The tool automates the extraction of greenspace morphology from landscape and city planning master plans in the service of predicting health indicators. This tool is designed to be used routinely by landscape

and city designers as well as policymakers to help estimate the likely health consequences of a design plan prior to implementation.

DEDICATION

To my parents Weiming and Yu, my husband Xingchen, and my advisor Dr. Tassinary, for their endless support.

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NOMENCLATURE

PLAND	Percentage of Coverage Index
PD	Patch Density Index
AREA_MN	Mean Size Index
SHAPE_AM	Area Weighted Shape Complexity Index
COHESION	Connectedness Index
AI	Aggregation Index

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1. INTRODUCTION

1.1. Greenspace for cities

Greenspace has great values for cities. Born nearly two centuries ago, the public park movement grew primarily out of a desire to improve health in the over-crowded conditions of the rapidly growing industrial towns [1]. It reflects the underlying understanding of greenspace's function of improving city sanitation as well as citizens' health among authorities and planners at that time. Frederick Law Olmsted, the father of American landscape architecture, laid out the political and philosophical case for public parks regarding three necessities in his 1870 address to the American Social Science Association entitled "Public Parks and the Enlargement of Towns." The three necessities were the need to improve public health, combat urban vice and social degeneration, and advance the cause of civilization. He believed these could be achieved by using greenspace to combat air and water pollution, to improve sanitation measures, to provide urban amenities that would be democratically available to all. Guided by the public parks movement and their belief that greenspace would help solve industrial cities' environmental issues, more public parks were opened between 1885 and 1914 than either before or after this period [1].

These ideas were borrowed and elaborated upon by Ebenezer Howard in his design of the "Garden City" (1998/1902). In this seminal work, Howard integrates nature into cities, uses green belting around cities to help solve urban problems and help cities functioning well. Though this design looks "normal" today, it was revolutionary at the time when Le Corbusier (1922) proposed his plan for “A Contemporary City of Three Million People.”

Olmsted and Howard both thought of city functions at the population level and realized greenspace could be utilized as a strategy for solving/preventing urban problems. When seeing the city from an individual perspective, Frank Lloyd Wright (1935), the spokesman for “organic architecture,” also acknowledged the importance of residents’ contact with nature/land. His well-known “Broadacre City” was based on the idea that every citizen of the United States would own a minimum of one acre of land. His small, efficient “Usonian” house formed the basis for the growing suburban areas which transformed the American landscape during the second half of the twentieth century.

With the growing awareness of greenspace’s value for the city, Ian McHarg (1969) published “Design with Nature,” which illustrated the critical role of nature and demonstrated how to do regional planning using natural systems. Though he pioneered the concept of ecological planning at the urban and regional scales, McHarg also believed that homes should be planned as well as designed with good garden spaces. He combined the idea of Howard and Wright and developed an ecological planning method for managing greenspace within a region as a whole to provide ecological services to cities.

After McHarg, the ecological function of greenspace gained more attention. Urban greenspaces are no longer treated as isolated physical objects in cities but rather as living systems that can provide ecological services to the urban fabric - not merely influencing the aesthetic aspect of a city but improving its living environment (clean air, water, cooling effects) for residents. A variety of city planning ideologies that value greenspace’s eco-system services for cities have recently emerged. Green Infrastructure and greenway had been advocated as planning strategies for cities [2,3]. It has also been argued persuasively that the best way to organize cities is through the design of the city's landscape, rather than the design of its buildings with the concept of landscape urbanism [4–7].

1.2. Greenspace for humans

In addition to nature's role in improving the function of cities, a growing focus has been placed on the landscape's function of enhancing people's lives. German-born American psychoanalyst Erich Fromm first used the word Biophilia in *The Anatomy of Human Destructiveness* (1973), to describe the natural connection between humans and other living forms of life as "the passionate love of life and of all that is alive" [8]. The term was later used by biologist Edward O. Wilson in his work Biophilia in 1984, which proposed that the tendency of human beings to focus on and to affiliate with nature and other forms of life has a genetic basis and could be a product of biological evolution. Because of our technological advancements, more and more time is spent inside buildings and cars and, it was argued, that the lack of biophilic activities and time spent in nature may lead to strong urges among people to reconnect with nature. This idea had also been described in Tuan's book "*Topophilia: A study of environmental perception, attitudes, and values.*" Tuan speculated that "once society had reached a certain level of artifice and complexity, people would begin to take note, and appreciate, the relative simplicities of nature" [9]. He also deemed suburbs and new towns as reflective of residents' search for the environment [9].

Built upon the Biophilia hypothesis, studies explored the relationship between humans and nature in urban context from a variety of different perspectives, including perception, aesthetics, preference, general health, mental and physical health, health behavior, morbidity, and mortality, etc. Two main psycho-evolutionary theories of the effects of residents' exposure to nature emerged. Based on past research showing the separation of attention into involuntary attention and voluntary attention, Attention Restoration Theory (ART) was developed by Rachel and Stephen Kaplan in the 1980s in their book "*The Experience of Nature: A Psychological Perspective*". ART asserts that people can concentrate better after spending time in nature or looking at natural scenes. This is because artifact-dominated environments require the routine use of effortful voluntary attentional control to filter relevant stimuli from irrelevant stimuli adequately, while nature-dominated environments elicit the use of less resource costly involuntary attention, thereby facilitating restoration [10,11]. To replenish resource-limited directed attention, nature-dominated environments must invoke psychological states characterized primarily as awe or fascination, perceived as coherent, and provide a respite [12].

In addition to ART, which focuses on the cognitive process, Ulrich developed the Stress Reduction Theory (SRT) in 1991, which focused more on emotional and physiological processes. SRT postulates that viewing or visiting natural environments after a stressful situation rapidly promotes physiological recovery and relaxation [13]. It activates our parasympathetic nervous system in ways that reduce stress and sympathetic arousal because of our innate connection to the natural world in a fashion consistent with the Biophilia Hypothesis. Viewing particular natural landscapes, which tend to provide human beings with "opportunities" for gain and places of "refuge," activates our physiology in effectively beneficial ways [14]. Evidence consistent with both the ART and the SRT has been found in a number of studies [15–18].

2. HEALTH BENEFITS OF CONTACT WITH NATURE: A REVIEW

Research show evidence that greater exposure to nature in urban settings is associated with a wide range of important benefits. These benefits have been found across various media of exposure, such as via photographs, videos, window views, or being present (on-site) and doing exercise in natural environments. Also, these effects from contact with nature have been assessed through various research methodologies including quantitative experimental and quasi-experimental studies, observational studies like cross-sectional, longitudinal, and cross-sequential, as well as qualitative studies. Corresponding to these study designs, the studies have been conducted across varying durations of exposure, including a few minutes of viewing photos, hour-long or multi-day experiences in nature, and having life-long proximity to greenspace. Additionally, studies had been done both at the individual level and population level at various geographical spatial scales, such as small local sites, neighborhoods, counties, cities, etc.

2.1. Definition of greenspace in urban settings

Currently, there are no universal definitions of greenspace that are widely accepted among studies exploring its relationship with human health. Nearly all definitions, however, have included places with "green elements". Some studies consider greenspace in a "categorical" way. They may include various types of greenspace, such as public parks, gardens, street trees, golf courses, residential open space, roof gardens, urban agriculture, commercial forests, vegetated wastelands, etc. These greenspaces tend to be intentionally designed. Other studies think about greenspace in a more continuous, integrated manner. They included any place where there is a natural surface or where plants are growing. This definition would also include green areas that are not intentionally designed by humans.

These two types of definitions appear to derive from the character of available data. If land-use data were used in greenspace and health studies, then because of the categorical characteristic of the data and the function orientation of the categories of land use classification, researchers tend to define greenspace as recreational land in a "categorical" way. It normally includes not only parks, gardens, often also includes public open spaces that may or may not have plants growing on them. When the land cover data has been used in research, researchers tend to define greenspace in a more "continuous" way. This is because the land cover data classifications are based on the land's physical appearance, derived from aerial images using remote sensing technology. The data by its nature characterizes land with plants growing on it as the same type, regardless of whether it is designed as a park, garden, or other specific function.

Greenspace herein is defined as all vegetated land, including agriculture, lawns, forests, wetlands, gardens, etc. in cities. The spatial scale used throughout the dissertation is the neighborhood. These greenspace selection criteria are based on the results of former studies suggesting that relatively small greenspaces may affect health and well-being.

2.2. Dependent variables: the health outcomes

Exposure to greenspace was associated with a wide range of health outcomes, including mental, physical, social, and general health. The outcome measures in the extant literature have ranged widely, including stress, attention, short-term memory, physical activity, obesity, cardiovascular diseases, cerebrovascular disease, diabetes, recovery from surgery, longevity, mortality, social ties, quality of life, etc. [15].

2.2.1. Improved stress recovery, cognitive function, and mental health

Over 40 years ago, Ulrich measured the emotions of mildly stressed subjects before and after exposure to nature scenes dominated by green vegetation and urban scenes lacking nature elements [19]. The findings suggested that stressed individuals feel significantly better after exposure to images of nature scenes versus urban scenes, such that nature exposure increased positive feelings of friendliness, playfulness, and elation. He also demonstrated that natural scenes had more positive influences via the recording of a variety of psychophysiological measures [13,20]. A series of similar studies have been conducted and have repeatedly demonstrated the validity of SRT. Parsons and colleagues used videotaped simulated drives dominated by either artifact versus natural elements. They found participants exposed to nature-dominated drives experienced quicker recovery from stress and greater immunization to subsequent stress compared to subjects exposed to artifact-dominated drives [18]. Van den Berg et al. used videos of natural and built environment stimuli to further illustrate that participants' exposure to nature videos reported higher happiness, lower stress, anger, depression, and tension; improved mood and concentration [21].

Hartig et al. conducted a series of quasi-experimental field studies as well as lab-based experiments and provided evidence of greater restorative effects arising from experiences in nature compared to other conditions [10]. University students whose dormitories had natural views were found to perform better on attentional measures [22]. Additional studies have found that exposure to nature stimuli restores depleted voluntary attention capacity and affects selective attention, supporting the validity of ART [23]. Time spent in the garden has also been found to increased powers of concentration when compared to time spent indoors [24].

Alongside the laboratory-based literature, a body of population-level observational studies has gradually merged focused on exploring the relationships between greenspace and health. For example, residents in buildings with nearby nature, (i.e., varying levels of surrounding trees and grass) had lower levels of mental fatigue and reported less aggression and violence [25]. Perceived neighborhood greenness has also been found to be more strongly associated with mental health than physical health [26]. In addition, individuals living in urban areas with better availability of greenspace, compared to controls who are living in areas with less greenspace, had a reduced stress level and improved well-being [27]. Moving to greener areas has also been associated with mental health improvements [28]. Higher neighborhood greenery is associated with not only a lower level of stress but also a lower level of depression and anxiety [29]. Greener surroundings at home and school led to evidence of improved working memory and reduced inattentiveness, which therefore improved the cognitive development of schoolchildren [30]. Pregnant women in the greener quintiles of an urban area were less likely to report depressive symptoms [31]. Self-reported hours of exposure to greenspace have been found to contribute to stress status [32] with the closer proximity of the home to the nearest park being associated with reduced odds of self-reported symptoms of depression [33] and lower blood pressure in pregnant women [34]. More time spent in greenspace is associated with improved mental health [35], as is increased walking and exercise in greenspaces [36–38].

In addition to these short-term mental health benefits from exposure to nature, studies have exploited disruptions in diurnal cortisol rhythms as a biomarker of chronic stress to demonstrate that contact with nature reduces chronic stress in adults in deprived urban neighborhoods [39–41]. Similar results also have been tested and proved by using hair cortisol as a biomarker of chronic stress [42,43].

2.2.2. Improved social health

Social ties and social relationships play a beneficial and protective role in the maintenance of psychological well-being [44]. Social isolation is a known risk factor for morbidity and mortality [45–47]. For fostering social interactions and cultivating a sense of community, exposure to greenspace is potentially ameliorative. Kuo et al. found that the presence of trees and grass in inner-city neighborhoods supports informal social contact among neighbors [48]. Quality of streetscape greenery has also been shown to be strongly associated with perceived social cohesion [49]. Similar social inclusion effects have been observed with youth from different cultures [50]. Conversely, the lack of greenspace has been related to feelings of loneliness and the lack of social support [51,52]. It is therefore not surprising that the provision of greenspace in a disadvantaged neighborhood may promote safety and reduce crime [53].

2.2.3. Enhanced healthy behavior

One of the functions of greenspaces in cities is to promote and maintain physical activity levels. Physical activity has been shown effective in preventing cardiovascular disease, diabetes, cancer, hypertension, obesity, depression, and osteoporosis [54]. Currently, physical inactivity has emerged recently as the fourth leading risk factor for global mortality, having been shown repeatedly to be the primary cause of many chronic diseases[55,56]. Globally, approximately 3.2 million deaths each year are due to insufficient physical activity [57]. Not only may greenspace help in facilitating physical activity levels, but physical activities conducted in natural settings as opposed to urban settings may also help achieve better health outcomes [58]. Specifically, recent evidence supports the thesis that the use of or access to greenspace is associated with increased physical activity and reduced sedentary time [59–64]. These results were found consistently among adults, youth, and senior citizens [65–67] across all seasons [68].

The quality of greenspace has also been associated with a higher level of routine physical activity. The operationalizations of “quality” have ranged from the presence of historical and cultural remains, natural species richness (lush), perceived peacefulness, wildness, and spaciousness [69,70]. Neighborhood open space, which is typically characterized by high levels of pleasantness, minimal nuisances, good paths, and accessible facilities, has been associated with increased walking in older people [71]. The greenness of residential areas also correlates with physical activity levels. Almanza et al. used satellite images, GPS tracking, and accelerometer data from children to measure momentary greenness exposure and found that this momentary greenness exposure was positively associated with the likelihood of contemporaneous moderate-to-vigorous physical activity [72]. The presence of and proximity to neighborhood greenspaces are associated with a higher likelihood of walking maintenance over time [73].

Physical activity in natural environments, (dubbed "Green Exercise") is more beneficial than doing exercise in other settings [74]. For example, running in parks is a more restorative experience compared to running in urban environments [75]. Similar results also exist for walking. Compared to group walks in urban environments, group walks in farmland or green corridors were associated with less perceived stress and reduced negative affect [76]. The literature suggests that physical activity in natural environments is better for mental health than activity elsewhere to the extent that each additional use of a natural environment per week is associated with a lower risk of poor mental health [77]. For urban residents with poor mental health, physical activity in greenspace is particularly beneficial compared to residents with good mental health, although greenspace has a restorative function for all residents [78].

2.2.4. Improved physical health and reduced physical illness

Contact with nature may also help in accelerating recovery after surgery, lowering the risk of insufficient sleep, and reducing obesity. Viewing natural elements through a window promotes recovery from surgery. For example, surgical patients assigned to rooms with windows that have a natural view had shorter postoperative hospital stays and fewer potent analgesics than patients with window views blocked by a brick wall [79]. People living in greener neighborhoods have been reported to have a significantly lower risk of insufficient sleep. Compared with participants living in areas with 20% greenspace land-use, the relative risk ratios for participants with 80%+ greenspace was reduced by two-thirds for less than 6 hours of sleep [80]. Similarly, access to the natural environment has been shown to decrease significantly the likelihood of reporting insufficient sleep [81]. For obesity, a systematic review on the relationships between objectively measured access to greenspaces and physical activity, weight, and obesity indicators reported that the majority (68%) of papers found the presence and/or access to greenspace is associated with reduced obesity [82]. More specifically, an increase in residential surrounding greenness and residential proximity to forests has been recently found to be associated with a lower relative prevalence of obesity and sedentary time [83]. Importantly, researchers from Ireland have reported that the relationship between greenspace in urban areas and obesity may be U-shaped with those living in areas with the lowest and highest shares of greenspace being the most at risk for obesity [84]. In general, physical activity is a reliable mediator of the association between greenness and obesity [85].

Additional evidence points to a positive relationship between exposure to greenspace and improved pregnancy outcomes. Neighborhood greenness within 100-m buffer is weakly yet positively associated with birth weight [86], and it is well-known that lower birth weight is a major cause of neonatal and infant mortality, and that low birth weight can negatively affect psycho-physiological development [87,88]. Modest increases in greenness were associated with statistically significant increases in birth weight [89]. Similar results had also been reported by other scholars [90–92]. A cohort study found that pregnant women living further away from city parks are associated with an increased risk of preterm birth and younger gestational age at birth [93,94].

Further studies have examined the relationship between the percentage of greenspace in people's living environment and morbidity. For example, the annual prevalence rate of a wide range of diseases (e.g., diseases of the cardiovascular, musculoskeletal, mental, respiratory, neurological, and digestive systems) were lower in environments with more greenspace in a 1 km radius of home [95]. Significant associations have also been shown to exist between the use of greenspace and reduced risk of cardiovascular disease [96]. Overall, the greenest neighborhoods have been found to have the lowest risk for poor mental health, and a reduced risk of cardiovascular disease has been found in neighborhoods with >15% greenspace availability [97]. Patients with coronary heart disease were found to exhibit improved cardiac function while walking in a park as opposed to walking along a busy urban street.[98] Finally, a protective association between variability of neighborhood greenness and coronary heart disease or stroke has been reported. Specifically, the odds of hospitalization and self-reported heart disease or stroke were lower among participants with highly variable greenness around their home address, compared to those in neighborhoods with low variability in greenness [99].

Concerning morbidity, it has been reported that greenspace help prevents Type 2 diabetes. As greenspace has been shown to promote physical activity and reduce obesity, it is plausible that it may also contribute to the prevention of Type 2 diabetes by encouraging a healthier lifestyle. The risk of Type 2 diabetes was found to be significantly lower for Australian residents who live in greener neighborhoods (>40%) compares to the one whose neighborhoods with less greenspace (0-20%) [100]. Similar results have been reported in the United Kingdom [101] and Germany[102],[103].

2.2.5. Improved general health and reduced mortality

Residential greenness, quality of greenspace, and subjective residential proximity to greenspaces have been associated with better general health [104,105]; putative mechanisms have included improved mental health, social support, and physical activity[51,70,49,106].

A wide variety of studies from across the globe have now reported that exposure to urban greenspace is linked to reduced mortality [107,108]. The five-year survival rate of older adults in Tokyo was higher when having access to more walking space, parks, and tree-lined streets [109]. Higher survival rates after ischemic stroke were associated with residential proximity to greenspace [110]. More greenness in a residential area was associated with a lower risk of stroke mortality in northwest Florida [111], lower all-cause mortality in England [112], lower cardiovascular mortality in Florida [113], and lower sudden unexpected death in North Carolina [114]. A longitudinal cohort study of approximately 575,000 adults in Canada found that increased residential greenspace within 500m buffer was associated with long-term reduction in mortality, including the mortality of non-accident, ischemic heart disease, stroke, and non-malignant respiratory disease [115]. A study from Spain showed that perceived surrounding greenness was associated with lower mortality risk during heat waves [116]. All these significant associations were found at the individual level and neighborhood spatial scales.

When zooming out to cities as the unit of analysis, this association seems to disappear. In a cross-sectional study, land use data of 49 US cities were utilized to quantify greenspace coverage, and no association was found between greenspace coverage and mortality from either heart disease, diabetes, lung cancer, or automobile accidents [117]. Also, with the 50 largest cities in England as the unit of analysis, no significant difference in risk of death has been found between the greenest and the least green cities [118].

2.3. Independent variables: the measures of greenspace

Among studies exploring the relationship between greenspace and health, a variety of greenspace indicators has been used. Measurements include greenspace availability, (e.g., greenness/percentage of greenspace, street tree density/greenery, park size, proximity, and accessibility, etc.), greenspace quality (e.g., aesthetics, maintenance, etc.), and greenspace usage (e.g., visits determined either by questionnaire, interview or by mobility tracking using a GPS-based system). To date, studies have varied widely with respect to the operationalization of such indicators, from ground-based perceptual assessments to satellite-based algorithmic outputs. As such, more research is needed to clearly understand the nature of the greenspace attributes that contribute to specific health outcomes [119].

2.3.1. Greenness

Greenness is typically defined as the amount of live, green vegetation present in an area. To assess greenness, some studies have used high-resolution aerial images processed using remote sensing algorithms and derived indicators such as the Normalized Difference Vegetation Index (NDVI). Others have calculated the percentage of greenspace within a defined area based on land cover or land use data. Land cover has also been derived using satellite imagery to quantify how much of a region is covered by vegetation. Such a metric potentially shows whether the landscape is used for residential, recreation, or other purposes. When calculating the percentage of greenspace, a calculating boundary must be defined. Some studies used census tract, county, the city as boundaries. Others used buffered boundaries with different radius of a residential location or a centroid of postal areas. The radius considered greenspace's reachable for residents. Frequently used buffer radius in the literature including100m, 250m, 500m, 1km, quarter mile, and half-mile

Studies have linked the NDVI measured more greenness with a wide range of health outcomes. Such as lower Body Mass Index in children and youth [120], lower mortality caused by various diseases [115], lower likelihood of low birth weight [121], better mental health [29], increased walking [122,123], higher likelihood of achieving moderate to high levels of physical activity [124], stronger perceived social support and better subjective general health [125,106].

A higher percentage of greenspace associated with better general health [104], lower mortality rates [105], lower socioeconomic disparities in mortality [112], better mental health [39,27,28,16], more physical activity [124,126], higher life satisfaction [27], etc. Also, greater variability in greenness has a protective effect on coronary heart disease or stroke in residents [99].

2.3.2. Street trees, tree cover/canopy density

The canopy form of urban trees (spreading, rounded and conical) had been tested and a positive emotional response to trees was found with spreading shapes and denser canopies compared to other forms [127]. A positive linear association was found among male participants between tree canopy density and objectively measured stress [128], as well as self-reported stress reduction [129]. The tree canopy was found to have a positive effect on social capital [130]. Higher density of street trees was associated with higher neighborhood satisfaction [131], higher odds of walking [122], and less obesity [132].

2.3.3. Accessibility

Accessibility is the quality of being able to be reached or entered. To measure the accessibility of greenspace, scholars often use the proximity or distance of individuals and households to greenspace, whether routes are available, and whether a greenspace is open to the public. A shorter distance to attractive open spaces (typically parks) was associated with recreational walking [133]. The proximity and accessibility to a larger size of greenspace near home were associated with the maintenance of walking [73]. Forests with different accessibility levels (path versus interrupted path) were compared and higher accessibility associated with higher pleasure [134]. The number of locked schools, which are inaccessible during weekends was associated with a significantly higher body mass index of young adolescent girls [135]. Better access to the green area are also related to narrower socioeconomic inequality in mental well-being [136].

2.3.4. Quality

Different studies tend to use different measures to quantify the quality of greenspace and there is no universal agreement on what aspects of greenspace qualities should be included. Grahn and Stigsdotter identified eight perceived sensory dimensions of urban parks/open spaces [137]. They found people, in general, prefer the dimension Serene, followed by Space, Nature, Rich in Species, Refuge, Culture, Prospect, and Social. Refuge and Nature are most strongly negatively correlated with stress. Relaxation and recreation characters of greenspace are an important factor in improving mental well-being [138]. The quality, of neighborhood open spaces, is more relevant to mental health than quantity [139]. Access to attractive, large public open spaces was associated with higher levels of walking [140]. A review of qualitative studies reported that safety, aesthetics, amenities, maintenance, and proximity could encourage park use and physical activity [141]. Accessibility, maintenance, the absence of litter, and safety were associated with residents' general health and such effects were independent of the quantity of greenspace [142].

2.3.5. Count and size

The number of neighborhood parks associated with residents' physical activity, which is true for both adults and adolescents [143,124,144]. The presence of nearby trees and grass which are visible from apartment buildings has been linked to lower levels of aggression and mental fatigue in residents, compared to those who only have barren vistas [25]. Perceptions of the presence of greenspace were significantly associated with a higher likelihood of recreational walking maintenance [73].

The size of greenspace is also important for achieving health benefits. The options for activity space provides may be more relevant for physical activity, as larger parks could potentially offer more activity options, one large park may be more preferred than several smaller parks [133]. There is a substantial increase in estimated time in physical activity for youth who lived near large parks [65]. Adults with larger attractive open spaces near home were more likely to walk 150 minutes or more in a week [133]. The area of the largest greenspace within 1600m buffer is associated with maintaining recreational walking [73].

2.4. Moderating variables: demographic factors and health outcomes of contact with nature

The health outcomes of contact with nature differentiate among subpopulations. Demographic factors such as age, gender, race, and socioeconomic status are all moderating these associations.

2.4.1. Gender

Women and men appear to differ in the degree to which health benefits are a function of exposure to nature, but the results are variable. Some studies found the impact of greenspace was higher in males than in females, while other studies found the opposite or no difference. Males experienced less state anger and stress when art posters including nature paintings were present in an office environment, but no significant influence on females [145]. A negative association was reported between increasing greenspace and cardiovascular disease as well as respiratory disease mortality rates for men, but not for women [146]. The percentage of greenspace was associated with better mental health among men but not among women; for men, the benefit of more greenspace emerged in early to mid-adulthood; for older women, those with a moderate availability of greenspace had better mental health [147]. A study in workplaces found that access to workplace greenery only significantly associates with the level of stress in males [148]. Also, the measured stress via skin conductance and salivary cortisol level is not associated with tree cover density among women; for men, there is a dose-response curve [128]. Access to the natural environment decreases the likelihood of reporting insufficient sleep, particularly among men [81].

Conversely, greenspace was found to correlate with cortisol levels in women, but not in men [40]. There was a greater benefit from exposure to natural settings relative to urban settings on stress and such effect was more significant for females than for males [41]. Moved to places that have more 'serene' greenspace associated with a decreased risk of changing to mental illness for women, not for men [149]. Better cognitive aging depended on more park provision in childhood and adulthood for females and less strong in males [150].

2.4.2. Age

The benefits of contact with nature have been found among various age groups, including in-utero development, children, youth, adults, and older adults. Better access to greenspace during pregnancy shows a beneficial effect on in-utero development, particularly, an increased birth weight [86,89,91,92]. Children with attention deficits concentrate better after a walk in the park [151–153]. Greenness surrounding a home, school, as well as during commuting associated with cognitive development in primary schoolchildren [30]. Duration of children playing in greenspace was inversely associated with mental health, emotional symptoms, and peer relationship problems [154]. Green areas around homes were found to reduce atopic sensitization in children [155]. Public urban greenspaces play an important role for children and youths in making contacts and friends across cultures, and therefore, promote social inclusion [50].

Neighborhood greenspace amount was more strongly associated with self-report health symptoms in senior citizens and housewives, compare to the general population [156]. The protective role of greenspaces in sleep deficiency is stronger for people aged 65 and older, compared to younger adults [81]. Greenspaces are beneficial for physical activity, morbidity, mortality/survival, perceived general health, and in individuals aged 60 years or older [157]. The presence and use of greenspaces also appear to promote social ties and a sense of community among older adults living in inner-city neighborhoods [158].

2.4.3. Deprived and minority population

Less formally educated people gain more benefits from greenspace in living environments, compare to people with a higher level of formal education [104,156]. A significant greenspace and health association was found in urban and low-income rural areas [105]. Residents who were exposed to greener environments had a lower level of health inequality related to income deprivation [112]. A study confirmed the association between greenspace and mortality [115], but only amongst the most socioeconomically deprived groups [66]. Socioeconomic inequality in mental health was 40% narrower among participants reporting good access to greenspace, compared to residents with poorer access [136].

There is a difference between ethnic groups in terms of the perception and use of greenspace. Surrounding greenness during pregnancy is associated with babies' birth weight in a white British population but not for those of Pakistani origin [91]. Many minorities ethnic groups also suffer socioeconomic deprivation, comparatively poor health, and poorer access to greenspace. A study in the United Kingdom reported that the quality, accessibility, and use of urban greenspace was associated only with general health for African Caribbean, Bangladeshi, Pakistani, and other BME groups, who were also those with the poorest health (Roe et al., 2016).

2.5. Mediating variables: the pathways linking urban greenspace to improved health

Multiple pathways, both direct and indirect, have been proposed for the observed linkage between greenspace and health outcomes. The potential mechanisms include improving psychological restoration, immune system function, social relationships, physical activity, and reducing noise pollution, air pollution, and heat island effects.

The psychological restoration function of contact with nature has long been recognized. Viewing greenspace, compared to artifact-dominated environments, yields psychological restoration effects. The natural element can be shown via photos, videos, or letting participants present in greenspace.

The immune system may benefit directly from relaxation provided by natural elements, or via contact with certain physical, chemical, or microorganisms matters in the greenspace. Visiting a forest instead of a city increases human natural killer activity and the expression of anti-cancer proteins [159]. City children with the highest exposure to specific allergens and bacteria in greenspace during their first year were least likely to have recurrent wheeze and allergic sensitization [160]. One of the major components of the beneficial effect of greenspace is the requirement for microbial input from the environment to drive immunoregulation [161]. Another study suggested enhanced immune function could be a central pathway between greenspace and health [162].

Greenspace has been shown to play an important role in fostering social interactions. The presence of parks, forests, and other green areas near home is important for children and youths in making friends [50]. The amount of greenspace surrounding the home is a predictor of residents' social capital [51,52]. The quality of streetscape greenery, which was assessed with five items: variation, maintenance, orderly arrangement, the absence of litter, and general impression, was found to be more strongly associated with perceived social cohesion than the quantity of streetscape greenery [49]. Physical activity is also one potential mediating factor that doing physical activity in green environments could achieve better health outcomes compared to doing the same activities in urban settings.

Vegetation has long been seen as means to reduce noise pollution [163]. . Vegetation belts of 1.5 – 3 m width and a similar height range showed significant reductions in traffic noise pollution [164]. The presence of landscape plants influences the perceived noise reduction and moderate or buffer the negative effects of traffic noise [165,166]. Trees, shrubs, herbs, and grass can improve air quality/reduce air pollution in urban areas providing benefits for public health [102,111,167]. Higher greenness exposure is significantly associating with lower insulin resistance in adolescents which might attribute to the reduced air pollution from higher greenness regions [102]. An increase in greenness decreased the relative risk of attention-deficit/hyperactivity disorder that might be mediated by PM_{10} and NO_2 [168]. Air pollution might also influence the association between greenness level and mouth and throat cancer and non-melanoma skin cancer [169]. Greenspace's water cleansing' abilities can help prevent the gastrointestinal disease from recreational use of infectious or toxic water [170]. An area with more green cover in cities also shows a cooling effect, which can be used as means to cope with the urban heat island effect [171–175] as well as to reduce the exposure to excessive heat, that associates with increased morbidity and mortality [176,177].

3. EFFECTS OF GREENSPACE MORPHOLOGY ON MORTALITY AT THE NEIGHBORHOOD LEVEL: A CROSS-SECTIONAL ECOLOGICAL STUDY[1]

3.1. Introduction

All-cause mortality and the leading causes of death [178,179] continue to command the attention of clinicians, epidemiologists, as well as city and urban researchers globally. The association between the greenspace and mortality risk has been identified by studies conducted in the United States, United Kingdom, Canada, Netherland, France, Rome, Australia, China, Korea, and Japan [109,112,115,180–186]. Studies in these fields, however, focus mainly on the effects of greenness per se. Few investigate greenspace morphology-related metrics in predicting mortality. While it is necessary to explore these relationships at the neighborhood level to reveal how human and nature interacts in cities, it is also critical that the morphological factors studied allow professionals to develop practical solutions. Landscape and city planning specialists strive to create healthy and sustainable urban environments, relying heavily on spatial maps to model land use alternatives.

We aimed to investigate the relations between the shape and distribution of urban greenspace and mortality. Our specific research objectives were fourfold. First, to identify if any characteristics of greenspace morphology in residential areas are associated with mortality risk. Second, to ascertain how strong the associations are if they

[1] This chapter is a slightly modified version of Wang, H., & Tassinary, L. G. (2019). Effects of greenspace morphology on mortality at the neighbourhood level: a cross-sectional ecological study. *The Lancet Planetary Health*, *3*(11), e460-e468. and has been reproduced here with the permission of the copyright holder.

exist. Third, to examine whether the effect of greenspace morphology on mortality is independent of greenness level. Finally, to ascertain whether the association varies as a function of age and education level.

3.2. Research in Context

3.2.1. Evidence before this study

We searched via Scopus and Google Scholar for studies of associations between mortality and exposure to natural environments. We used the terms “greenspace”, “green”, “nature”, “natural environment”, “park”, and “mortality” in English. We included peer-reviewed studies published up to June 7th, 2019, regardless of the location of the study. We also examined the bibliographies of relevant articles and published reviews. We identified 35 journal articles that looked at associations with mortality. Greenspace is reported to be significantly associated with the deaths of all-cause, suicide, heat-related, respiratory, cardiovascular, cerebrovascular, circulatory diseases, as well as neonatal and infant mortality. Twenty-seven of the 35 studies used the amount of green area (greenness) in measuring greenspace. Two also measured accessibility and one counted the number of greenspaces. Another study measured the number of visits, one assessed the presence of green elements, and one measured the perceived lack of greenspace. Only two studies considered green structures and reported that fragmentation and size of the largest patch were associated with the deaths from cardiovascular and respiratory disease. These metrics, however, were calculated based on very low-resolution land cover data with 50 x 50 m cell size. In addition, the sample sizes were small (48 districts), and the studies were limited to highly mixed-used and compact Asian urban areas which differ significantly from western cities. A review of the evidence of greenspace and health concluded that there is a need for evidence on the effects of configuration and connectivity of greenspace on health outcomes.

3.2.2. Added-value of this study

The amount, fragmentation, connectivity, aggregation, and shape of greenspace were found to moderate several leading causes of death. As such, the overall greenness index widely used in greenspace and health studies, while predictive, can be improved significantly through the addition of local shape metrics. We calculated landscape metrics based on 1 x 1m high-resolution data, which was rarely used in earlier studies. This is the first greenspace and mortality study on western cities that examines greenspace morphology explicitly.

3.2.3. The implication of all the available evidence

We provide evidence that brings us closer to understanding the mechanisms underlying the protective effects of greenspace on mortality. These findings have notable practical and policy implications concerning the optimal spatial arrangement of greenspace at the neighborhood level.

3.3. Methods

3.3.1. Study design

This cross-sectional study employed an ecological research design. The 381 census tracts in Philadelphia were chosen as the spatial units because they are the most granular statistical units to afford access to cause-specific mortality data. Twelve census tracts were excluded due to an absence of population. We, therefore, assessed 369 census tracts and selected causes of death that the prior literature had suggested should be negatively associated with exposure to greenspace.

3.3.2. Data

The raw data consisted of 1 m x 1 m high-resolution land cover for 2008 from the Pennsylvania Spatial Data Access (PASDA) database. The database uses seven categories, within which tree canopy and grass/shrub cover, two relevant land cover types that capture vegetation cover on the land surface, were selected and served as our operationalization of greenspace. Two datasets were prepared for calculating landscape metrics. The first one included all designated greenspace as they can be visually exposing to, which benefits health [18,187]. The second, however, removed greenspace with areas less than 83.6 square meters (900 square feet) based on a custom python-GIS script. This threshold was determined based on the minimum size of the pocket parks in Philadelphia for recreational purposes [188] and the size of greenspace necessary to achieve a positive microclimate effect [189,190]. Also, greenspace larger than 83.6 square meters are typically designed or designated areas, as opposed to smaller size neighborhood parcels, thus providing a connection with landscape and urban planning practice. As our geographical units, we created a half-mile Euclidean buffer, which is about ten minutes walking distance, for each census tract to ensure that residents would have a genuine likelihood of real-world exposure to the greenspaces in appurtenant tracts. We calculated six landscape metrics (Table 3.1) using GIS 10.5 and Fragstats 4.2 [191] programs to measure the area, fragmentation, connectivity, aggregation, and shape of greenspace for each buffered census tract. The 369 census tracts have a mean population of 4149 and a mean physical area of 84 hectares.

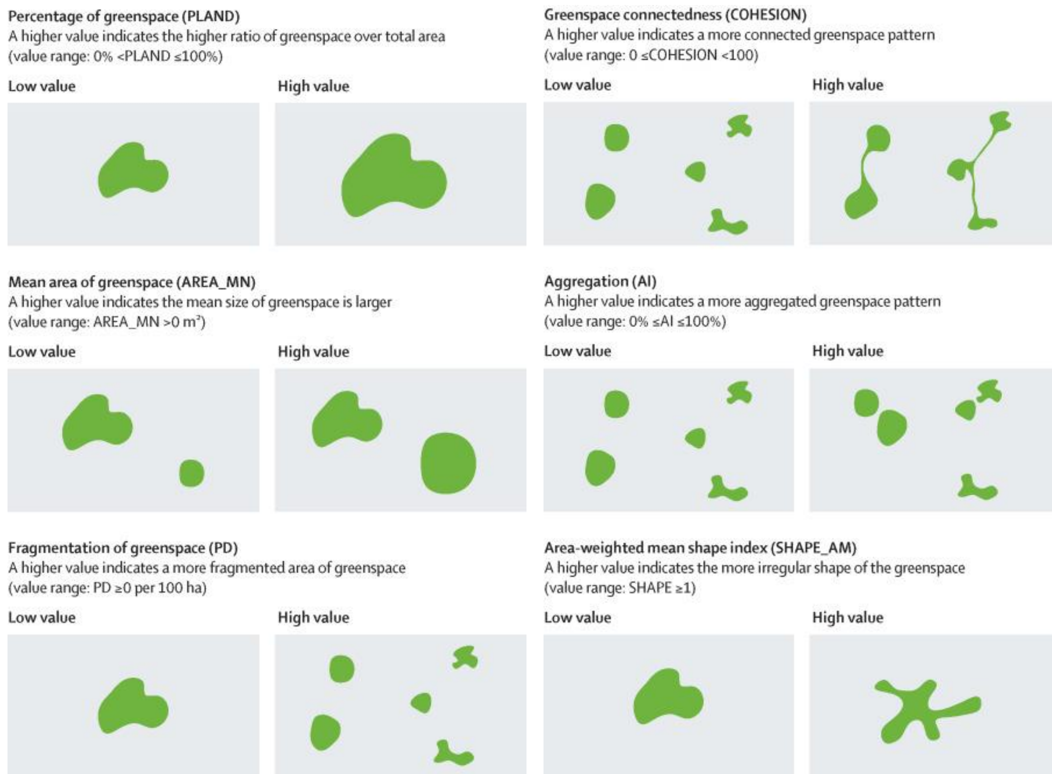

Figure 3.1 Landscape metrics selected in reflecting greenspace spatial distribution

We obtained the most recent census tract level mortality data in 2006 from the Department of Public Health of Philadelphia. The city of Philadelphia stopped publishing census tract level data after 2006 to avoid the risk of identification. In addition to all-cause mortality, we purposefully selected three causes of death that were plausibly related to greenspace. We examined deaths from heart diseases because some important associated risk factors (physical inactivity and psychosocial stress) are moderated by exposure to nature-dominated environments. We examined chronic lower respiratory diseases morality, as greenspace provides ecological benefits including reduced air pollution, and exposure to air pollutants was found to be significantly associated with respiratory causes of death [192,193]. We also selected neoplasm-based mortality as visits to forested areas have been shown to affect the immune system; specifically to increase both human natural killer (NK) activity and the number of NK cells as well as promote expression of anti-cancer proteins [194].

Geographic, demographic, and socioeconomic variables have been considered and controlled. Data on covariates were acquired from the 2005-2009 American Community Survey from the United States Census Bureau. Social-demographic factors which have been reported in the literature to influence mortality (i.e., age, gender, race, education, and income) were controlled in the model. We also controlled population density to adjust its impact on mortality. As census tracts have varying areas, the land area was also included in the model.

3.3.3. Statistical analysis

We employed a negative binomial regression model to examine the associations between each landscape metric and all-cause and cause-specific mortality. Poisson models were considered and rejected because of over-dispersion. The occurrence of spatial autocorrelation for each of the studied mortality rates was assessed using Moran's I index and found to be absent or negligible. The land area of each census tract, the percentage of people who are 65 years old and over, the percentage of female, the percentage of white residents, median household income, the percentage of holders of a bachelors' degree or higher, and population density were controlled in the model using the population of each census tract as an offset variable. Except for the model exploring the relationship between the percentage of greenspace (PLAND) and mortality, all the other models controlled for the total area of greenspace. We used Stata (Ver. 15) for these analyses.

The models that included each of the landscape metrics and mortality were examined one by one due to significant evidence of multicollinearity between landscape metrics. The variance inflation factor (VIF) of each model was tested and found to be less than 4 in all cases, signifying minimal evidence of multicollinearity. To examine how the landscape distribution as a whole influenced mortality, a principal component analysis was conducted, and only one component was identified with an eigenvalue greater than one. The relationship between this principal component and all-cause mortality by age and education was also examined.

3.4. Results

A total of 14700 deaths were recorded in Philadelphia in 2006. Landscape metrics and mortality across census tracts constituted the independent and dependent variables, respectively. Descriptive statistics and detailed regression coefficients are provided in the appendix.

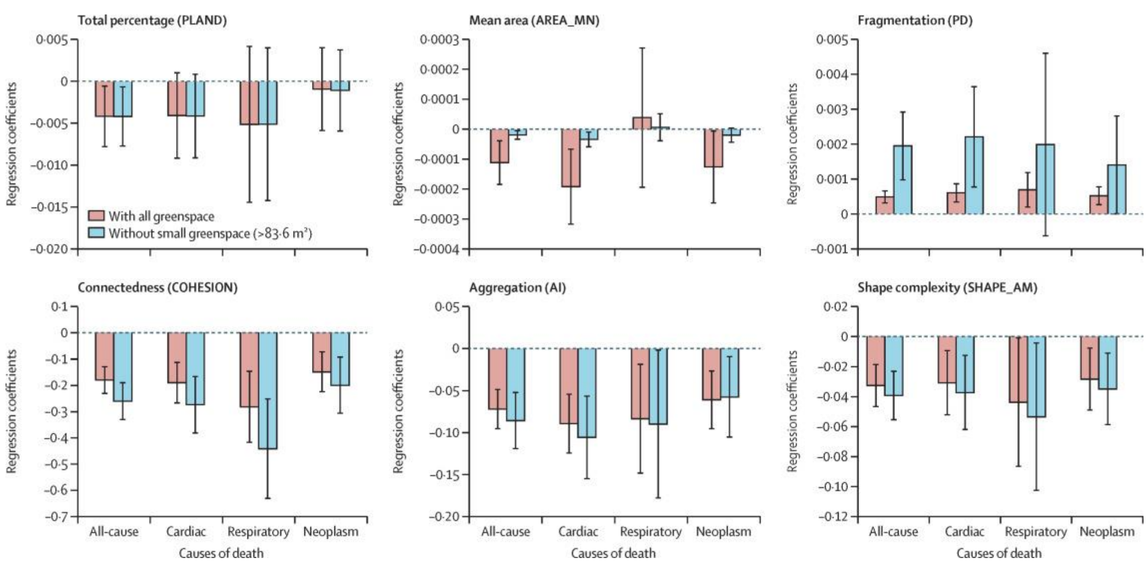

Figure 3.2 Regression Coefficients of each landscape spatial metric predicting mortality. A.C.: all-cause mortality; HD: heart diseases mortality; LRD: chronic lower respiratory diseases mortality; Neo.: neoplasms mortality. Error bars indicate 95% CIs.

Figure 3.2 illustrates the relationships between each landscape metric and each mortality, controlling for geographic, demographic, and social-economic factors. In general, a clear and consistent protective effect of greenspace spatial pattern on mortality was observed.

The mean area of greenspace was negatively associated with all-cause mortality and cardiac deaths. An increase in AREA_MN of 1 m^2, considering only green areas larger than 83.6 m^2, would contribute to a 0.002% (95% CI 0.001–0.003) decrease in all-cause mortality. When including all small (⩽83.6 m^2) greenspaces, an expansion by 1 m^2 yielded a 0.011% (95% CI 0.004 – 0.018) fall in all-cause mortality. An even stronger relationship was reported between the mean area of greenspace and death by heart disease. Growth in AREA_MN by 1 m^2 yielded a 0.003% (95% CI 0.001–0.006) reduction in cardiac deaths when only considering green areas larger than 83.6 m^2, and a 0.019% (95% CI 0.007–0.032) decrease was seen when considering all green areas. A similar increase in AREA_MN led to a decrease of 0.013% (95% CI 0.001–0.025) in neoplasm-based mortality risk for all greenspaces. The first principal component was the only one with an eigenvalue larger than one (4.84) and explained 81% of the total variance. The absolute value of each landscape metric's factor loading ranged from 0.37 to 0.44, revealing a relatively uniform contribution to the component. The association between the greenspace component and the area-weighted all-cause mortality rate was found to be moderated by age and education. When the percentage of older adults increases, the association becomes more pronounced. It is also moderated negatively by the proportion of residents holding a college degree.

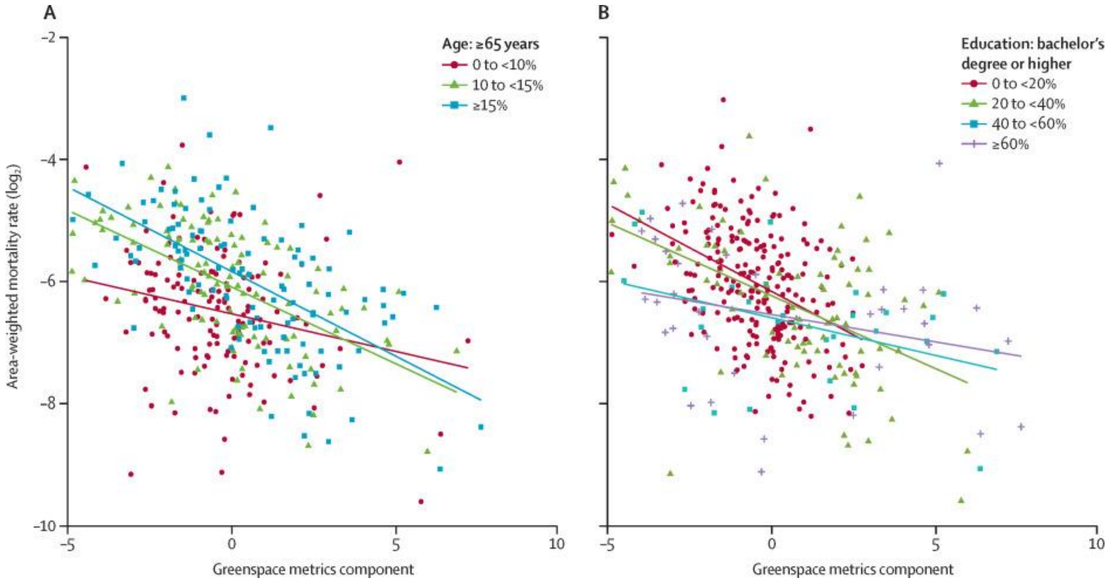

Figure 3.3 Association between greenspace metrics component and mortality by age (A) and education (B).

3.5. Discussion

Our findings show that residents who live in urban areas characterized by a larger total percentage of greenspace and larger mean area of greenspace seem to have a reduced risk of all-cause mortality, and lower fragmentation of greenspace, better connectivity and aggregation of greenspace distribution, and increased complexity of greenspace shape also seem to decrease the risk of deaths from heart disease, chronic lower respiratory disease, and neoplasms. These significant relations were identified by analysis of high-resolution landcover data, established (yet generally unfamiliar) landscape metrics, and valid health outcomes from reliable data sources.

The negative association we found between the total percentage of greenspace area (PLAND) and all-cause mortality is consistent with former studies. We did not observe any relationship between PLAND and the mortality of heart disease, lower respiratory disease, or neoplasms. This was expected as studies have long been reporting conflicting results when using PLAND in capturing “greenness” in predicting health. Some studies have found significant inverse associations while others have reported null findings [108,112,195,196]. Our study revealed that measures of greenspace morphology predict mortality independent of greenness, as all statistical models in our analysis simultaneously controlled the total area of greenspace and the total land area of a census tract. We believe these underlying greenspace morphology characteristics, which failed to be captured in former studies, might help to reconcile those conflicting findings previously reported.

We also noted that the mean size of greenspaces (AREA_MN) had an inverse association with three of the studied mortality risks. We believe the mean size of greenspaces is an important indicator, as it reflected the type of greenspace to which residents may be exposed. High values indicate residents may have an increased likelihood of exposure to large parks; low values suggesting that residents could encounter small green land parcels mainly near their residence which may not afford diverse types of health-related activities. When considering all greenspaces, with the AREA_MN increase, there is a decrease in neoplasm mortality risk. The underlying mechanism may involve an increased human natural killer activity level, intracellular anti-cancer proteins, an optimized microbial input to our immune systems gained by contact with nature [197]. or even a preferred microclimate [198]. Residents have to be present inside greenspaces to gain beneficial phytoncides and microbial inputs and the greenspace size must be large enough to provide necessary facilities and to afford desired activities, as residents have been observed to be less likely to walk into and stay in small green land parcels as compared to larger parks [133,199,200]. In addition, AREA_MN indexes a greenspace's ecosystem service (ex: biodiversity) and therefore may also affect the presence of beneficial phytoncides and microbes. Our results revealed, however, that the association between AREA_MN and neoplasms mortality disappeared when greenspaces less than 83.6 square meters were removed from the analysis. This suggests that the current standard minimum size for a "pocket park" may be sufficient to support biodiversity- and microclimate-mediated health.

Patch density (PD) measures the fragmentation level of greenspace. Our study revealed a modest but positive association with mortality. When controlling for the total area of greenspace, increasing PD captures the increasing number and decreasing size of greenspaces. This will result in a more fragmented distribution, which we found to be associated with higher mortality risk. When considered in conjunction with the effect of mean size, it supports the idea that a small number of larger parks performs better in reducing mortality risk than large numbers of small green parcels in living environments. The potential mechanisms may at least partially involve the positive psychophysiological affordances of larger size greenspaces, and the improved ecosystem afforded by less fragmented greenspace.

The relationship we found between greenspace fragmentation regardless of the size of each green region and chronic lower respiratory disease mortality is consistent with a former study conducted in Taiwan, which reported fragmentation of green structures increased primary and secondary air pollutants and leads to a higher mortality risk [201]. This association in our study disappeared after removing smaller greenspace. This again suggests that the greenspace's ecosystem function, such as reducing air pollution, may require a certain size to be effective. Future studies will be needed to unravel such relationships.

It is important to note that our study counted small green parcels down to one square meter as greenspace and found a positive relationship of greenspace density with all the studied mortality. Prior studies reported negative associations between the number of greenspaces and health [118]. It is necessary to differentiate the concept of density used in this study and the number of greenspaces frequently used in former studies. PD is a fragmentation spatial distribution measure. The metric itself has no relationship with the total area of greenspace or percentage of greenspace. In our study, when holding the total green area constant, the mean size of greenspace decreases with density increases. While the number of greenspaces is a discrete, continuous measure, it is highly correlated with measures of total greenspace area, especially in studies based on land use data that considered a much larger size of green area as greenspace. More connected and aggregated distributed greenspace was inversely associated with all the studied mortality. Such distributions may increase the likelihood of residents' exposure to or usage of natural elements in cities. A more continuous greenspace may also afford residents the opportunity for physical activity such as walking, biking, jogging, etc. The results suggest that linking existed parks through greenways or adding new connected parks may be fiscally accessible strategies for promoting health. Finally, with respect to urban design, the results revealed that the complexity of the park shape was positively associated with a lower risk of the studied mortality. This might be due to the increased number of access points provided by complex shape greenspace. Further study is necessary for identifying the mechanism in operation.

Most experts who have examined the relationships between greenspace and health have concluded that the associations are complex. Our evidence suggests that there are at least two potential mechanisms that deserve further scrutiny. First, the morphology of greenspace may influence the likelihood of residents encountering natural elements in their daily life. Greenspace exposures have been previous linked to improved cognition, reduced stress, decrease hospital stays, as well as increased physical activity, less obesity, higher quality sleep, and improved cardiovascular health [30,79,80,99,106]. Influencing the likelihood of routine encounters may play a role in these associations. For instance, unevenly distributed greenspaces may aggravate the health inequity in cities, via unequal accessibility to greenspace resources [112], and may be linked to racial discrimination as well as policies that privilege economic growth over equity [202–204]. Alternatively, linear-shaped parks could increase their accessibility to more residents than parks with compact shapes [205]. And large parks may provide additional benefits when compared to small parks by providing alternative recreational options [65,206]. The second potential pathway is via the influence of landscape morphology on the ecological function of greenspace [207]. A number of studies have found that for a fixed amount of greenspace, the size, fragmentation, and aggregation influences urban microclimate, including land surface temperature and air pollution [198,208–211]. And these latter variables are found to be associated with respiratory disease [212] and morality risk [213–215]. We think future studies should examine whether these mediating effects exist to better understand human-nature interaction in cities.

The association of greenspace morphology with all-cause mortality was moderated by the percentage of older adults and residents with a bachelor's degree or higher in census tracts. This effect is consistent with findings of former studies that the elderly and less educated people in cities seem to benefit more from contact with nature [81,104,156]. These people are also the population who tend to have limited access to greenspace. As the morphology of greenspace plays a role in these associations, the optimal spatial arrangement of greenspace might be used as strategies to promote health equity.

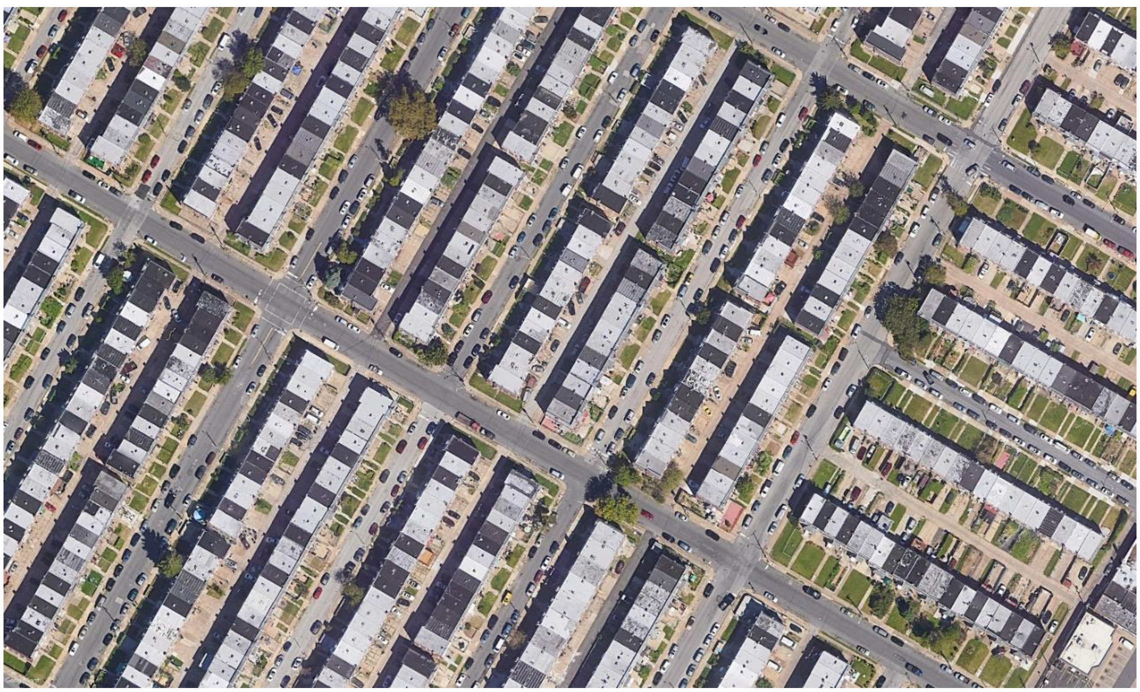

Figure 3.4 Area with small size, unconnected, fragmented, and uniform shape greenspace in Philadelphia (Map data: Google, 2018)

The aerial images in Figures 3.4, 3.5, and 3.6 illustrate what the statistical analysis revealed. The images in Figures 3.5 and 3.6 illustrate what the results suggest are more health-beneficial greenspaces compared to the image in Figure 3.4. The image in Figure 3.5's greenspace likely affords the residents a wide range of accessible activities, albeit at the expense of larger front yards. Figure 3.6 illustrates a single-family home area with the large connected green cover which is thought to support more sustainable and healthy ecosystems. The image in Figure 3.4 illustrates a single-family home area with an equivalent total amount of greenspace to that shown in Figure 3.5, yet the area appears barren, there are no greenspace areas large enough to support diverse common activities, and ecosystems are uncoupled due to their small size and fragmented distribution. Overall, these findings support public health and urban planning practice by demonstrating the health consequences of failing to consider the shape and connectedness of urban greenspace.

Figure 3.5 Area with large size and integrated greenspace in Philadelphia (Map data: Google, 2018)

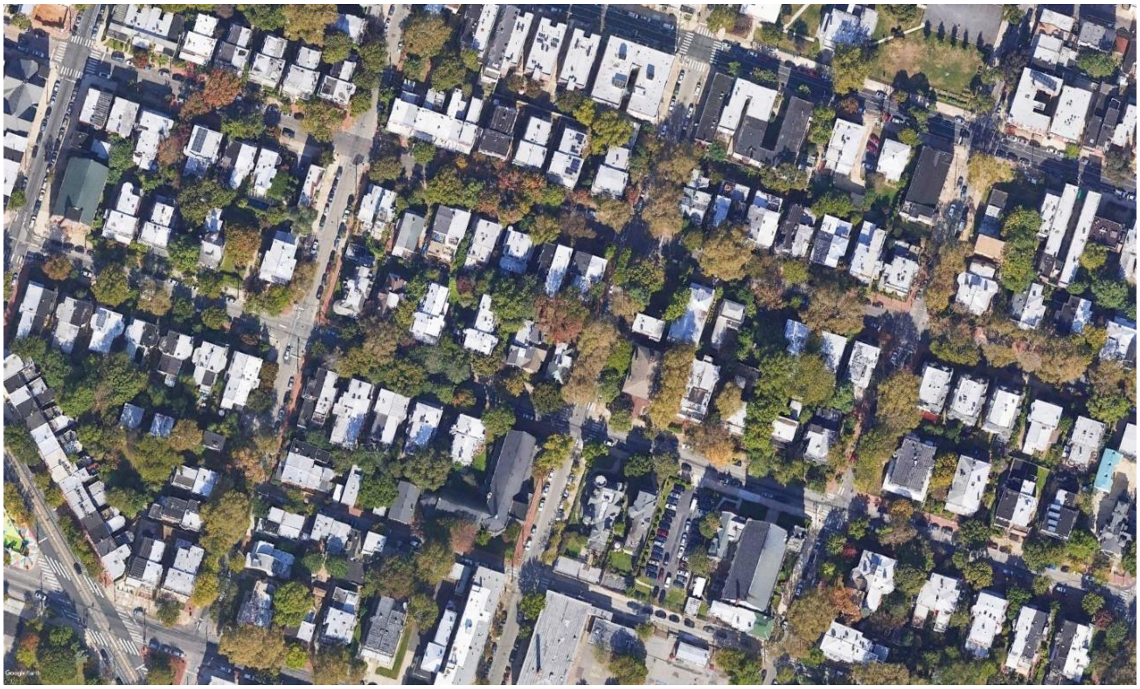

Figure 3.6 Area with connected and complex shape greenspace in Philadelphia (Map data: Google, 2018)

The study did have several limitations, however. First, although an ecological approach conducted at the population level provides data at precisely the right resolution for urban planners making decisions at the neighborhood level, the level of analysis is still too coarse-grained to discern the multiple mechanisms involved. We do not have a direct measure of greenspace exposure, and therefore do not know if residents visited or indeed spent time in any of these greenspaces. To do this would require additional studies conducted at the individual level. Second, the study site was limited to Philadelphia, a large city located in the northeast of the United States. We considered all the land with vegetation cover in the city without controlling their type, quality, or features. Finally, this study is cross-sectional, which is limited to the mortality data in 2006. We had no means of knowing the extent to which residents were interacting with the various distribution of green environments throughout their lifetime. Migration before death might also place residents into distinctly different environments.

Further studies are needed to more fully understand the complex relationships between greenspace morphology and human health. Mortality risk has been predicted by greenspace morphology in our study. If the underlying mechanisms, which are mediating the likelihood of exposure to greenspace and ecological services are operative, additional health outcomes should vary in predictable ways as a function of greenspace morphology. Effects of the spatial distribution of varying types, qualities, features of greenspace can be explored to further clarify what type of green area is the most effective operational surface for practice. For example, future research should examine the effect of park greenspace and non-park greenspace morphology on health outcomes, with the intent to test recreational opportunities as one of the pathways, as parks are one of the important accessible venues for public recreation. The analytical unit of our study is the small geographical scale census tract. This may help in explaining why previous studies which used greenness alone in predicting mortality did not find a significant result at a larger city scale [37,38]. Studies conducted at a range of scales, therefore, will be necessary to fully explicate the role of greenspace morphology.

3.6. Conclusion

In conclusion, nearly all the extant studies at the community level that have investigated the effects of natural environments on human health have focused primarily on the amount of “nature”. We now have substantial evidence that the shape or form of such greenspace plays a significant role in this association. The effect of greenspace morphology on mortality is significant, modest, independent of greenness level, and varies by age and education. This study provides hints as to what greenspace spatial layout is most salubrious and also provides insights into the reason for conflicting results in the literature. We believe that particular spatial morphologies increase the likelihood of routine exposure to greenspace and thereby positively affect health outcomes. If these findings are replicated, such relationships will be of importance to city designers and planners as they seek to create healthier living environments through the intentional layout of the cityscape.

4. GREENSPACE MORPHOLOGY PREDICTS MORBIDITY OF CHRONIC DISEASES AND UNHEALTHY BEHAVIOR

4.1. Introduction

Chronic diseases are the leading causes of death and disability worldwide [216]. In the United States, six in ten adults have a chronic disease, and four in ten adults have two or more. Such diseases are leading drivers of the nation's $3.3 trillion in annual health care costs [217]. In addition, gas emissions from the health care sector rose in the last decade and now account for over 8% of total US emissions [218]. Sustainable strategies to promote public health that protects and preserve the natural environment are no longer improvident. Accessible greenspace has been shown repeatedly to be associated with a variety of health outcomes and offers a promising sustainable way to promote human health. Exposure to greenspace is associated with improved mental health [219–221], reduced heart disease risk [222], higher survival rates after ischemic stroke [110], decreased occurrence of diabetes [223], increased physical activity [224], and lower odds of chronic obstructive pulmonary disease (COPD) [225]. Greenspace also directly mitigates climate change and therefore reduces the overwhelmingly negative impact of climate change on public health [226].

The operationalization of greenspace has varied widely yet has typically been "greenness", which quantifies the amount of green [51,227]. Indicators frequently used include the percentage of green coverage [105], normalized difference vegetation index [228], presence and number of parks in neighborhoods [229], and tree canopy density [230]. The putative mechanism proposed for the observed positive health effects has been an increase in the likelihood of residents 'exposure to nature, which has been shown independently to result in better mental health, better self-reported health, increased physical activity, and increases in social cohesion [173,231–233]. In addition, increased greenspace improves the local ecology through reductions in thermal load [173], air pollution [201], and noise, as well as improves psychophysiological health through attention restoration [234], enhanced cardiovascular function, and improved quality of life [235–237]. Despite the mounting evidence of the health benefits of greenspace exposure, the actual quantity of greenspace, both in absolute and relative terms, is unfortunately almost always pre-determined in real-world design practice. Factors such as building density, client preference, flora hardiness, soil conditions, etc., co-determine the green cover ratio, which limits severely most opportunities for policy makers and urban designers to increase the amount of greenspace. What urban planners and landscape designers can do, however, is to propose alternative spatial configurations which meet the pre-established program of requirements [238].

A few studies have reported associations between greenspace spatial morphology and mortality risk [201,239]. Whether the association with greenspace morphology is specific or applies to a broader spectrum of population health outcomes such as morbidity, however, is unknown. And to what degree such effects are independent of various city characters, such as city size and the geographic location remains undetermined. Given greenspace spatial morphology significantly altered the two aforementioned greenspace-health pathways - viz., the likelihood of green exposure and the ecological function [207,240] - we investigate whether such greenspace morphology is associated with the prevalence of chronic diseases and unhealthy behavior. We also examine whether any such associations vary across cities and greenspace conditions.

We use data extracted from 500 Cities: Local Data for Better Health project together with one-meter high-resolution National Agriculture Imagery Program (NAIP) satellite images [241]. Five major city areas were selected based on a strategy of deliberate sampling for heterogeneity [242]. Census tract-level prevalence of poor mental health, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and physical inactivity data were used, as they have been linked previously to exposure to nature [51,95,225,243,244]. Unlike most previous studies that only captured greenness, the current study calculated landscape spatial pattern metrics using green land cover data classified from aerial imagery, measuring the verdancy, fragmentation, connectedness, aggregation, and shape of greenspace. The metrics selection is for two purposes. One is to examine the specific contribution of each greenspace spatial character on health, over and above the contributions of the greenspace amount. The other is to explore morphology attributes that could be easily adopted by city planners and policymakers in real-world settings.

4.2. Method

4.2.1. Study Area and Morbidity

We examined the associations in five major urban areas[2] in the United States successively. They are New York City, New York; Los Angeles, California; San

[2] The city of Chicago was initially selected and dropped due to an unusually strong spatial autocorrelation of the residuals (Moran's I > 0.5). This often indicates the model may be missing a key independent variable [245]. As we were unable to determine why this happened, we decided it prudent to exclude this metropolitan area from the present analysis.

Antonio, Texas; Seattle, Tacoma, Bellevue, Renton, Kent, Federal Way, and Auburn, Washington; And a cluster of cities in southeast Florida, including Miami, Miami Beach, Miami Gardens, Hialeah, North Bay Village, Pembroke Pines, Hollywood, Plantation, Fort Lauderdale, Pompano Beach, Coral Springs, Boca Raton, Boynton Beach, West Palm Beach, Davie, Deerfield Beach, Lauderhill, Miramar, and Sunrise (Appendix Figure B-2 to Figure B-6). Because the selected cities in Washington and Florida are neighboring cities with few census tracts, we combined their data into two single datasets for relatively larger sample sizes for statistical analysis, hereinafter referred to as Greater Seattle and Greater Miami. These five urban areas were purposefully selected for capturing maximum heterogeneity to examine the external validity/generalizability of such associations. Census tracts were chosen as the study units, given they are the most granular statistical units to afford access to the prevalence of diseases and unhealthy behaviors data. Tracts with an absence of population, mismatched geographic boundaries with social-economic data, and dominated by mountains with limited residential areas were excluded. Therefore, 3975 census tracts (mean population, 4292 people; mean physical area, 544 ha), which consists of a population of 17 million people, were assessed (Appendix Figure S2).

We obtained the 2015, 2016 estimates of the annual crude prevalence of mental health not good, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and no leisure-time physical activity data for census tracts from the 500 Cities project provided by the Centers for Disease Control and Prevention (CDC). These estimates were computed from the Behavioral Risk Factor Surveillance System data, wherein the survey respondents are 18 years or older. Poor mental health was defined as reported 14 or more days during the past 30 days that mental health was not good. No leisure-time physical activity was recorded when "no" was the response to the following question: "During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?". Coronary heart disease, stroke, chronic obstructive pulmonary disease, and diabetes were defined as ever diagnosed by a health professional that a responder has such a disease.

4.2.2. Quantification of Greenspace Morphology

1 m x 1 m high-resolution land cover data for New York city was obtained from the city's Department of Parks and Recreation. For the rest four urban areas, greenspace land cover maps were classified from remote sensed aerial imagery given the unavailability of such data products. High resolution (0.6 m x 0.6 m) satellite images were obtained from the National Agriculture Imagery Program (NAIP) offered by the United States Geological Survey (USGS). NAIP imagery is orthophotography which is geometrically corrected with less than 10% cloud cover. These images represent the earth's surface status during the leaves-on season from 2015 to 2016. The downloaded dozens to hundreds of imagery pieces for each city area were mosaiced into one single image. The water surface was removed from the mosaiced image to avoid its impact on image classification and improve the accuracy of morphology metrics calculation. Water bodies shapefile data used were either obtained from publicly available data or classified from aerial imagery (Table S3). Mosaic and clip of these images were processed via ArcGIS 10.5 version. Normalized difference vegetation index (NDVI) maps were generated based on these pre-processed city images via ENVI 5.3. An NDVI threshold

value for each urban area was determined based on visual identification of green and non-green space compared based on aerial imagery (Table S4). A pixel value greater or equal to the threshold was classified as greenspace, and one less than the threshold value was classified as non-greenspace. Grassland, shrubs, meadows, and forests were all considered greenspace under this criterion. The effectiveness of image classification was verified by the following accuracy assessment. 600 points were generated for each city area using a stratified random method in ArcGIS. Ground truth information was identified by using aerial images and 3D Google Street View and a confusion matrix of ground truth and classified land cover type of these points was constructed. The overall accuracies ranging from 97% to 98%, with a kappa coefficient ranging from 0.93 to 0.96 across cities (Table S4). Then these green cover maps were resampled into 1 m x 1 m resolution to match the resolution of New York city data, as well as increase the efficiency of morphology metrics calculation.

For each census tract, we created a 0·5-mile Euclidean buffer, which is about 10 min walking distance, to ensure that residents would have a genuine likelihood of real-world exposure to the greenspaces in appurtenant tracts. Individual buffered tract size green cover maps were clipped out from the classified city size green cover data. These were achieved by a custom Python–Geographical Information System (GIS) script. We calculated six landscape metrics for each tract measuring the area, fragmentation, connectivity, aggregation, and shape of greenspace via Fragstats version 4.2. They are the percentage of greenspace (PLAND), mean area of greenspace (AREA_MN), patch density (PD), greenspace connectedness (COHESION), aggregation of the greenspace pattern (AI), and complexity of greenspace shape (SHAPE_AM) for each buffered census tract. The detailed formula for calculating these metrics can be accessed through the software product's user document [246].

4.2.3. Statistical Analyses

We used eigenvector spatial filtering spatial regression models with globally standardized rook contiguity spatial matrix to analyze associations between each morphology metric and the prevalence of diseases and unhealthy behavior. Linear multiple regression models were considered but rejected due to the evidence of spatial autocorrelation of model residuals which were tested by using Moran's I index. We adjusted models for potential confounding by other known risk factors identified by previous studies. In the model, we controlled geographic, social-economic, and demographic factors. These are the total area of greenspace, population, median household income, percentage of people aged 65 years and older, the percentage of females, the percentage of white residents, and population density. The percentage of bachelor's degrees or higher holders and the land area of census tracts were considered but removed because they are highly correlated (correlation coefficients $r > 0.7$) with education and total greenspace area, respectively. Because of significant evidence of collinear relationships between landscape metrics, models of each landscape metric-health pairs were examined separately for each city. The variance inflation factor of each model was tested and found to be less than 4 in all cases, signifying minimal evidence of multicollinearity. Data for covariates were acquired from the 2011–16 American Community Survey from the US Census Bureau. We used Stata version 15 for the multiple regression analyses, ArcGIS for the Moran's I calculation, and ESF Tool [247] for the eigenvector spatial filtering models.

4.3. Results

The prevalence of the studied diseases and unhealthy behavior of 3975 census tracts from five major city areas across the United States were examined. The sample sizes of Los Angeles, San Antonio, Greater Miami, Greater Seattle, and New York City are 941, 257, 498, 243, and 2036, respectively. Greenspace spatial metrics constituted the independent variable. Characteristics of the urban landscape morphology and population are provided in Appendix Table S1.

Figure 1 shows the associations between individual landscape morphology metrics and specific prevalence of health indicators of every single city, controlling for demographic, socioeconomic, and geographical factors. In general, there is a consistent protective effect of greenspace spatial patterns on the studied prevalence. The significance and strength of such effects varied across cities and health outcomes. Greenspace morphology metrics also captured significant variation in local health outcomes where the amount of greenspace failed to do so. Regression coefficients of all the tested associations between greenspace metrics and morbidity across cities are provided in Appendix Table S2.

The six greenspace morphology metrics predict all the studied health outcomes significantly in Los Angeles. For example, a one-unit increase in the aggregation index would be expected to decrease the prevalence of poor mental health, CHD, stroke, diabetes, physical inactivity, and COPD by 0.20%, 0.08%, 0.09%, 0.24%, 0.40%, and 0.13%, respectively. Such a health effect is comparable to an increase in annual median household income of about $6000 in the neighborhoods (see Appendix B for calculation detail). Greater Seattle reported the least number of significant correlations with only the fragmentation index predicting health outcomes. A one-unit increase in the fragmentation index resulted in a 0.0002%, 0.0006%, and 0.0008% increase in the prevalence of stroke, diabetes, and physical inactivity. With a mean fragmentation index of 2040.14 in Greater Seattle, reducing the index by 200 can be easily achieved in real-world design practice, resulting in a predicted health effect comparable to an increase in annual median household income of $5600 (Appendix B). Additionally, the fragmentation index was the most consistent predictor, showing moderate but positive associations with the studied morbidities across all cities. The shape, cohesion, and aggregation indices were associated significantly with health outcomes in San Antonio, while the mean area metric and greenspace percentage did not emerge as significant predictors. A one-unit increase in shape complexity index in San Antonio is associated with decreasing prevalence of CHD, stroke, diabetes, and physical inactivity by 0.03%, 0.02%, 0.06%, and 0.11%, respectively.

In New York City, poor mental health and stroke prevalence were associated with all but one of the studied morphology metrics. Specifically, a one-unit increase in greenspace percentage, mean area, shape complexity, cohesion, aggregation, and decrease in fragmentation, the prevalence of stroke is expected to decrease by 0.005%, 0.0002%, 0.01%, 0.05%, 0.03%, and 0.0003%, respectively. Several health outcomes were predicted by all the studied greenspace morphology metrics in Miami. For example, the diabetes morbidity is expected to decrease 0.05%, 0.002%, 0.04%, 0.37%, 0.25%, and 0.001%, with one unit increase in percentage, mean area, shape complexity, cohesion, aggregation, and decrease in fragmentation, respectively.

Figure 4.1 Regression coefficients of each landscape spatial metric predicting the prevalence of diseases and unhealthy behavior. Error bars indicate 95% confidence intervals.

4.4. Discussion

To our knowledge, this is the first epidemiological study to report the impact of greenspace morphology on the prevalence of chronic diseases and unhealthy behavior at the population level while controlling for spatial autocorrelation. Such an analysis represents a statistical sophistication that has yet to be widely adopted among studies on greenspace and health relationships. Neighborhood greenspace morphology, including the mean size, connectedness, cohesion, aggregation, and shape were associated with the prevalence of poor mental health, heart disease, stroke, diabetes, COPD, and physical inactivity. Such effect varies across health outcomes and cities, suggesting that design interventions need to be tailored somewhat to the local conditions.

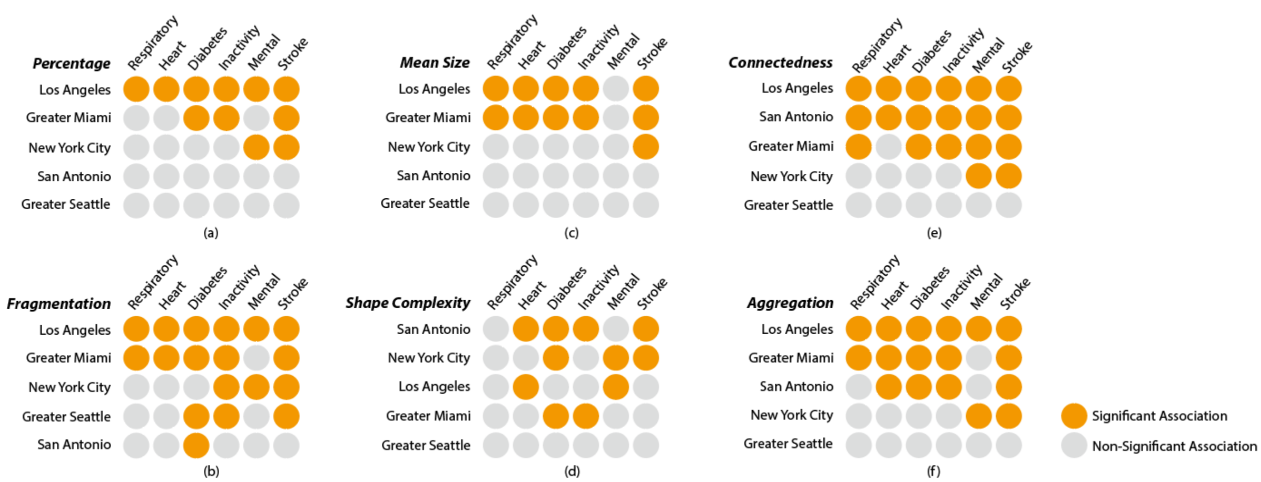

Figure 4.2 Varying effects of greenspace structure on morbidity across cities and morbidity types. The dots showing the significance of the associations between greenspace structure metrics and health across cities. The orange dot illustrates it is statistically significant at 0.05 level, and the grey dot shows non-significant relationships at 0.05 level.

We observed that an increase in greenness (PLAND) was associated with reduced mortality risk in some of the cities. It was significantly correlated with all the studied morbidity risks in Los Angeles, predicted stroke, diabetes, and physical inactivity morbidity in Greater Miami, and was associated with poor mental health and stroke morbidity in New York City. No significant relationships, however, were found in San Antonio and Greater Seattle (Figure 2a), both with relatively high existing greenspace coverages (min=24% and 11%). It is tempting to speculate that such a result derives from a relationship characterized by diminishing returns. This is consistent with a former study from Ireland which reported residents living in areas with the lowest and highest shares of greenspace both to have the highest probability of being obese [84]. More study is needed to ascertain whether such associations persist in high green coverage regions. Fifty-two percent of U.S. households describe their neighborhood as suburban according to the 2017 American Housing Survey yet few studies to date have been conducted in these areas.

Increased morbidity risk is associated with greater greenspace fragmentation. This means that a census tract with fragmented green land parcels is not as beneficial as one with more cohesive parks, even if the two tracts have equal amounts of greenspace. The PD index is consistently positively associated with morbidity risk across the five studied cities but varies with respect to specific health outcomes (Figure 2b). It is significantly correlated with all of the six studied morbidities in Los Angeles, census tracts within which showed the highest mean fragmentation level (mean=5123.516). In stark contrast, San Antonio had the lowest level of mean fragmentation (mean=883.995) and the variance in this metric was only predictive of diabetes. The data suggest the greatest health benefits derived from altered greenspace morphologies may be most likely to be found in urban areas with highly fragmented greenspaces.

We found some indications for a decreased morbidity risk associated with increasing mean size (AREA_MN) of greenspace in census tracts (Figure 2c); i.e., census tracts with a few large parks appear to outweigh tracts with a large number of small green land parcels with respect to reducing morbidity risk. Such effects are strongest in Los Angeles which reported the smallest average greenspace size (mean=52.862). No significant associations were found in San Antonio which recorded the largest average greenspace size (mean=668.191). An optimal range of greenspace size might exist that balances the benefits of daily contacts with nature versus the advantages of proximity to city facilities, such as grocery stores and healthcare systems. Further study is necessary to ascertain if such a range exists.

Shape complexity is significantly associated with a lower morbidity risk across cities, except for Greater Seattle (Figure 2d). The shape index is defined as the perimeter of a greenspace divided by the minimum perimeter of a greenspace possible for a maximally compact patch (a square or almost square). We adopted an area-weighted shape index such that larger greenspaces were weighted more than smaller ones to correct for the impact of a substantial number of small green land parcels. As a result, for two parks with equal area, the one with a more complex shape is expected to afford greater health benefits. A more complex shaped park offers more boundary area and access points and therefore is potentially able to serve a greater population compared to a compact shaped one. Studies at the individual level are necessary to uncover the underlying mechanisms behind such relationships.

Significant associations were noted between a decreased morbidity risk and increasing connectivity (COHESION) as well as aggregation (AI) of greenspace in census tracts (Figures 2e & 2f), except Greater Seattle. The connectedness index is associated with all the studied morbidity risks in Los Angeles and San Antonio. It predicts some of the studied health outcomes in Greater Miami and New York City. The connectedness index yields the largest number of significant associations compare to other studied morphology metrics in our analysis. It suggests that parks linked via "green belts" and parks clustering together are more beneficial than parks that are isolated.

Greater Seattle stands out in our analysis in that morbidity risk was affected solely by fragmentation. This metropolitan area also had both the smallest number of census tracks and a notably lower prevalence of the studied diseases and unhealthy behaviors compared to other studied cities (Appendix Table S1). There is no evidence to suggest that the paucity of effects was due to a lack of statistical power and so, as mentioned above, it may simply be a case of diminishing returns. More studies are required to assess the differential impact of greenspace morphology as a function of the overall “wellness” of the population.

4.4.1. Available Evidence and Potential Underlying Mechanisms

We are not aware of previous studies on the impact of greenspace morphology on actual morbidity. It is not currently possible, therefore, to compare our findings with others. Our findings, however, are in line with several previous observations. Residential greenness has been associated with a lower risk of self-report mental health, diabetes, cardiovascular, musculoskeletal, neurological disorders morbidity [51,95,243,244]. Compare to non-park-users, park users showed a significantly lower prevalence of diabetes mellitus [96]. Greenspace spatial structure was associated with respiratory mortality in Taiwan [201]. Our previous analysis in the city of Philadelphia PA showed a protective impact of greenspace morphology on the leading causes of death [239].

Behavioral mechanisms might link greenspace spatial morphology to a decreased risk of morbidity. More connected, aggregated, cohesive distributed, complex-shaped large parks might increase the likelihood, specifically, the duration, frequency, and intensity of residents ’exposure to nature. Connected and aggregated greenspace distribution might be able to afford a “continuous” natural experience compared to scattered and fragmented park layouts at the neighborhood level. This provides preferable environments for “linear” type physical activities, such as walking, biking, and jogging, activities that promote physical and mental health [58]. This continuous exposure might also contribute to a longer time-spend in green that helps in achieving health benefits, given the likelihood of reporting good health became significantly greater with natural contact ≥ 120 mins [233]. A more complex shaped or linear-shaped greenspace is spatially more extensive, and therefore may be able to serve a larger region/greater population compared to a compact-shaped park with an equal total area; it may also provide more entry points via a longer green and non-green boundary area. Large greenspaces might more likely to be selected and visited for recreational purposes compare to small green land parcels; it also affords diverse health-related activity types, including exercise and social interaction, and the opportunity to stay longer [133].

Ecological services offered by greenspace might also explain the underlying pathway between greenspace morphology and health. Increasing greenspace size, aggregation, and decreasing fragmentation are associated with less air pollution and cooler temperature [198,211]. Air pollution is known to contribute to the risk of respiratory and cardiovascular diseases, reproductive and central nervous system dysfunctions, diabetes, and cancer [248–250]. The ambient temperature is associated with acute myocardial infarction, hospitalization, cardiovascular, respiratory, and all-cause morbidity and mortality [251]. Large park soils had significantly greater overall microbiota diversity than small residential green land parcels [252], therefore, might provide sufficient microbial input which drives immunoregulation [197], as well as promote gut health and mental health [253]. Connected, aggregated, cohesive, complex-shaped, and increase in the border of greenspace significantly linked with higher biodiversity level [254], which related to better well-being [255], associated with increased microbial diversity that resulting in lower inflammatory disorder risk [256].

4.4.2. Implications for Practitioners and Policymakers

Local policies focusing on specific communities should be developed, although the general protective effects are observed in studied urban areas. We found the selected greenspace morphology metrics significantly associated with almost all the studied health outcomes in Los Angeles, while only the fragmentation index predicted some of the outcomes in Seattle. Given that city-specific variation exists, it is necessary to examine greenspace morphology conditions before implementing greenspace interventions for health-promoting projects. Policies should focus on the most effective greenspace morphology characters for a specific local site.

Linking current greenspace via green belts along streets is expected to be a feasible way to increase size, connectedness, aggregation, and reduce fragmentation of greenspace distribution, which associates with the studied morbidity. Former studies reported higher greenness associates with better health outcomes, while our study revealed a positive association between greenspace fragmentation and health. This indicates the health benefits of adding a large number of very small discrete greenspaces, such as isolated small lawn land parcels in front of each building are likely limited. If fragmented but spatial closed lawn parcels already exist, planting trees near the gap areas is a practical way to help in spatially linking them together given that trees provide a large canopy and occupy a limited land surface which minimally impacts other functions on the ground. If possible, considering the shape of greenspace to create more entry points and border areas which might increase the accessibility of a park to a greater population. A detailed illustration of favored and unfavored greenspace morphology for health-promoting purposes is provided in Appendix Figure S1.

Cautions should be paid to the operating scale. We conducted this study on census tracts which is at a neighborhood level. Therefore, the greenspace morphology is thought to be effective in community-size areas. Further studies are necessary to ascertain the effect on a larger scale, such as the city scale, which might be different from the findings in this study.

4.4.3. Strengths and Limitations of Study

This study was based on repeated tests of greenspace morphology and morbidity relationships across cities to quantify different aspects of greenspace in varying city conditions. We assessed exposure to nature by characterizing the community greenspace morphology via landscape spatial pattern metrics on very high-resolution (1m x 1m) satellite and land cover data. This enables us to account for small green land parcels down to one square meter, and more importantly, extend the greenspace measurements from a quantity focus to the structure and form perspective. We applied eigenvector filter regression model [257] to lessen the impact of residual spatial autocorrelations.

Our study also faced some limitations. The ecological approach at the population level, although precisely the right resolution for providing evidence for practice purposes, is still too coarse-grained to discern possible underlying mechanisms. We had no direct measure of exposure to greenspace. We do not know, therefore, whether citizens visited or indeed spent time in any of these greenspaces. Individual-level studies would be necessary to ascertain the impact of greenspace structure and form on real-world exposure to natural elements. Our green assessment focused on all vegetated land cover, overlooking the varying type, accessibility, and quality of greenspace, and is therefore ill-suited to answer questions such as whether the spatial structure of formal parks yields fungible health effects compare to residential yards. Investigating the effects of these attributes of greenspace presents opportunities for future studies. We focused on urban greenspace, which may overlook other relevant urban factors that contribute to health, such as food accessibility. Further study with additional data would help in identifying the factors.

4.5. Conclusions

Less fragmented, larger mean size, more complex-shaped, more connected, and aggregated greenspaces were associated with a reduced morbidity risk of poor mental health, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and physical inactivity at the neighborhood level in major metropolitan areas in the United States. The effect is significant, modest, and independent of the absolute amount of green area. Our observed beneficial associations were generally consistent yet vary across cities and health outcomes, indicating local level health-promoting greenspace programs. We believe that spatial morphologies might influence the likelihood, specifically, the frequency, intensity, and duration of residents ’routine exposure to greenspace, as well as the ecological system service of greenspace, and thereby, affect health outcomes. The study provides a direct connection to landscape planning and design practice by offering spatial information beyond the amount of green. This helps the formation of evidence-based greenspace design to sustainably promote public health.

5. A TOOL FOR ASSESSING THE HEALTH EFFECTS OF GREENSPACE INTERVENTIONS

5.1. Introduction

Chronic diseases are the leading causes of death and disability worldwide.[216] In the United States, six in ten adults have a chronic disease, and four in ten adults have two or more. Chronic diseases are also leading drivers of the nation's $3.3 trillion in annual health care costs.[217] Greenspace has long been known associate with a variety of health outcomes.[51,219,220,225,227,232,258,259] The reduction of several chronic diseases and associated symptoms, including poor mental health, physical inactivity, cardiovascular disease, stroke, diabetes, and COPD has been associated with contact with nature in cities.[260–264] Using urban greenspace planning and design to promote public health is thought to be an economic and practical remedy, given it is a one-time investment that yields growing long-term benefits. The understanding of how to design and deliver effective greenspace interventions, therefore, is critical to ensuring that greenspace delivers positive health outcomes. A health effect simulation tool would be very valuable in landscape and urban planning research and practice to estimate the health outcomes before the implementation of a greenspace design project.

There would appear to be no such tool currently available, despite the availability of a wide variety of landscape performance simulation software designed to estimate the influence of greenspace on stormwater retention, urban heat islands, air quality, and wind.[265–268] In practice, health impact assessment is often based on questionnaires answered by investigators, which examine whether a design project addressed particular aspects that related to health subjectively and qualitatively.[269] The real monitoring of the health effects (e.g., the number of people doing physical activities in the space) can only be quantified after the implementation of a landscape design project. One possible reason is that studies exploring greenspace and health relationships often capture greenspace by using the amount measures, such as greenness, tree cover, number of parks, etc., and concluded that the more the better with varying strength.[270] However, in landscape and urban planning practice, the amount of greenspace area is often pre-determined by other factors, such as built density, opinion of clients, and land suitability for plants. Landscape planners often have limited opportunities to increase the green cover ratio, which makes a tool that is based exclusively on greenspace amount not useful. Instead, designers work on maps dealing with land use alternatives and spatial arrangement of greenspace at the population level. Given landscape planning and design is the operational surface of greenspace interventions in cities, it is necessary to include greenspace spatial morphology for such a health evaluation tool to be practically more meaningful.

A few recent studies have reported the significant association between greenspace morphology and health, which makes the inclusion of morphology into a health evaluation tool possible. The reduced mortality risk of pneumonia and chronic lower respiratory diseases as well as cardiovascular diseases is associated with minimizing greenspace fragmentation and increasing the largest patch percentage.[271,272] Large greenspace patches that are well interspersed with the built environment are also associated with lower levels of poor health.[273] Census tracts with more connected, aggregated, coherent, and complex shape greenspaces had a lower risk of all-cause and cause-specific mortality as well as a variety of chronic disease morbidity.[239] Other studies reported that greenspace morphology affects land surface temperature [274] and air pollution [275], which are the risk factors of cardiovascular disease including stroke, poor mental health, and respiratory disease.[193,276–278]

Herein, we take the first step to establish a tool for assessing the health outcome of urban greenspace design by using a random forests decision tree model accompanied by a spatial Gaussian process model with the aim of improving prediction accuracy. It is based on our former study on greenspace morphology and morbidity across five metropolitan areas in the United States in terms of data for training and testing the model. The tool can automatically extract greenspace cover in a landscape and city design master plan and estimate health outcomes. It relies on openly available computational tools and can enable comparability across design plans.

5.2. Methods

For the present analysis, we reused the data from the previous chapter and utilized a random forests decision tree model in conjunction with a spatial Gaussian process model. Due to the consistent spatial autocorrelations observed within each city area, adopting a spatial Gaussian process model to predict the residual of the tree model should control for the spatial variation and thereby improve the prediction accuracy. Centroid point coordination of each census tract was obtained from its boundary shapefile in ArcGIS 10.5 version and used as the location information to the spatial model. A separate random forest decision tree model and specific spatial Gaussian model were developed for each of the health outcomes. 70% of the five urban areas data were randomly selected for training the model, and the rest 30% were used for testing the performance. The optimal value of the *mtry* parameter was searched with respect to out-of-bag error each time we ran the model. The *ntree* parameter was set to 1500, which is large enough to stabilize the error in our analysis[3]. We repeated each model 50 times by randomly bootstrap the data to better understand model performance.

We adjusted models for potential confounding by other known risk factors identified by previous studies. Except for the six greenspace morphology metrics, we also included geographic, social-economic, and demographic factors. They are census tract area, the total area of greenspace, population, median household income, percentage of people aged 65 years and older, the percentage of females, the percentage of white residents, percentage of the population with a bachelor's degree or higher, and population density. Data for covariates and census tract boundary shapefiles were acquired from the 2011–16 American Community Survey and the US Census Bureau. A landscape design plan map was used to mock a prediction case. We used *randomForest* [279] and *GeoR* [280] packages in the R v3.6.3 version for fitting the models. The programming codes are provided in Appendix Codes.

[3] In random forest decision tree model, *mtry* is the number of variables randomly sampled as candidates at each split, and *ntree* is number of trees to grow.

To quantify the greenspace morphology of a landscape design master plan, we extracted the area on a plan map that shows a green color based on RGB intensity color value. This extracted map was then used to calculate landscape spatial pattern metrics. The mean value of the social-demographic and geographic variables in the training data, together with these calculated landscape metrics were used for predicting health outcomes. All of these steps were conducted in R programming language in 3.6.3 version, given it has readily available image processing packages *raster* and *rgdal* [281,282], as well as landscape pattern calculation package *landscapemetrics* [283].

5.3. Results

In 2015 and 2016, the prevalence of the studied diseases and unhealthy behavior of 3975 census tracts from five major city areas across the United States were examined. The average poor mental health, heart diseases, stroke, diabetes, COPD, and physical inactivity morbidity are 12.867%, 5.497%, 3.109%, 11.040% 5.756%, and 28.560% respectively. Detailed characteristics of the urban landscape morphology and population are provided in Appendix table1.

We learned from the test dataset, the model predicts 92% (R^2 = 0.929, 95%CI, 0.928-0.930) of the variance in poor mental health morbidity, 81% (R^2 = 0.810, 95%CI, 0.804-0.816) for heart disease morbidity, 80% (R^2 = 0.799, 95%CI, 0.793-0.806) for stroke morbidity, 88% (R^2 = 0.880, 95%CI, 0.877-0.883) for prevalence of diabetes, 81% (R^2 = 0.812, 95%CI, 0.808-0.817) for COPD prevalence, and 93% (R^2 = 0.934, 95%CI, 0.933-0.936) for physical inactivity morbidity. Model accuracy measured by root mean square error is 0.822 (95% CI, 0.816-0.828) for predicting the prevalence of poor mental health, 0.786 (95% CI, 0.762-0.810) for coronary heart diseases, 0.546 (95% CI, 0.530-0.562) for stroke, 1.271 (95% CI, 1.254-1.288) for diabetes, 0.793 (95% CI, 0.780-0.807) for obstructive pulmonary disease, and 2.390 (95% CI, 2.362-2.418) for no leisure-time physical activity.

In the design plan prediction case, Figure 1 shows the real-world community design master plan image and the extracted green cover map. The percentage of greenspace of this design is 22.936%, the mean area of greenspace size is 265.674 square meters, patch density (fragmentation) is 863.313, connectedness index (COHESION) is 98.306, aggregation index (AI) is 92.638, and shape complexity index is 4.117. The predicted prevalence of poor mental health is 12.165%, 5.328% for heart disease morbidity, 2.875% for stroke prevalence, 9.788% for diabetes, 5.780% for COPD, and 32.520% for physical inactivity prevalence.

Figure 5.1 Community design master plan[4] (left) and extracted green cover map (right)

In this study, we combined random forest decision tree models with spatial Gaussian process models, used greenspace morphology metrics as well as social demographic variables across five major urban regions in the US, to develop a tool for evaluating the health effect of community-level greenspace design plans. This is based on previous studies on the relationship between greenspace morphology and health[239]. The tool is developed by using data from publicly available data sources and based on R programming language which is a free software environment for it to be easier adopted and used. As we illustrate, landscape and city planners, as well as policymakers, could

[4] Original image was obtained from: TSW - City of Alpharetta Downtown Master Plan. TSW. Accessed December 8, 2020. https://www.tsw-design.com/portfolio-items/city-of-alpharetta-downtown-master-plan/, and was modified by the author.

easily use a community greenspace design map as the input information to estimate the health outcome before the implementation of the project.

The models reported relatively high R-square values and low root mean square errors, and therefore could be effective for estimating the six studied morbidities in metropolitan urban areas. More studies are necessary to ascertain greenspace-health associations in small cities and suburban areas before using the tool to estimate the health outcome in these regions. Little evidence exists in the literature regarding the relationships in such areas, although 52 percent of U.S. households describe their neighborhood as suburban according to the 2017 American Housing Survey. With a much higher percentage of greenspace coverage in suburbs compare to urban areas, whether the health effects from greenspace fade or change is beyond exploration.

The results also tell us that the model could predict well at the census tract level. It is not recommended to apply the tool to a much larger spatial scale, such as city or regional level, as well as a much smaller individual scale, given very limited knowledge is available regarding the greenspace-health relationship across spatial scales. One former study at the city level reported a null relationship between the amount of greenspace and mortality[117], which illustrates applying the tool to a larger scale might lead to a false conclusion. More studies conducted at a range of scales will be necessary to fully explicate these associations and ascertain whether such relationships vary with changing scales. The health effect of greenspace morphology at the city scale particularly worth further exploration, because the larger the spatial scale, the potentially more important the greenspace spatial distribution for providing equitable recreational resources for citizens.

The prediction accuracy reflected by the root mean square error values tell us that the models predict stroke prevalence the best follows by heart disease, lung disease, poor mental health, diabetes, and finally the physical inactivity. Therefore, if the purpose is to estimate the health condition of a region with data scarcity, the absolute number of the predicted prevalence of stroke has the least error and should be referenced. While the proportion of variation (R-square) explained by the model varies across the studied morbidity. Physical inactivity and poor mental health reported the highest R-square value, follows by diabetes, stroke, COPD, and heart disease morbidity. Thus, if the purpose is for health effect comparison, the predicted physical inactivity prevalence values are the most comparable and should be referenced.

In real-world practice, the tool can be used for estimating the health conditions for regions with delayed updates on health data for programs focused on promoting public health through greenspace design. We believe the most valuable application of this tool is for comparing the health effect of greenspace change instead of getting the absolute value of morbidity, given it is often unrealistic to quantify the social-demographic information before a greenspace design project is built and city conditions vary across geographic locations. The tool could be most useful in four scenarios. First, to estimate the change of health outcomes before and after adopting a city greenspace design plan prior to its construction. Second, to compare the health outcomes of different landscape design plans of the same site. Third, landscape and city designers could use this tool to experiment with what-if scenarios during the planning and design work. Fourth, to compare the short-term and long-term health outcomes of greenspace, as trees grow, and the expected benefits would increase through time.

It should be noted that the extraction of the green cover map from a design plan is based on an algorithm which calculates the green color reflection by using the red, green, and blue color value on the map. Users must therefore generate a master plan that shows all greenspace areas as color green, and non-greenspace with a different color. Given a real-world spatial scale is needed for calculating greenspace metrics, the map needs to be changed into the right scale by change the number of pixels before inputting it into the model. Detailed instruction on how to do this is provided in Appendix Figure1.

The importance of our work lies in the ability to estimate health outcomes by using a landscape design plan before its implementation and therefore provides opportunities to modify and improve the design plan. Before the development of this tool, the evaluation of the health benefits of a design project needs to be conducted after the construction of a plan and relies on an on-site observational survey. This is the first study that provides such a tool for landscape and urban planners to use and links the previous research findings with the universally used master plan map in design practice.

5.4. Limitations

This study has some limitations. First, due to the limitation of random forest decision tree models to do extrapolation, the prediction accuracy for city conditions outside the range of the training dataset would be low. The model now focusing on major metropolitan areas in the United States, it would be valuable to continuing enriching the model by researching and adding training data from smaller cities and suburban areas to expand the application scope.

Second, a variety of environmental factors affect population health, and the developed tool only considered the greenspace amount and morphology. Future studies could also incorporate other variables shown in the literature to have an impact on health. It could include city facilities, such as road network[284], urban sprawl index[285], spatial accessibility to healthcare[286] and healthy food[287]; the climate factors, such as air pollution[288] and temperature[289]; as well as chemical exposures, such as toxic waste[290] and heavy metals[291] in the daily living environment. If the data of these health risk factors are available, it well worth further improve the models to increase the prediction accuracy. Third, given the data used in this study is at the census tract level, the tool can best predict at the community and neighborhood level. However, extending the tool to a city-scale design project may lead to a false conclusion. More research is necessary before the inclusion of larger-scale prediction abilities into the tool.

5.5. Conclusions

Our study takes the first step towards developing a tool to allow practitioners to estimate the health outcomes of a greenspace design plan at the neighborhood level prior to its implementation. The tool would be most valuable if used for comparing the health outcomes of alternative greenspace designs. On one hand, to enlarge the application scope of this tool, our future efforts will focus on incorporating climate change factors, such as heatwaves, extreme weather events, etc. as well as other health outcomes, such as respiratory allergies, heat-related illness and death, and injuries into the model. In such a way, it may help provide guidelines for designing health resilient communities to reduce the impact of climate change at the neighborhood level. On the other hand, we believe it would be valuable to turn this tool into an online interactive version so that it can be easier used by a broader audience.

6. CONCLUSION

This dissertation examined the influence of greenspace morphology on population health as well as developed a tool for assessing the health impact of greenspace interventions. Specifically, we ascertained whether greenspace fragmentation, mean size, shape, connectedness, and cohesion associates with mortality and morbidity risk at the census tract level in the United States. This is done by integrating landscape spatial pattern metrics with public health measures in two cross-sectional observational studies. Base on the second study, which examined the relationship between greenspace morphology on morbidity of chronic diseases, a health effect evaluation tool was established by combining machine learning methods and spatial regression models.

In the first study, we ascertained the association between greenspace morphology and all-cause mortality and cause-specific mortality (related to heart disease, chronic lower respiratory diseases, and neoplasms) in the city of Philadelphia. We found census tracts with more connected, aggregated, coherent, and complex shape greenspaces had a lower mortality risk. The negative association between articulated landscape parcels and all-cause mortality varied with age and education, such that the relationship was stronger for census tracts with a higher percentage of older and less well-educated adults. The results support the idea that environment-based health planning should consider the shape, form, and function of greenspace.

The second study is a generalization of the first one, in that it expanded the scope to include five distinct metropolitan city-regions in the US and examined the associations between greenspace morphology and morbidity risk. It aimed to ascertain whether the greenspace morphology and population health relationships persist across geographic regions as well as hold for other health outcomes except for mortality. To our knowledge, this is the first epidemiological study to report the impact of greenspace morphology on the prevalence of deadliest chronic diseases and unhealthy behavior at the population level. We found neighborhood greenspace morphology, including the mean size, connectedness, cohesion, aggregation, and shape were associated with the prevalence of poor mental health, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and no leisure-time physical activity. We also found such an effect varies across health outcomes and cities that for regions with poor greenspace morphology, the effect is more likely to be significant and strong, indicating the potential to improve the greenspace shape and form in such city areas. The conclusion is generally consistent with the first study.

Based upon the previous two studies, the third study exploited a machine learning model for assessing the health effects of greenspace interventions. Before this study, the health effect of a landscape design project could only be evaluated through empirical post-occupancy evaluation. This is usually done by an on-site survey observing user activities. For example, counting the number of people using the space and the manner in which they used them (related to physical activity types). No evaluation tools are currently available that are able to predict health outcomes at the population level based either on a community greenspace design plan or prior to the construction of the project. A tool was developed by combining random forest decision tree models and spatial gaussian process models. These combined models were implemented into five metropolitan cities in the US at the census tract level. The study examined six health outcomes, including the prevalence of poor mental health, coronary heart disease, stroke, diabetes, chronic obstructive pulmonary disease, and no leisure-time physical activity. The models reported high R-square values (0.783-0.924) and low root mean square errors (0.559-2.591), and therefore are effective for estimating the six studied morbidities in metropolitan urban areas. Given the models could predict morbidity risk based on landscape plans, they are most useful in four scenarios. To estimate the change of health outcomes before and after adopting a city greenspace design plan prior to its construction. To compare the health outcomes of different landscape design plans of the same site. To experiment with what-if scenarios during the planning and design work by landscape and city designers. To compare the short-term and long-term health outcomes of greenspace, as trees grow, and the expected benefits would change through time.

These studies have a few limitations and point out some future research directions. First, all these studies are cross-sectional. Longitudinal studies are necessary to further identify the causal relationships between greenspace morphology and health. Second, the studies were focusing on examining the associations. We do not have a direct measure of the potential mediating factors. To further examine the underlying mechanisms, there are at least two potential mediating factors worth exploration. One is the likelihood of residents exposing to greenspace that is influenced by the morphology. The other is the ecological functions of greenspace which contribute to healthier living environments that are influenced by its morphology. Third, these three studies are all conducted at the population level. Individual-level studies are needed to help ascertain the causal relationship. Fourth, these studies are focusing on metropolitan regions in the United States at the neighborhood level. We are not sure if the association exists for small cities and suburban areas, in other countries, as well as at a larger county or city scale. More studies are necessary to ascertain the relationship under those conditions.

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APPENDIX A

Table A-1 Characteristics of landscape distribution and population in the study area

Variables	Mean	SD	Min	Max
Landscape metrics variables				
PLAND	30.54	13.28	1.58	65.19
AREA_MN	0.23	0.17	0.03	0.99
PD	172.41	64.76	21.29	321.96
COHESION	98.96	0.81	95.99	99.95
AI	95.94	1.16	92.26	98.23
SHAPE_AM	6.26	4.56	1.93	30.17
Geographic variables				
Population density	6390.73	3906.01	1.61	21168.47
Land area	0.84	0.68	0.17	5.65
Demographic variables				
All-cause mortality	39.84	27.06	0	152
Heart diseases mortality	9.95	7.79	0	67
Chronic lower respiratory diseases mortality	1.57	1.69	0	12
Neoplasms mortality	9.34	6.70	0	36
Percentage of people 65 years old and over	13.11	8.42	0	100
Percentage of female	53.40	8.03	0	100
Percentage of white residents	44.54	34.93	0	100
Socioeconomic variables				
Percentage of bachelors' degree or higher	23.31	20.97	0	100
Median household income	40010.79	22859.1	2500	250000

Table A-2 Regression coefficients (95%CI) of models exploring landscape distribution metrics' influence on mortality

Landscape Metrics	All-cause mortality		Heart disease mortality		Chronic lower respiratory disease mortality		Neoplasms mortality	
	Coefficients (95%CI)	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**
PLAND °	**-0.0042*** (-0.0077, -0.0006)	0.021	-0.0041 (-0.0091, 0.0009)	0.11	-0.0051 (-0.0142, 0.0040)	0.27	-0.0011 (-0.0059, 0.0038)	0.67
PLAND	**-0.0042*** (-0.0078, -0.0005)	0.024	-0.0041 (-0.0092, 0.0010)	0.12	-0.0051 (-0.0145, 0.0042)	0.28	-0.0009 (-0.0059, 0.0041)	0.72
AREA_MN °	**-0.1911**** (-0.3340, -0.0482)	0.0088	**-0.3383**** (-0.5848, -0.0918)	0.0071	0.0649 (-0.3869, 0.5166)	0.78	-0.1958 (-0.4312, 0.0396)	0.10
AREA_MN	**-1.1146**** (-1.8433, -0.3860)	0.0027	**-1.9140**** (-3.1654, -0.6625)	0.0027	0.3889 (-1.9355, 2.7133)	0.74	**-1.2574*** (-2.4569, -0.0579)	0.040
PD °	**0.0019***** (0.0010, 0.0029)	0.0001	**0.0022**** (0.0008, 0.0036)	0.0026	0.0020 (-0.0006, 0.0046)	0.14	**0.0014*** (0.0000, 0.0028)	0.050
PD	**0.0005***** (0.0003, 0.0007)	0.0000	**0.0006***** (0.0003, 0.0009)	0.0000	**0.0007**** (0.0002, 0.0012)	0.0061	**0.0005***** (0.0003, 0.0008)	0.0001
COHESION °	**-0.2594***** (-0.3293, -0.1895)	0.0000	**-0.2731***** (-0.3800, -0.1662)	0.0000	**-0.4402***** (-0.6290, -0.2513)	0.0000	**-0.1993***** (-0.3054, -0.0932)	0.00023
COHESION	**-0.1792***** (-0.2299, -0.1285)	0.0000	**-0.1891***** (-0.2660, -0.1122)	0.0000	**-0.2809***** (-0.4157, -0.1461)	0.0000	**-0.1487***** (-0.2237, -0.0737)	0.00010
AI °	**-0.0852***** (-0.1185, -0.0518)	0.0000	**-0.1052***** (-0.1542, -0.0562)	0.0000	**-0.0894*** (-0.1770, -0.0018)	0.045	**-0.0572***** (-0.1048, -0.0096)	0.018
AI	**-0.0715***** (-0.0948, -0.0482)	0.0000	**-0.0888***** (-0.1237, -0.0539)	0.0000	**-0.0830*** (-0.1476, -0.0184)	0.012	**-0.0605**** (-0.0948, -0.0263)	0.00053
SHAPE_AM °	**-0.0391***** (-0.0552, -0.0231)	0.0000	**-0.0372**** (-0.0617, -0.0127)	0.0029	**-0.0533*** (-0.1020, -0.0046)	0.032	**-0.0349**** (-0.0584, -0.0113)	0.0038
SHAPE_AM	**-0.0325***** (-0.0464, -0.0186)	0.0000	**-0.0307**** (-0.0519, -0.0095)	0.0045	**-0.0437*** (-0.0862, -0.0012)	0.044	**-0.0284**** (-0.0488, -0.0079)	0.0065

° Landscape metrics after deleting greenspace less than 83.6 square meters (900 square feet)

*Statistically significant at 0.05 level.

** Statistically significant at 0.01 level.

*** Statistically significant at 0.001 level.

Table A-3 Principal component analysis: eigen values

Component	Eigenvalue	Proportion	Cumulative
Comp 1	4.8461	0. 8077	0.8077
Comp 2	0.6506	0.1084	0.9161
Comp 3	0.2678	0.0446	0.9607
Comp 4	0.1177	0.0196	0.9804
Comp 5	0.0694	0.0116	0.9919
Comp 6	0.0485	0.0081	1.0000

Table A-4 Principal component analysis: Factor loadings

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
PLAND	0.4356	0.1224	0.1619	0. 6144	-0.1436	-0.6091
PD	-0.4219	0.3130	0.1608	0. 6783	0.2170	0.4370
AREA_MN	0.3708	0.6027	-0.5701	-0.0085	-0.2946	0.2957
COHESION	0.4104	-0.4368	0.3226	0.1620	-0.4443	0.5595
AI	0.4166	-0.3487	-0.3868	0.1895	0.7048	0.1501
SHAPE_AM	0.3909	0.4599	0.6076	-0.3165	0.3890	0.1225

Scopus search code

(TITLE (greenspace) OR TITLE (green) OR TITLE (nature) OR TITLE (natural AND environment) OR TITLE (park) AND TITLE (mortality)) AND (EXCLUDE (SUBJAREA , "AGRI ") OR EXCLUDE (SUBJAREA , "BIOC ") OR EXCLUDE (SUBJAREA , "IMMU ") OR EXCLUDE (SUBJAREA , "VETE ") OR EXCLUDE (SUBJAREA , "MATH ") OR EXCLUDE (SUBJAREA , "PHAR ") OR EXCLUDE (SUBJAREA , "ARTS ") OR EXCLUDE (SUBJAREA , "ENGI ") OR EXCLUDE (SUBJAREA , "COMP ") OR EXCLUDE (SUBJAREA , "ECON ") OR EXCLUDE (SUBJAREA , "BUSI ") OR EXCLUDE (SUBJAREA , "CENG ") OR EXCLUDE (SUBJAREA , "CHEM ") OR EXCLUDE (SUBJAREA , "PHYS "))

APPENDIX B

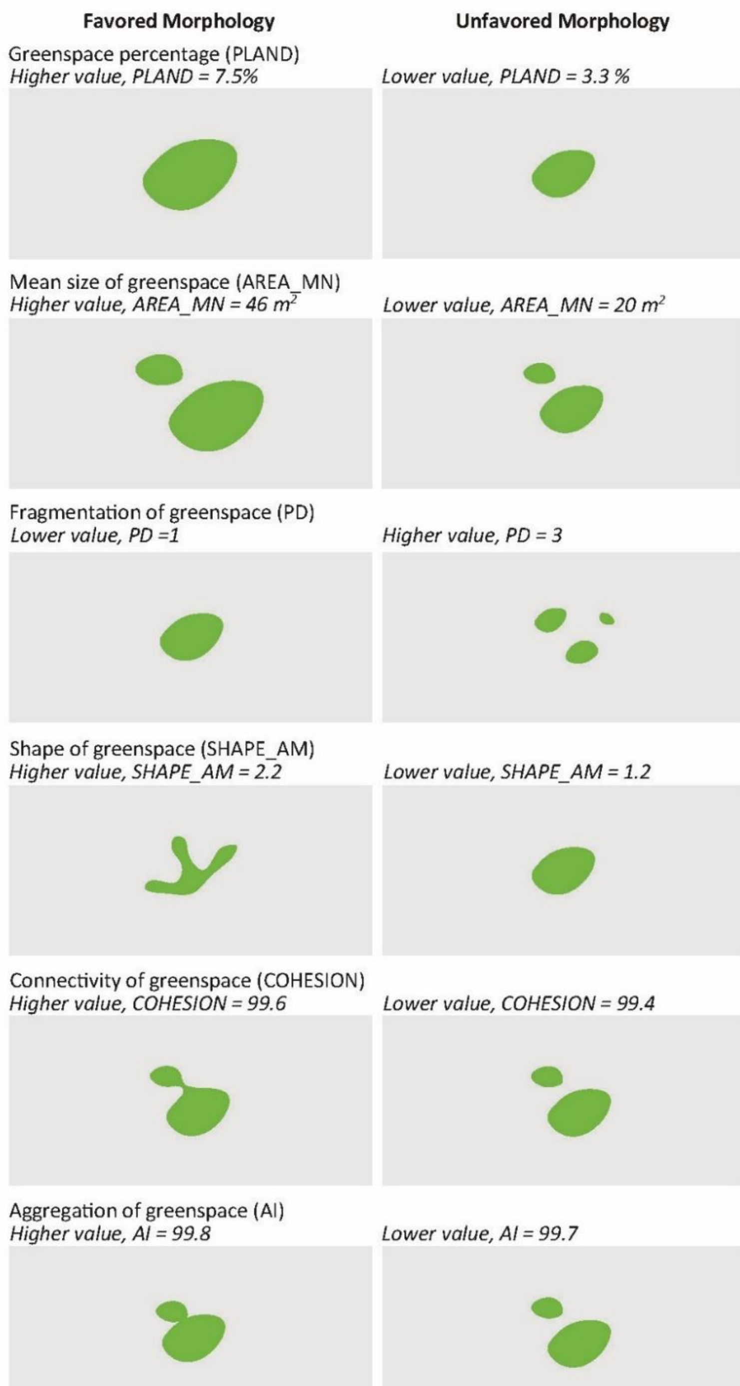

Figure B-1 An illustration of favored and unfavored greenspace morphology for health-promoting planning and design practice

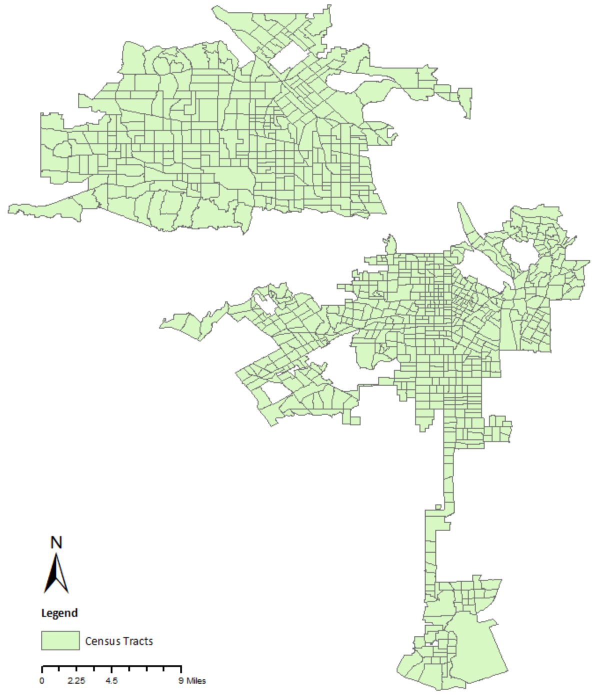

Figure B-2 Census tracts selected in Los Angeles City

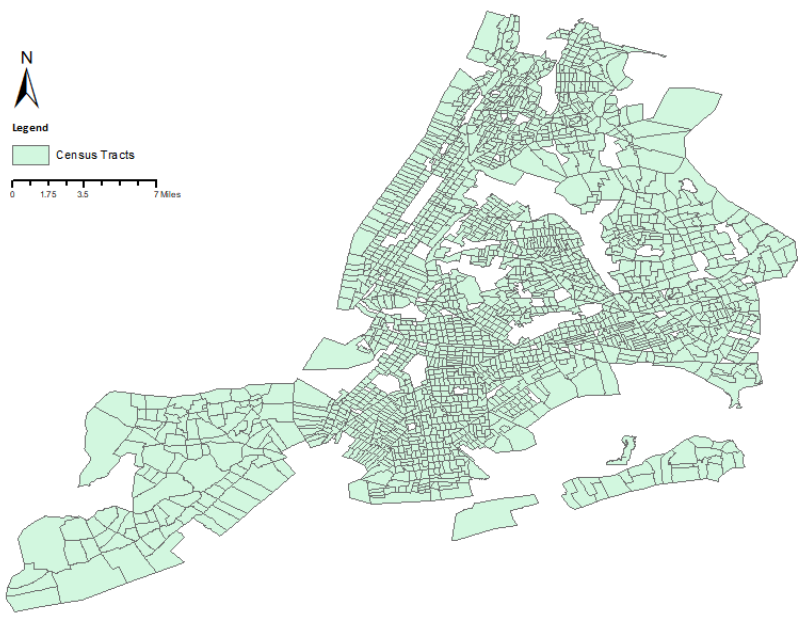

Figure B-3 Census tracts selected in New York City

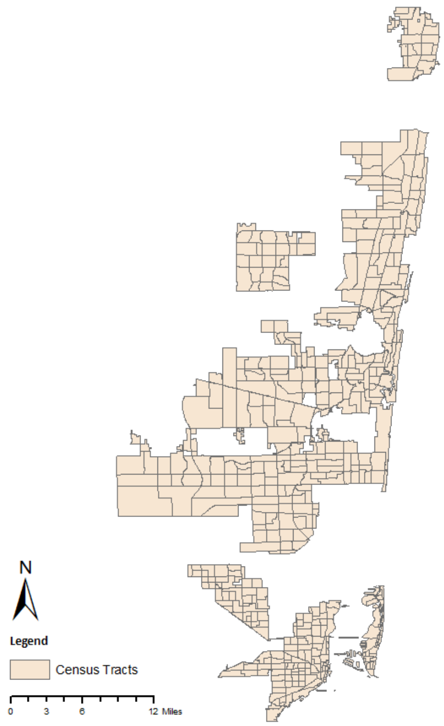

Figure B-4 Census tracts selected in Miami and surrounding cities

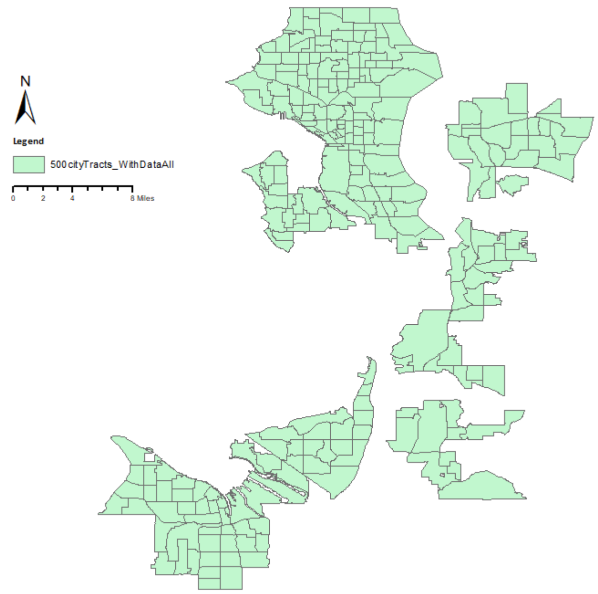

Figure B-5 Census tracts selected in Seattle and surrounding cities

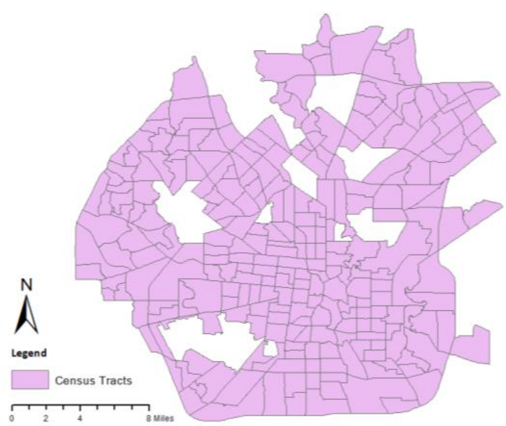

Figure B-6 Census tracts selected in San Antonio City

Table B-1 Characteristics of landscape morphology, the prevalence of the disease, and socio-economic conditions of the studied census tracts

Landscape Metrics Variables	Mean	Std. Dev.	Min	Max
Percentage coverage (PLAND)				
Los Angeles	24.160	7.513	9.557	64.075

Greater Miami	39.557	12.122	7.460	66.518
New York	29.510	11.429	5.627	75.350
San Antonio	53.172	8.805	23.941	73.981
Greater Seattle	37.203	11.309	10.741	65.825
Fragmentation (PD)				
Los Angeles	5123.516	1500.331	2088.313	13599.770
Greater Miami	1562.953	618.128	478.991	3981.304
New York	927.014	210.182	187.453	1606.962
San Antonio	883.995	228.369	398.380	1488.166
Greater Seattle	2040.137	491.753	1037.907	3537.644
Mean Area (AREA_MN)				
Los Angeles	52.862	29.143	19	236
Greater Miami	320.870	210.070	50	1336
New York	367.577	303.546	81	3931
San Antonio	668.191	284.106	189	1707
Greater Seattle	198.054	96.655	63	634
Shape Complexity (SHAPE_AM)				
Los Angeles	8.685	9.481	2.347	113.410
Greater Miami	11.958	8.512	2.369	55.184
New York	5.713	3.506	1.920	31.937
San Antonio	16.320	8.709	5.124	54.912
Greater Seattle	14.342	9.783	2.815	54.104
Connectedness (COHESION)				
Los Angeles	96.317	2.257	89.521	99.955
Greater Miami	98.78	1.152	93.965	99.933
New York	98.121	1.159	93.375	99.949
San Antonio	99.569	0.337	98.241	99.951
Greater Seattle	98.997	0.931	95.842	99.952
Aggregation (AI)				
Los Angeles	82.085	3.423	74.369	92.104
Greater Miami	91.45	2.563	84.761	96.4
New York	91.814	2.256	86.033	98.37
San Antonio	94.621	1.399	90.636	97.351
Greater Seattle	91.303	2.383	85.943	96.623
Geographic Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Population				
Los Angeles	3971.802	1218.592	73	10384
Greater Miami	4980.534	2298.683	64	23388
New York	4080.503	2151.474	512	28926

San Antonio	5029.568	1941.457	1187	13147
Greater Seattle	5120.840	1674.472	861	8843
Population Density				
Los Angeles	691.976	237.397	5.576	1451.804
Greater Miami	953.337	1361.283	4.687	15672.880
New York	1098.081	638.590	94.933	5438.730
San Antonio	527.018	188.987	52.114	1268.867
Greater Seattle	928.738	430.042	57.705	2938.520
The total area of greenspace (Hectares)				
Los Angeles	156.288	101.614	41.165	1048.007
Greater Miami	305.655	211.700	6.805	1919.458
New York	120.879	85.188	14.940	1145.283
San Antonio	552.011	275.878	175.371	1914.138
Greater Seattle	245.829	156.366	25.373	1281.217
Demographic variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Prevalence of poor mental health				
Los Angeles	13.275	3.302	7	24.1
Greater Miami	12.692	2.916	6	22.3
New York	12.943	3.023	5.9	22.8
San Antonio	12.828	2.635	6.9	22
Greater Seattle	11.06	2.654	6.7	20.4
Prevalence of coronary heart disease				
Los Angeles	4.998	1.193	0.5	12.6
Greater Miami	6.89	2.474	0.6	19.5
New York	5.369	1.61	1	34.6
San Antonio	6.261	1.946	1.3	10.8
Greater Seattle	4.842	1.463	0.9	10.4
Prevalence of stroke				
Los Angeles	2.91	0.935	0.3	9.7
Greater Miami	3.711	1.542	0.3	9.9
New York	3.119	1.186	0.6	21.3
San Antonio	3.172	1.197	0.8	7.4
Greater Seattle	2.497	0.862	0.5	5.5
Prevalence of diabetes				
Los Angeles	10.536	3.077	1.2	26.9
Greater Miami	12.457	4.109	1.1	25.7
New York	10.962	3.457	1.9	38.9
San Antonio	13.474	4.402	3.1	23.1
Greater Seattle	8.166	2.66	1.7	19.2
Prevalence of no leisure-time physical activity				

Los Angeles	23.159	7.772	9.4	44.1
Greater Miami	32.987	10.404	16.7	58.5
New York	31.13	7.296	12.4	59.6
San Antonio	31.715	9.44	14.3	52.1
Greater Seattle	15.529	5.424	7.8	33.7
Prevalence of chronic obstructive pulmonary disease				
Los Angeles	5.389	1.388	1.7	14.5
Greater Miami	6.962	2.202	1.6	15.4
New York	5.749	1.784	1.4	25
San Antonio	5.660	1.656	2.4	10.1
Greater Seattle	4.865	1.630	2.3	9.9
Percentage of people 65 years old and over				
Los Angeles	11.421	5.561	0	53.793
Greater Miami	17.279	11.204	0	81.302
New York	13.057	6.305	0	88.495
San Antonio	12.017	4.822	0.410	33.304
Greater Seattle	12.351	4.817	0.240	26.841
Percentage of female				
Los Angeles	50.427	4.480	2.313	71.233
Greater Miami	50.810	5.029	9.375	67.338
New York	52.308	4.232	12.109	66.917
San Antonio	50.755	3.879	27.154	63.038
Greater Seattle	49.672	4.170	32.418	61.123
Percentage of white residents				
Los Angeles	51.451	20.466	6.346	93.704
Greater Miami	67.840	27.419	0.339	99.414
New York	42.901	30.120	0	100
San Antonio	79.705	10.249	36.475	97.075
Greater Seattle	65.397	17.522	8.837	93.935
Socioeconomic variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Median household income				
Los Angeles	53968.05	27963.48	0	224167
Greater Miami	52168.5	27234.12	0	178438
New York	58458.26	28604.95	0	250001
San Antonio	47757.25	22643.27	11922	151750
Greater Seattle	72530.95	28561.45	10865	159652

Table B-2 Regression coefficients (95%CI) of models examining the association between greenspace morphology and morbidity

Metrics	Poor Mental		CHD		Stroke		Diabetes		Physical Inactivity		COPD	
Los Angeles	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**	**Coefficients (95%CI)**	**P-value**
PLAND	**-0.0720*** **	0.000	**-0.0262*** **	0.000	**-0.0258*** **	0.000	**-0.0724*** **	0.000	**-0.0671** **	0.007	**-0.0209** **	0.003
	(-0.0937, -0.0503)		(-0.0378, -0.0146)		(-0.0345, -0.0171)		(-0.0956, -0.0492)		(-0.1153, -0.0189)		(-0.0348, -0.0070)	
PD	**0.0003*** **	0.000	**0.0001*** **	0.000	**0.0001*** **	0.000	**0.0004*** **	0.000	**0.0006*** **	0.000	**0.0002*** **	0.000
	(0.0002, 0.0004)		(0.0001, 0.0002)		(0.0001, 0.0002)		(0.0003, 0.0005)		(0.0004, 0.0008)		(0.0001, 0.0002)	
AREA_MN	-0.0042	0.106	**-0.0060*** **	0.000	**-0.0070*** **	0.000	**-0.0133*** **	0.000	**-0.0166** **	0.006	**-0.0076*** **	0.000
	(-0.0092, 0.0009)		(-0.0089, -0.0031)		(-0.0091, -0.0050)		(-0.0190, -0.0075)		(-0.0283, -0.0049)		(-0.0108, -0.0044)	
SHAPE	**-0.0151* **	0.039	**-0.0106** **	0.004	-0.0048	0.081	-0.0123	0.104	-0.0315	0.064	-0.0084	0.057
	(-0.0293, -0.0008)		(-0.0178, -0.0035)		(-0.0102, 0.0006)		(-0.0272, 0.0025)		(-0.0648, 0.0018)		(-0.0171, 0.0002)	
COHESION	**-0.2953*** **	0.000	**-0.1000*** **	0.000	**-0.1036*** **	0.000	**-0.3891*** **	0.000	**-0.6348*** **	0.000	**-0.1412*** **	0.000
	(-0.3572, -0.2334)		(-0.1375, -0.0626)		(-0.1290, -0.0781)		(-0.4600, -0.3181)		(-0.7879, -0.4816)		(-0.1833, -0.0991)	
AI	**-0.1971*** **	0.000	**-0.0838*** **	0.000	**-0.0927*** **	0.000	**-0.2393*** **	0.000	**-0.4001*** **	0.000	**-0.1264*** **	0.000
	(-0.2398, -0.1545)		(-0.1094, -0.0582)		(-0.1099, -0.0755)		(-0.2874, -0.1913)		(-0.4931, -0.3072)		(-0.1528, -0.0999)	
San Antonio												
PLAND	0.0111	0.426	-0.0057	0.643	-0.0070	0.315	-0.0233	0.317	-0.0284	0.515	0.0047	0.637
	(-0.0162, 0.0385)		(-0.0295, 0.0182)		(-0.0205, 0.0066)		(-0.0687, 0.0222)		(-0.1136, 0.0568)		(-0.0147, 0.0241)	
PD	0.0002	0.775	0.0000	0.931	0.0002	0.593	**0.0019* **	0.047	0.0026	0.127	-0.0003	0.412
	(-0.0008, 0.0011)		(-0.0009, 0.0008)		(-0.0004, 0.0007)		(0.0000, 0.0038)		(-0.0007, 0.0059)		(-0.0011, 0.0004)	
AREA_MN	0.0002	0.624	0.0002	0.505	-0.0001	0.557	0.0007	0.296	-0.0010	0.404	0.0003	0.221
	(-0.0006, 0.0009)		(-0.0004, 0.0008)		(-0.0005, 0.0003)		(-0.0006, 0.0020)		(-0.0032, 0.0013)		(-0.0002, 0.0009)	
SHAPE	-0.0047	0.708	**-0.0257* **	0.018	**-0.0173** **	0.008	**-0.0589** **	0.006	**-0.1082** **	0.007	-0.0113	0.232
	(-0.0290, 0.0197)		(-0.0468, -0.0046)		(-0.0298, -0.0047)		(-0.1003, -0.0175)		(-0.1861, -0.0303)		(-0.0297, 0.0072)	
COHESION	**-2.0981*** **	0.000	**-2.0074*** **	0.000	**-1.1993*** **	0.000	**-4.7778*** **	0.000	**-10.1109*** **	0.000	**-1.3011*** **	0.000
	(-2.6726, -1.5235)		(-2.4556, -1.5592)		(-1.4714, -0.9271)		(-5.6851, -3.8704)		(-12.7251, -7.4967)		(-1.7195, -0.8827)	
AI	-0.0412	0.699	**-0.4734*** **	0.000	**-0.1317* **	0.017	**-0.4568** **	0.017	**-0.7204* **	0.042	-0.0226	0.782
	(-0.2498, 0.1675)		(-0.5958, -0.3509)		(-0.2394, -0.0239)		(-0.8295, -0.0840)		(-1.4092, -0.0316)		(-0.1825, 0.1373)	
New York City												

PLAND	**-0.0092***	0.049	0.0045	0.197	**-0.0050***	0.038	0.0053	0.321	0.0050	0.635	-0.0040	0.285
	(-0.0184, -0.0001)		(-0.0023, 0.0112)		(-0.0096, -0.0003)		(-0.0052, 0.0157)		(-0.0157, 0.0258)		(-0.0112, 0.0033)	
PD	**0.0012*****	0.000	0.0003	0.066	**0.0003****	0.002	0.0002	0.479	**0.0012***	0.014	0.0002	0.270
	(0.0008, 0.0016)		(0.0000, 0.0005)		(0.0001, 0.0005)		(-0.0003, 0.0006)		(0.0002, 0.0021)		(-0.0001, 0.0005)	
AREA_MN	-0.0001	0.548	-0.0001	0.359	**-0.0002***	0.027	-0.0002	0.322	-0.0003	0.381	-0.0002	0.091
	(-0.0004, 0.0002)		(-0.0003, 0.0001)		(-0.0003, 0.0000)		(-0.0005, 0.0002)		(-0.0009, 0.0003)		(-0.0004, 0.0000)	
SHAPE	**-0.0258***	0.036	0.0058	0.469	**-0.0135***	0.029	**-0.0337***	0.011	-0.0489	0.070	**-0.0407*****	0.000
	(-0.0499, -0.0018)		(-0.0100, 0.0216)		(-0.0255, -0.0014)		(-0.0598, -0.0077)		(-0.1019, 0.0041)		(-0.0590, -0.0223)	
COHESION	**-0.0888***	0.023	0.0133	0.617	**-0.0466***	0.015	-0.0750	0.074	0.0501	0.530	-0.0095	0.735
	(-0.1650, -0.0125)		(-0.0389, 0.0655)		(-0.0842, -0.0089)		(-0.1573, 0.0073)		(-0.1062, 0.2063)		(-0.0646, 0.0455)	
AI	**-0.0389***	0.047	0.0049	0.716	**-0.0264****	0.005	0.0021	0.923	0.0423	0.342	-0.0218	0.160
	(-0.0773, -0.0005)		(-0.0216, 0.0315)		(-0.0449, -0.0079)		(-0.0402, 0.0444)		(-0.0450, 0.1295)		(-0.0523, 0.0086)	
Greater Miami												
PLAND	-0.0086	0.224	-0.0073	0.345	**-0.0123****	0.007	**-0.0451*****	0.000	**-0.1461*****	0.000	-0.0139	0.068
	(-0.0223, 0.0052)		(-0.0223, 0.0078)		(-0.0211, -0.0034)		(-0.0685, -0.0218)		(-0.1950, -0.0972)		(-0.0287, 0.0010)	
PD	0.0001	0.562	**0.0003****	0.005	**0.0002****	0.004	**0.0008*****	0.000	**0.0019*****	0.000	**0.0003***	0.017
	(-0.0002, 0.0003)		(0.0001, 0.0005)		(0.0001, 0.0003)		(0.0005, 0.0012)		(0.0012, 0.0027)		(0.0000, 0.0005)	
AREA_MN	0.0000	0.968	**-0.0012****	0.001	**-0.0008****	0.001	**-0.0024*****	0.000	**-0.0064*****	0.000	**-0.0009***	0.012
	(-0.0007, 0.0007)		(-0.0019, -0.0006)		(-0.0012, -0.0003)		(-0.0035, -0.0012)		(-0.0087, -0.0041)		(-0.0016, -0.0002)	
SHAPE	-0.0021	0.803	-0.0135	0.090	**-0.0127****	0.009	**-0.0434****	0.001	**-0.0965****	0.001	-0.0149	0.054
	(-0.0184, 0.0142)		(-0.0291, 0.0021)		(-0.0222, -0.0033)		(-0.0682, -0.0186)		(-0.1508, -0.0423)		(-0.0300, 0.0002)	
COHESION	**-0.1519***	0.026	-0.1090	0.129	**-0.1116****	0.009	**-0.3724****	0.001	**-1.0198*****	0.000	**-0.1674***	0.019
	(-0.2849, -0.0188)		(-0.2496, 0.0316)		(-0.1949, -0.0283)		(-0.6000, -0.1448)		(-1.4844, -0.5552)		(-0.3063, -0.0284)	
AI	-0.0407	0.193	**-0.0842***	0.014	**-0.0998*****	0.000	**-0.2488*****	0.000	**-0.7586*****	0.000	**-0.0962****	0.004
	(-0.1019, 0.0205)		(-0.1511, -0.0172)		(-0.1386, -0.0611)		(-0.3554, -0.1421)		(-0.9835, -0.5336)		(-0.1615, -0.0309)	
Greater Seattle												
PLAND	0.0108	0.382	0.0025	0.693	0.0028	0.466	0.0105	0.391	-0.0037	0.873	0.0049	0.509
	(-0.0134, 0.0351)		(-0.0099, 0.0150)		(-0.0047, 0.0103)		(-0.0134, 0.0343)		(-0.0483, 0.0410)		(-0.0097, 0.0195)	
PD	0.0001	0.764	0.0000	0.842	**0.0002***	0.045	**0.0006****	0.005	**0.0008***	0.041	0.0000	0.954
	(-0.0004, 0.0005)		(-0.0002, 0.0003)		(0.0000, 0.0003)		(0.0002, 0.0010)		(0.0000, 0.0016)		(-0.0003, 0.0003)	

AREA_MN	0.0020	0.126	0.0002	0.838	0.0001	0.836	0.0006	0.667	-0.0019	0.436	0.0012	0.170
	(-0.0005, 0.0046)		(-0.0013, 0.0016)		(-0.0008, 0.0010)		(-0.0021, 0.0033)		(-0.0067, 0.0029)		(-0.0005, 0.0028)	
SHAPE	0.0158	0.172	0.0053	0.390	0.0031	0.418	0.0055	0.638	-0.0013	0.950	0.0050	0.480
	(-0.0068, 0.0384)		(-0.0068, 0.0174)		(-0.0044, 0.0105)		(-0.0172, 0.0281)		(-0.0416, 0.0391)		(-0.0089, 0.0189)	
COHESION	-0.0931	0.442	-0.0550	0.421	-0.0512	0.248	-0.2282	0.067	-0.1594	0.467	-0.0316	0.683
	(-0.3297, 0.1436)		(-0.1889, 0.0788)		(-0.1378, 0.0354)		(-0.4713, 0.0148)		(-0.5885, 0.2697)		(-0.1833, 0.1201)	
AI	-0.0155	0.741	0.0085	0.771	-0.0159	0.370	-0.0368	0.462	-0.0820	0.377	0.0123	0.695
	(-0.1074, 0.0763)		(-0.0486, 0.0655)		(-0.0506, 0.0188)		(-0.1347, 0.0611)		(-0.2638, 0.0997)		(-0.0492, 0.0738)	

*Statistically significant at 0.05 level.

** Statistically significant at 0.01 level.

*** Statistically significant at 0.001 level.

Table B-3 Detailed water surface data sources for removing water bodies

City Areas	Data Sources
New York (NY)	Coast Shoreline and rivers data: New York University Spatial Data Repository. (https://geo.nyu.edu/catalog/nyu-2451-34507). Accessed June 16, 2020. Lakes and reservoirs data: NYS GIS Clearinghouse. (http://gis.ny.gov/gisdata/inventories/details.cfm?DSID=928). Accessed June 16, 2020.
Los Angeles (CA)	Extracted from National Hydrography Dataset (NHD).
San Antonio (TX)	(https://viewer.nationalmap.gov/basic/?basemap=b1&category=nhd&title=NHD%20View). Accessed June 16, 2020.
Greater Seattle (WA)	DNR Hydrography – Water Bodies: Washington geospatial open data portal. (http://geo.wa.gov/datasets/28a0f93c33454297b4a9d3faf3da552a_1?geometry=-131.836%2C44.617%2C-109.798%2C49.834). Accessed June 16, 2020.
Greater Miami (FL)	Classified based on the NAIP satellite image by using the support vector machine (SVM) method in ENVI 5.3. Followed by a manual correction in ArcGIS 10.5. Accuracy is assessed by 600 equalized stratified randomly generated points. Overall accuracy is 99.3% with a Kappa of 0.987.

Table B-4 Normalized difference vegetation index (NDVI) threshold values and accuracy of greenspace classification

City	NDVI threshold	Greenspace producer's accuracy	Greenspace user's accuracy	Overall accuracy	Kappa
Greater Seattle	0.31	0.963	0.975	0.975	0.948
Los Angeles	0.11	0.983	0.957	0.970	0.940
San Antonio	0.10	0.988	0.980	0.982	0.963
Greater Miami	0.11	0.940	0.989	0.967	0.933

Calculation of the health effect comparable to income raise

The calculation is based on the beta coefficient values of the median household income variable divided by the beta coefficient of landscape metrics variables. The detailed calculations are as follows:

In the city of Los Angeles, the effect of one unit increase of the Aggregation Index on

- poor mental health morbidity is comparable to a median household income increase of (-0.19711)/(-0.00006) = USD 3283.

- CHD morbidity is comparable to a median household income increase of (-0.0838)/(-0.00002) = USD 4190.
- stroke morbidity is comparable to a median household income increase of (-0.0927)/(-0.00002) = USD 4635.
- physical inactivity morbidity is comparable to a median household income increase of (-0.40014)/(-0.00013) = USD 3078.
- diabetes morbidity is comparable to a median household income increase of (-0.23933)/(-0.00004) = USD 5983.
- COPD morbidity is comparable to a median household income increase of (-0.12635)/(-0.00003) = USD 4211.

In the city of Greater Seattle, with the fragmentation index decrease of 200, the effect on

- stroke morbidity is comparable to a median household income increase of 0. 00015 * 200 / 0.00001 = USD 3000.
- diabetes morbidity is comparable to a median household income increase of 0.00056 * 200 / 0.00002 = USD 5600.
- physical inactivity morbidity is comparable to a median household income increase of 0.00081 * 200 / 0.00008 = USD 2025.

APPENDIX C

Table C-1 Characteristics of landscape morphology, the prevalence of the diseases, and socio-economic conditions of the studied census tracts

Variables	Mean	Std. Dev.	Min	Max
Landscape metrics variables				
PLAND	31.505	12.916	5.627	75.350
AREA_MN	0.030	0.029	0.002	0.393
PD	2065.471	1902.919	187.453	13599.770
COHESION	97.923	1.757	89.521	99.955
AI	89.615	4.979	74.369	98.370
SHAPE_AM	8.412	7.672	1.920	113.410
Geographic variables				
Population	4292.488	1994.931	64.000	28926.000
Population Density	936.603	711.225	4.687	15672.880
Total area of greenspace (Hectares)	187.873	176.486	6.805	1919.458
Land area (Hectares)	544.191	302.808	46.302	3201.101
Demographic variables				
Prevalence of poor mental health	12.867	3.073	5.900	24.100
Prevalence of coronary heart disease	5.497	1.783	0.500	34.600
Prevalence of stroke	3.109	1.200	0.300	21.300
Prevalence of diabetes	11.040	3.654	1.100	38.900
Prevalence of no leisure-time physical activity	28.560	9.295	7.800	59.600
Prevalence of chronic obstructive pulmonary disease	5.756	1.815	1.400	25.000
Percentage of people 65 years old and over	13.088	7.018	0.000	88.495
Percentage of female	51.413	4.473	2.313	71.233
Percentage of white residents	51.804	28.594	0.000	100.000
Socioeconomic variables				
Percentage of bachelors' degree or higher	23.040	16.589	0.000	80.836
Median household income	56775.720	28387.420	0.000	250001.000

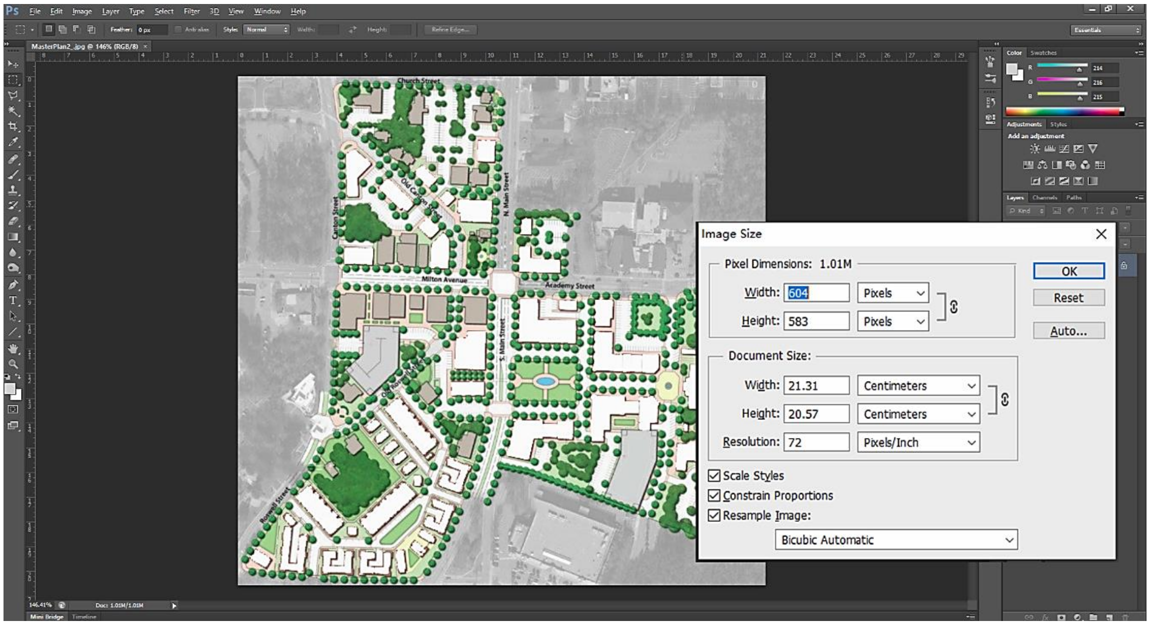

Figure C-1 Change the number of pixels into a number that corresponds to real-world size in meters in Photoshop

In this case (Figure C-1), the real-world distance from the left to the right borders is 604 meters, therefore, change the number of width pixels to 604. The document size does not influence the computing, therefore can be left with the designer's preference.

R programming code of the tool in predicting poor mental health prevalence

The code for predicting other health outcomes is the same except for a change of the variable names.

```
####Random Forest and Spatial Gaussian process model for predicting
poor mental ####health prevalence ####

library(xlsx)
library(randomForest)
library(fields)
Sys.setenv(JAVA_HOME="C:\\Program Files\\Java\\jre1.8.0_251\\jre")
path <-
"C:\\Users\\whq\\Dropbox\\20201119_STAT647_Final\\z20201119_FiveCityDat
aXY.xls"
data <- read.xlsx(path, sheetIndex = "z20201119_FiveCityDataXY")
```

```
#### prepare 70% of the data for training, and the rest 30% for testing
####
data_set_size=floor(nrow(data)*0.70)
index <- sample(1:nrow(data), size = data_set_size)
train <- data[index,]
test <- data[-index,]
predictor <- cbind(train$Age65Old_1, train$FemalePerc,
train$WhitePerce,train$Income, train$Edu_Bachel, train$PLAND, train$PD,
train$AREA_MN_Me, train$SHAPE_AM, train$COHESION, train$AI +
train$LandArea, train$CA, train$PopuDensit, train$Population)

#### estimate the best mtry parameters through out of bag error method
###########
mtry_Mental <- tuneRF(predictor,train$MHLTH_Crud, ntreeTry=500,
stepFactor=1.5,improve=0.01, trace=TRUE, plot=TRUE)
best.m_Mental <- mtry_Mental[mtry_Mental[, 2] == min(mtry_Mental[, 2]),
1]

#### fit the random forest model ########################
rf_Mental <-randomForest(MHLTH_Crud ~ Age65Old_1 + FemalePerc +
WhitePerce + Income + Edu_Bachel + PLAND + PD + AREA_MN_Me + SHAPE_AM +
COHESION + AI + LandArea + CA + PopuDensit + Population, data=train,
mtry=best.m_Mental, ntree = 1500, importance=TRUE)

#### calculate the predicted value of the training dataset and testing
dataset
predictedTrainRF <- predict(rf_Mental,train)
PredictedTestRF <- predict(rf_Mental, test)

RMSE(test$MHLTH_Crud, PredictedTestRF)

##### Spatial Gaussian process model#####################
#### get the residual from the random forest model #######
y <- train$MHLTH_Crud - predictedTrainRF

#### fit the spatial gaussian process model ##############
library(geoR)

lat <- train$X
long <- train$Y
s=cbind(long,lat)
sigma2 <- var(train$MHLTH_Crud)/3
phi <- (max(rdist(s))-min(rdist(s)))/3

fit_mle <- likfit(data=y,coords=s,
                  trend = ~ s[,1]+s[,2],
                  fix.nugget=F,cov.model="exponential",ini = c(sigma2,
phi))
```

```
################ predict ################
############## predict using test dataset #################

coords <- cbind(test$Y, test$X)
krigecontrol=krige.control(type.krige = "OK", trend.d = ~ s[,1] +
s[,2], trend.l = ~ coords[,1] + coords[,2],obj.model = fit_mle)

pred<-krige.conv(data=y,coords=s,locations=coords,krig=krigecontrol)

Y <- PredictedTestRF  + pred$predict
RMSE(Y, test$MHLTH_Crud)
summary(lm(test$MHLTH_Crud~Y))


#############predict by use a design master plan################
#### extract green cover map ####
library(raster)
library(rgdal)
library(magick)

#### Load the design master plan into R ########################
map =
stack("C:\\Users\\whq\\Dropbox\\20201119_STAT647_Final\\MasterPlan2_.jp
g")

plot((map[[2]]-map[[1]]>10) & (map[[2]] - map[[3]]> 10))
green <- ((map[[2]]-map[[1]]>10) & (map[[2]] - map[[3]]> 10))
green_Bnry <- as.matrix(green)*1
green_ras <- raster(green_Bnry)

#### change the size of the map back to real world size ##########
extent(green_ras) <- c(0, dim(green_ras)[2], 0, dim(green_ras)[1])

LandArea <-  dim(green_ras)[2]*dim(green_ras)[1]/1000000

##### Calculate greenspace morphology Metrics ###################
library(landscapemetrics)
library(sp)
library(spatstat)

projection(green_ras) = "+proj=utm +zone=15 +datum=NAD83"

check_landscape(green_ras)
res(green_ras)

pland<-lsm_c_pland(green_ras)
pd<-lsm_c_pd(green_ras)
area_mn <- lsm_c_area_mn(green_ras)
cohesion <-lsm_c_cohesion(green_ras)
ai <- lsm_c_ai(green_ras)
```

```
ca <- lsm_c_ca(green_ras)

lsm_c_np(green_ras)

shape_p_mn <-lsm_p_shape(green_ras)
shape_p_mn
shape_p.df <- as.data.frame(shape_p_mn)

shape_p_value <- subset(shape_p.df, class > 0)
area_p <- lsm_p_area(green_ras)
area_p.df<-as.data.frame(area_p)
area_p_value <- subset(area_p.df, class > 0)
sum(area_p_value[,6])

area_shape_patch<-cbind(shape_p_value[,6], area_p_value[,6])
area_shape_patch <-as.data.frame(area_shape_patch)

area_shape_patch$temp <- NA
colnames(area_shape_patch) <- c("shape", "area", "temp")

area_shape_patch$temp <-
(area_shape_patch$shape)*(area_shape_patch$area/sum(area_shape_patch$ar
ea))
shape_am<-sum(area_shape_patch$temp)


PLAND <-pland[[2,6]]
PD <- pd[[2,6]]
AREA_MN_Me <- area_mn[[2,6]]*10000
COHESION <- cohesion[[2,6]]
AI <- ai[[2,6]]
SHAPE_AM <- shape_am
CA <- ca[[2,6]]

#### prepare social-demographic data for the design plan #############
#### pre-determined variable values used mean values from the dataset
####
regionID <- 5
Population <- mean(train$Population)
PopuDensit <- mean(train$PopuDensit)
Age65Old_1 <- mean(train$Age65Old_1)
FemalePerc <- mean(train$FemalePerc)
WhitePerce <- mean(train$WhitePerce)
Income <- mean(train$Income)
Edu_Bachel <-mean(train$Edu_Bachel)
X_co <- -8934012
Y_co <- 2990113
```

```
new <- data.frame(CA , regionID , Population , PopuDensit , Age65Old_1,
FemalePerc , WhitePerce , Income , PLAND , PD , AREA_MN_Me , SHAPE_AM ,
COHESION , AI, Edu_Bachel)

Y <- predict(rf_Mental, new)

coords <- cbind(Y_co, X_co)
krigecontrol=krige.control(type.krige = "OK", trend.d = ~ s[,1] +
s[,2], trend.l = ~ coords[,1] + coords[,2],
                           obj.model = fit_mle)
pred<-krige.conv(data=y,coords=s,locations=coords,krig=krigecontrol)

DesignY_Mental <- Y +  pred$predict

DesignY_Mental
```