Depression, Equity, and Greenspace in Parks and Residential Areas

by

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Dedication

For my daughter, Wren. I'm looking forward to a lifetime of days at the park with you.

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Abstract

Humans have an innate desire to form connections with the natural world which has prompted many to consider the health implications of decreased engagement with nature due to urbanization, especially concerning mental health. Greenspaces like parks, gardens, forests, and nature preserves may be used to preserve and rekindle our relationship with nature.

Depression is one of the most pressing mental health issues of our time and a growing body of research suggests that greenspace may relieve depression. Our scientific understanding of this phenomenon is still limited. Further research is needed to understand which kinds of greenspace are most salubrious and how individual, ecologic, and societal factors influence how people benefit from greenspace.

The first two aims of this dissertation help deepen our understanding of how different types of greenspace in residential areas and within parks might relieve depression. For both aims, we leveraged data from a long running nationally representative cohort of older adults in the United States. In Aim 1 we quantified vegetation using satellite images. We estimated the association between residential vegetation and the prevalence of major depression. We further examined how these associations varied across climate. In Aim 2 we paired a newly curated catalog of parks in the United States with a high resolution landcover dataset to measure access to different types of greenspace within parks. We estimated the association between access to different types of park space and depressive symptoms.

The goal of Aim 3 was to expand on previous research concerning equity in greenspace access by investigating how the amount and type of vegetation within parks is related to the

sociodemographic characteristics of surrounding neighborhoods. For this aim, we used a high-resolution landcover dataset, publicly available park boundaries, and American Community Survey data for three of the most populous cities in the United States.

In Aim 1 we found more residential vegetation is associated with a lower prevalence of major depression. These associations were modest, and it appeared that vegetation may be most beneficial in cold and tropical climates. Associations were more nuanced or non-existent in arid and temperate climates. In Aim 2 we found having access to grassy park area was associated with fewer depressive symptoms, the opposite was true for non-vegetated spaces, and there was no association with tree covered park area. In Aim 3 we confirmed parks are an important source of greenspace for urban populations, but different populations have access to varying types of vegetation in parks. Parks in neighborhoods with more Black, Hispanic/Latino, or low socioeconomic status residents had less tree canopy but more grass cover and impervious surfaces or soil.

This dissertation shows that the relationship between greenspace and depression is complex and depends on many factors including climate, types of vegetation, and where that greenspace is located relative to one's home. It also shows that the composition of greenspace within parks is related to sociodemographic characteristics of surrounding neighborhoods. These findings have implications for future research in the field in that they emphasize the importance of exposure measures that disaggregate different types of vegetation, differentiate residential exposures from exposures in parks, and consider factors like climate that bear heavily on greenspace abundance and composition. This research can also be used to inform greening interventions, park design, and initiatives to increase greenspace equity.

Chapter 1 : Introduction

1.1 Greenspace as a Determinant of Mental Health

Humans are becoming an urban species. More than half of people worldwide reside in urban settings, and that number will likely increase dramatically in the next several decades.[1] While there are undeniable societal benefits to urbanization, these environments and the modern life-styles they facilitate have been linked to poor mental health outcomes.[2] One contributing factor may be a lack of engagement with nature.[3] According to the biophilia hypothesis, humans have an innate desire to form connections with the natural world and being deprived of such connections in modern society has led to unintended negative consequences on the human psyche. Greenspace may be a vital resource that can be used to rekindle and preserve our relationship with nature.

While not formally defined in the scientific literature, greenspace is generally considered to be spaces like parks, gardens, forests, and nature preserves that are rich in vegetation or other natural features.[4] Markevych et al. provide us with a useful conceptual framework for thinking about why greenspace is important for mental health. Under this framework, greenspace promotes better health by protecting us from harmful exposures (e.g., environmental noise and air pollution), encouraging healthful practices like physical activity and social engagement, and helping individuals recover from stress.[5] This is supported by a significant body of scientific research that shows greenspace in its various forms is associated with a range of positive mental health outcomes like better cognitive functioning[6] and less dementia risk[7], loneliness[8], behavioral problem in children[9], psychological distress[10], and depression.[11]

1.2 The Population Burdens of Depression

Depression has a myriad of meanings. Depression can describe general sadness or discontentment, but depression is also a clinically defined psychiatric condition known as major depressive disorder (MDD). MDD is defined by the Diagnostic and Statistical Manual of Mental Disorders as the presence of depressed mood and/or anhedonia plus additional symptoms related to weight fluctuation, trouble concentrating, sleep disturbances, fatigue, feelings of worthlessness, abnormal physical functioning, and thoughts of death within the same 2-week period. Those diagnosed with MDD must have five or more of these symptoms present.

MDD leads to a range of poor health outcomes and functional limitations, including difficulty maintaining relationships, trouble at work, and mortality.[12,13] In the United States, the 12-month and lifetime prevalence of MDD is 10.4% and 20.6%, respectively.[14] MDD is becoming more common in the United States[12,15] along with dramatic increases in mortality from suicide, for which MDD is a frequent precursor.[16]

In the United States it is estimated that in 2016 depressive disorders accounted for 67.5 billion dollars in healthcare spending, most of which was paid for by public insurers.[17] Unfortunately, this is not an isolated problem for the United States. The World Health Organization estimates that, worldwide, over 264 million people live with depression. This makes depression one of three leading causes of disability.[13] The public health burden and recent trends in depression underscore the need to prioritize research into the determinants, preventive factors, and effective interventions for this disease.

1.3 Environmental Causes of Depression

Historically, people believed that the cause of major depression was biochemical. The so-called "monoamine hypothesis" posited that abnormally low synaptic levels of monoamine neurotransmitters, namely serotonin, and norepinephrine cause major depression.[18] Indeed, several genetic polymorphisms related to monoamine pathways are associated with the development of major depression, including genes encoding MAOA, SLC6A, TPH2, and DRD4.[19] The reality, however, is that the causes of major depression are much more complex.[20,21] This is partially evident because even when accompanied with psychotherapy, up to a third of patients may not respond to treatment with traditional antidepressant medications.[22] As a result, environmental causes of depression are garnering increased attention, but our understanding of this is still in its infancy.[23]

Many individual-level socioenvironmental risk factors for major depression consistently emerge in epidemiologic literature. Marital status, employment status, and socioeconomic status are all strong predictors.[14,24] Stressful events and major life transitions such as losing a loved one, financial hardships, food insecurity, adolescence, pregnancy, and menopause are also well-recognized risk factors for major depression.[25–30] Of course, not all individuals develop depression when faced with stressful events or major life transitions.[19] Many factors including income, history of trauma, age, social supports, and chronic disease determine psychological resilience to such experiences.[31]

Evidence is emerging that suggests features of the physical environment like air pollution, noise, and greenspace can also affect depression.[23] Whereas air pollution and noise can adversely impact mental health, a number of high-quality epidemiologic studies have shown that more greenspace is associated with less depression and better mental health overall.[32–38] Interventional research on the therapeutic effects of walks in the forest, viewing natural imagery, and aromatherapy provide a biological basis for these hypotheses, showing moderately consistent positive effects on parasympathetic nervous system activity and negative effects on salivary cortisol, sympathetic nervous system activity, blood pressure, and prefrontal cortex activity; all biological phenomena thought to be related to depression.[39–41] The literature on the environmental determinants of depression is still relatively sparse, however, and more research is needed to better understand greenspace as an environmental source of resilience to depression as this could represent a prime target for public health interventions.

1.4 Greenspace Equity

As the scientific community and society at large move towards recognizing greenspace as a determinant of human health, there is growing interest in how factors such as race, ethnicity, and socioeconomic status impact people's access to greenspace. The existing literature tells us that greenspace is not equitably distributed in the United States. At the national scale, traditionally marginalized groups including ethnic and racial minorities and those of lower socioeconomic status live in places that have less vegetation and park space when compared to Whites and those of higher socioeconomic status.[42] Even more troubling is that those who have less access greenspace also have experienced long-term declines in this resource during the 21st century.[43]

Yet the relationships between sociodemographic factors and greenspace are highly complex and depend on factors such as the spatial extent investigated, the location under study, and what researchers consider to be greenspace. For example, an analysis by Park and Guldman showed that income was a primary driver of greenspace inequity in Columbus, Ohio but race was the primary driver in Atlanta, Georgia.[44] Similarly, in an analysis of 10 cities in the United States, Nesbitt et al. found that park area was more equitably distributed than urban vegetation and that relationships between sociodemographic characteristics and greenspace were often different depending on the city.[45] Another study raised issues of the interplay between park accessibility and quality. In an investigation of neighborhood features in Phoenix, Arizona, Cutts et al. found that traditionally marginalized groups actually had more walkable access to parks but these parks were smaller in size when compared to parks in more affluent neighborhoods.[46]

1.5 Knowledge Gaps

While the existing literature broadly suggests that greenspace can reduce depression and promote psychological resilience throughout the lifespan,[47] there is still much work to be done. In their 2017 commentary, Frumkin et al. proposed an extensive research agenda for addressing knowledge gaps in our understanding of the relationship between contact with nature, including greenspace, and human health. For epidemiologic studies estimating the association between contact with nature and human health, they propose prioritizing the following research questions: 1. "How do these associations vary across different populations, life stages, and other factors?" and 2. "Which forms of nature contact are most beneficial?"[47] These questions are supported by a 2018 systematic review of greenspace and health by Fong, Hart, and James, which indicated that though greenspace is associated with better mental health and less depression, the findings differed depending on the measure of greenspace used and the study population in question.[11] Therefore, two areas that warrant additional exploration are relationships with different types of greenspace and who has access to these types of greenspace in neighborhoods and nearby parks.

1.5.1 Climate May Influence How People Benefit from Greenspace

The concept that natural environments, not just green vegetation, benefit human health underpins the idea that greenspace may positively impact mental health. A primary driver of the amount of vegetation and the types of vegetation in an area is climate, a wide variety of which are represented in the United States. As a result, climate may be an important effect modifier of the association between greenspace and mental health because of how existing studies have often quantified the impacts of nature using the amount of greenspace present. For example, a pristine desert landscape would have less green vegetation when compared to forests in a temperate region but both locations would provide contact with nature and may confer benefits via stress recovery, harm reduction, and capacity building. In fact, a study of nursing students living in the desert climate of El Paso, Texas found that more brownness (i.e. the absence of greenspace or impervious surfaces) but not greenspace was associated with a reduced incidence of depression.[48] Interestingly, this pattern may depend on the health outcome being studied as Olvera-Alvarez et al. found that more greenspace but not brownness was associated with lower fasting glucose among young adults in the same city.[49]

Other features of climate may also influence how people benefit from greenspace. One potentially important function of greenspace is as protection from other environmental hazards. For example, there is evidence that the health impacts of extreme heat events can be mitigated by greenspace, presumably by providing shade to nearby residents.[50] Furthermore plants may promote health by filtering air pollution or dampening noise.[51,52] Yet these protections are not equal across species and different species are not suitable for all climates. For all of these reasons, climate may be an important consideration when conducting analyses of greenspace and health. However, there is a dearth of research exploring the health benefits of greenspace across climates. More studies are needed to improve our understanding of this important topic, especially in the context of understudied arid climates.

1.5.2 Parks as Greenspace

Researchers often assume that parks promote health by providing access to greenspace.[45] However, parks can take many forms and contain resources that do not include nature or greenspace such as sports facilities or event shelters.[53] Some researchers have found that more greenspace is associated with better outcomes but access to public parks is not. For example, Gariepy et al. found that residential vegetation was associated with a lower hazard of depression among individuals with type-2 diabetes but the proportion of land devoted to parks or sports facilities near one's home was not.[54] McEachan et al. found that total vegetation within 100m and 300m of a residential address was associated with fewer depressive symptoms among pregnant women in England but a weaker and less robust association was shown with access to a large greenspaces within 300m.[55] If access to greenspace underlies the mental health benefits of parks, one reason that parks do not seem to be very beneficial may be that not all parks are very green or have extensive tree canopies.[24] Instead they may be filled with more hardscapes such as basketball courts and playgrounds that provide opportunities for social connections but not contact with nature.

Researchers have yet to investigate how the greenspace within public parks themselves tracks with the demographics and socioeconomics of the neighborhoods surrounding them. This is surprising given that promoting equitable access to greenspace within parks could be a way to reduce health disparities in mental health outcomes along with health more generally.[56,57] Additionally, while some studies have investigated the mental health benefits of access to parks, few studies consider the role of amount and type of vegetation within parks. Identifying inequalities in the greenspace within public parks and improving our understanding of the relationship between the greenspace within public parks and mental health could shed light on why some research has shown that more residential greenspace is associated with better outcomes but access to public parks is not. Furthermore, research in this area would help target greening interventions and park design that are feasible and effective in increasing park usage and improving health .[58,59]

1.6 Specific Aims

Through the following aims, this dissertation attempts to deepen our understanding of how greenspace affects mental health, specifically depression, while considering access at the home and in parks, the type of greenspace present, and the equitable distribution of greenspace across race, ethnicity, and socioeconomic status.

1.6.1 Aim 1

Investigate whether residential greenspace is associated with depression in older adults living in urban and suburban areas and explore whether these associations vary with climate.

1.6.2 Aim 2

Investigate whether access to parks is associated with depression in older adults living in urban areas and explore how these associations may differ depending on specific types of vegetation within parks.

1.6.3 Aim 3

Investigate how the distribution of specific vegetation types within urban public parks is related to the sociodemographic characteristics and greenspace of surrounding neighborhoods.

Chapter 2 : Residential Greenspace and Major Depression among Older Adults Living in Urban and Suburban Areas with Different Climates across the United States

2.1 Introduction

Major depression is a highly prevalent psychiatric condition[14] and a leading cause of disability[60], particularly among older adults[61]. Historically, people believed that the etiology of major depression was biochemical. The so-called "monoamine hypothesis" posits that abnormally low synaptic levels of monoamine neurotransmitters, namely serotonin, and norepinephrine, cause major depression.[18] The reality, however, is that the causes of major depression are much more complex.[21] This is evident by the fact that even when accompanied by psychotherapy, up to a third of patients may not respond to treatment with traditional antidepressant medications.[22]

Features of the physical environment such as access to nature are garnering increased attention as determinants of major depression.[23] Access to nature is thought to improve mental health through a variety of mechanisms including protection from harmful exposures that may increase depression (e.g. environmental noise and extreme heat[23]), stress reduction, and facilitation of social cohesion.[5] Residential vegetation (also known as greenness or greenspace) is one type of contact with nature[3] that has been linked to less major depression in several high-quality observational studies.[32,62–64] If causal, such findings suggest that increasing greenspace could represent an opportunity to address major depression at the population level.

Despite existing connections between greenspace and major depression, key gaps remain in the literature. To our knowledge, no studies have considered the role that climate plays in the association between residential greenspace and major depression. This is likely important since climate is a primary driver of both the amount and type of vegetation present in a given place.[65] Research has yet to elucidate the comparative health benefits of say, deciduous forests versus desert landscapes. Furthermore, climate may impact how people benefit from residential greenspace. For example, in warmer climates individuals may benefit more from the ability of residential greenspace to mitigate extreme heat while in more temperate or cold climates it may be visual beauty that is more important. In this study we investigated whether residential greenspace is associated with a lower prevalence of major depression in older adults living in urban and suburban areas and explored effect modification of these associations by climate.

2.2 Methods

2.2.1 Study population

We used data from the Health and Retirement Study (HRS), a nationally-representative cohort study of adults over the age of 50, and their spouses who live in the United States. HRS participants have provided interviews biennially since 1992 and the study recruits new participants every six years. The HRS follows all participants from enrollment until death and collects a wide range of demographic, economic, health, familial, biological, and psychosocial measures.[66]

We restricted our analysis to participants living in urban or suburban areas who contributed interviews between 2008 and 2016. We selected these years since the HRS began collecting data on major depression starting in 2008, and 2016 is the most recent year for which we had geocoded home addresses. We excluded participants living in rural areas because we were interested in the effects of variability in greenspace as a feature of the built environment rather than contrasts between people in urban vs. rural areas. We chose to exclude rather than stratify our results because there was a lack of variability in greenspace among rural participants (interquartile range: 0.08) and too few participants living rural areas across climate regions to appropriately investigate effect modification by climate.

2.2.2 Outcome assessment

The outcome of interest in our study was the occurrence of a major depressive episode in the 12-months before each participant's interview. A major depressive episode is a two-week period during which an individual experiences depressed mood and/or anhedonia and additional symptoms related to weight fluctuation, trouble concentrating, sleep disturbances, fatigue, feelings of worthlessness, abnormal physical functioning, and thoughts of death.[67] As an assessment tool, we used the Composite International Diagnostic Interview-Short Form (CIDI-SF), a validated instrument used to assess major depression[68] with a cut-point of ≥5. Although researchers have used multiple scoring methods for qualifying a major depressive episode using the CIDI-SF,[69] our cutoff maps directly to the Diagnostic and Statistical Manual of Mental Disorders criteria for major depression.

2.2.3 Exposure assessment

We used Normalized Difference Vegetation Index (NDVI) to quantify a participant's exposure to residential greenspace. NDVI indicates the amount of vegetation present in a given area and is frequently used in epidemiologic studies to measure greenspace.[70] It ranges from -1 to 1, and surfaces dense with vegetation such as forests will have values close to 1, while water, ice, pavement, bare soil, and rock will have low positive or negative values.[71] We used Google Earth Engine[72] to access pre-processed NDVI data derived from images collected by the Moderate Resolution Imaging Spectroradiometer aboard NASA's Terra satellite (MODIS-Terra). These data are available at 250m resolution starting in February of 2000 up to the present day. Our primary exposure measure was the maximum NDVI for the year of each survey, averaged within a 1km buffer around a participant's home address. We chose the maximum NDVI for the year to capture the presence of vegetation regardless of whether it is green at any particular time and for how long it is green throughout the year. One thousand meters roughly corresponds to the average distance of walking trips in the United States.[73]

2.2.4 Climate

To further differentiate the types of vegetation where participants live, we used the Köppen-Geiger system to classify regions into five climates (Figure 2-1): tropical, arid, temperate, cold, and polar based on temperature and precipitation. This system is explicitly designed to map vegetation biomes such that places with the same climate will have similar types of vegetation even if the exact species differ.[74]

2.2.5 Other covariates

For the individual-level covariates, we used self-reported demographic data on age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, labor force status, and home ownership. For ecologic-level covariates, we focused on urbanicity, climate, neighborhood socioeconomic status, open water landcover, and state-level annual days of sunshine. Specifically, we used the United States Department of Agriculture's urban-rural continuum codes to classify home addresses into urban, suburban, or rural. We similarly measured neighborhood socioeconomic status at participant addresses using a composite score constructed via Principal Component Analysis of census tract level American Community Survey 2011 5-year estimates.[75] To measure the amount of open water or "bluespace" around participants' homes and annual days of sunshine, both of which have been associated with mental health[37], we used the 2016 National Land Cover Database[76] and the 2018 comparative climate data from the National Oceanic and Atmospheric Administration, respectively.[77] We also assigned environmental noise from National Parks Service models[78], artificial light at night from the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellites[79], and air pollution ($PM_{2.5}$, $PM_{10-2.5}$, NO_2, and O_3) from high-resolution spatiotemporal models.[80] Finally, we used spatial basis functions with 10 degrees of freedom to capture residual confounding by any other unmeasured characteristics that may vary with geography.[81]

2.2.6 Statistical analysis

We conducted all statistical analyses on observations that had complete data on the outcome, exposure, and covariates using analytic weights provided with HRS datasets. First, we examined the distribution of all covariates in our study population overall and stratified by quartiles of NDVI. This helped us understand the characteristics of our study population and how NDVI is related to individual and ecologic-level factors which may independently affect the risk of major depression. Then, we fit a series of Poisson regression models in stages:

$$Model\ 1\ (Crude): \ln(\Pr[Y_{it}]) = \beta_0 + \beta_1 GS_{it}$$

$$Model\ 2\ (Adjusted): \ln(\Pr[Y_{it}]) = \beta_0 + \beta_1 GS_{it} + \beta_2 I_{it} + \beta_3 E_{it}$$

$$Model\ 3\ (Adjusted\ with\ interaction\ by\ climate): \ln(\Pr[Y_{it}]) = \beta_0 + \beta_1 GS_{it} + \beta_2 I_{it} + \beta_3 E_{it} + \beta_4 GS_{it} * C_{it}$$

Where GS_{it} represents NDVI for the year of interview t around individual i's home address. I_{it} represents individual-level covariates, E_{it} ecologic-level covariates, and C_{it} represents climate. Note that C_{it} is a component of E_{it} in model three. We adjusted model standard errors to account for repeated measures and complex sampling design,[66] and scaled our results to the interquartile range of NDVI. The primary dataset was cleaned and constructed using SAS 9.4 and all analyses were performed using R.[82–90]

2.2.7 Sensitivity analysis

As a sensitivity analysis, we tested the assumption of a linear relationship between $\ln(\Pr[Y_{it}])$ and GS_{it} by fitting models two and three with a restricted cubic spline with 3 degrees of freedom. To illustrate results from our non-linear models, we created visualizations depicting the predicted prevalence of major depression across the range of NDVI. We also substituted the minimum NDVI for the maximum NDVI for the year and substituted a 250m buffer for the 1km buffer. Two hundred and fifty meters is the resolution limit for MODIS-Terra and NDVI within smaller buffers correlates with perceived neighborhood greenspace and may better reflect greenspace that is visible from homes.[91] Lastly, we fit primary models with additional adjustment for covariates that may act as confounders or potential intermediates between residential greenspace and major depression including one-year averages of environmental noise, artificial light at night and air pollution ($PM_{2.5}$, $PM_{10\text{-}2.5}$, NO_2, and O_3).

2.2.8 Results

We identified 21,611 HRS participants as eligible for our study, of whom nearly all (99%) had complete data on the outcome, exposure, and covariates. On average, each participant contributed three interviews, so our analytic dataset contained 69,177 observations. As shown in Table 2-1, our study population was 65 ±10 years old on average, 81% were White, 12% were Black, and 8% were some other race or multi-racial, and 10% were Hispanic/Latino. Additionally, 55% were female, 31% had at least a 4-year college degree, and 78% owned a home. The overall 12-month prevalence of a major depression was 8%.

The distribution of many covariates differed across quartiles of NDVI. Notably, participants living in the lowest quartile of NDVI were much more likely to be Black/African American, Hispanic/Latino, in the lowest quartile of wealth, living in an urban area or an arid climate. The overall mean of NDVI within 1km was 0.78 ±0.15. On average, NDVI was lowest in arid climates (0.59 ±0.16) and highest in cold climates (0.82 ±0.12).

Overall, we found evidence that higher residential greenspace was associated with a modestly lower prevalence of major depression. In fully adjusted models (Figure 2-2), one interquartile range higher NDVI was associated with a 9% lower prevalence of a major depressive episode (PR: 0.91, 95% CI:0.84-0.98). There was some evidence of effect modification of this association by climate (p-value for interaction: 0.062). We observed the strongest associations between greenspace and major depression in tropical (PR: 0.69, 95% CI: 0.47-1.01) and cold (PR: 0.83, 95% CI: 0.74-0.93) climates and null associations in arid (PR: 0.99, 95% CI: 0.90-1.09) and temperate (PR: 0.98, 95% CI: 0.86-1.11) climates.

We also found some evidence for non-linearity in our models that included an interaction term between NDVI and climate (Figure 2-3, p-value for spline: 0.051). In temperate, tropical, and cold climates associations flattened out at the highest levels of NDVI. Conversely, in arid climates, the association was stronger at the highest levels of NDVI.

In sensitivity analyses, we observed very similar results when using a 250m buffer. One exception is in arid climates where, in contrast to the null association observed when using a 1km buffer, one interquartile range higher NDVI was associated with 12% lower prevalence of a major depressive episode (PR: 0.88, 95% CI: 0.76-1.02). Results from models using the annual minimum NDVI within 1km and 250m were generally null (Table 2-2). As shown in Table 2-3, pooled associations and associations in cold climate were somewhat sensitive to adjustment for noise pollution, artificial light at night, and air pollution.

2.3 Discussion

In a large, nationally representative cohort of older adults in the United States, we found that more residential greenspace within 1km was robustly associated with a lower prevalence of major depression among individuals living in urban and suburban areas. These associations differed by climate with especially strong associations in cold and tropical climates but more limited or no evidence of these associations in arid and temperate climates. We also found some indication that the relationship between residential greenspace and major depression may be non-linear. In temperate, tropical, and cold climates there was a strong inverse association at the lowest values of NDVI whereas in the arid climate, the association was strongest across the highest values of NDVI. However, in most climates, there were few participants with very low NDVI values which limits statistical inference in this range. As such, more research is needed to confirm these observed patterns.

Overall, we observed a nearly 10% lower prevalence of major depression per interquartile range higher NDVI after adjustment for individual, neighborhood, and regional confounding. These differences were even stronger in certain climate regions, with estimated differences that were comparable to those differences between individuals who have a less than a high school education as compared to some college education.[14] As a result, our findings indicate that existing and future greening interventions like planting street trees[92], greening vacant lots[59], and, installation of “green screens”[93] could be important public health interventions for reducing depression.

The results of our study corroborate existing studies of greenspace and major depression.[32,62–64] For example, Banay et al. found that the risk of major depression among Nurse's Health Study participants living in the highest quintile of NDVI within 1.25 km of their residence was 10% lower than those living in the lowest quintile. This is very similar to our overall findings although that study did not account for climate. In a cohort of Chinese adults, Zhang et al. also found a 15% lower hazard of major depression per interquartile range higher NDVI within 1km. That study used hospitalization with depression diagnosis as determined by electronic health records linkages for their outcome, a much higher threshold for classifying major depression than our work or that in the Nurse's Health Study.

An interesting finding of this research was evidence that the association between residential greenspace and major depression differed across climates. Whereas strong associations were found in cold and tropical climates when using a 1km buffer, we observed a null association in arid and temperate climates. In arid climates greenspace may reflect more manicured or artificial landscapes such as golf courses or grass lawns. Since greenspace is partially thought to provide health benefits by increasing connectedness with nature,[37,47,94] it may be that greenspace in these settings represents a loss of natural desert landscapes. This finding is consistent with a study by Nazif-Munoz et al. who found that more brownness (i.e. the absence of greenspace or impervious surfaces) but not greenspace was associated with a reduced incidence of depression among nursing students in El Paso, Texas.[48] However, this may not be the whole picture as our non-linear and 250m buffer models suggest that less greenspace was associated with more major depression in arid climates at higher values of NDVI. We were surprised to find a null association in temperate climates because green vegetation is abundant in these regions and there is no obvious reason why individuals in temperate climates would not benefit from greenspace similar to cold climates. Interestingly, Sarkar et al. observed a relatively weak association between greenspace and major depression among adults living in the United Kingdom which has a temperate climate.[64]

Residential greenspace appeared to be most beneficial in cold and tropical climates. In cold climates, greenspace could be more important because of the relatively harsh winters. Having more vegetation around may provide psychological benefits in the late fall and early spring when temperatures are low, but foliage and spring flowers are uplifting. For comparison, Gonzales-Inca et al. found a weaker inverse association between NDVI within 1km and major depression (OR: 0.94, 95% CI: 0.83–1.08) among adults living in Finland, another cold climate.[62] The only tropical regions represented in the HRS is a relatively small geographic area in Florida and there was much statistical uncertainty in this estimate. It is difficult to say why we observed such a strong association in that region; perhaps the ability of greenspace to mitigate the health effects of extreme heat is especially important.[50,95] Unfortunately, however, we were unable to fully explore this pathway in our analyses.

Our study has several notable strengths. First, we explored effect modification by climate, a primary driver of vegetation motifs and other factors that may influence how people benefit from residential greenspace. This is something that no previous study on the topic has done but was prime for exploration given that our study population was a cohort of older adults living across the entire United States. The quality of information available on HRS participants also allowed us to adjust for a wide range of potential individual and ecological-level confounders; improving confidence in our effect estimates. Additionally, we observed that associations were only slightly sensitive to adjustment for noise pollution, artificial light at night, and air pollution. This suggests that protection from harmful exposures like noise reduction and air pollution filtration do not fully explain the mental health benefits of greenspace. Lastly, we used a validated instrument for detecting major depression that is based on DSM criteria and administered to all study participants uniformly. This helps to avoid potential information bias that may result from using medical claims data to asses major depression as there is heterogeneity in treatment for mental health conditions across demographic groups.[97,98]

The inherent complexity in measuring the concept of greenspace is one of the more important limitations of our study. NDVI has been justifiably criticized because it does not capture features such as accessibility or aesthetics that likely play into the mental health benefits of residential greenspace.[99] Our evaluation of effect modification by climate provides some insight as to how the types of greenspace relate to mental health although clearly more research is needed. Furthermore, practical computational limitations related to our large national study led us to use 250m resolution MODIS-Terra images in our study as opposed to 30m resolution Landsat images. While some studies have shown these higher resolution measures to have higher correlation with "gold-standard" vegetation classification metrics at an exact location, MODIS images should accurately reflect the neighborhood around people's homes.[70] In fact, when using 1km buffers and quintile bins for NDVI exposure, MODIS and Landsat 8 images have a similar misclassification rate (≈25% vs. ≈19%) when compared to 1m^2 data.[100] Nonetheless, future studies of residential greenspace and depression could utilize data sources such as EPA's Meter Scale Urban Land Cover[65] or Google Street View images[101] to better identify specific vegetation types.

2.4 Conclusions

Mental health is one of the most prominent public health issues of our time.[102] Our study adds to a maturing body research that shows that exposure to nature in the form of residential greenspace could reduce the prevalence of major depression. Although this suggests that increasing population exposure to nature could be an effective way to improve mental health, our work also indicates that the relationship between residential greenspace and mental health is complex. Since we found evidence of effect modification of these relationships by climate, future research should delve deeper into how climate affects the benefits of residential greenspace.

2.5 Tables and Figures

Table 2-1: Descriptive statistics of Health and Retirement Study participants (2008-2016) living in urban and suburban areas by quartiles of residential greenspace.

			Maximum 1km NDVI			
		Total	1st Quartile -0.04,0.69	2nd Quartile 0.70,0.81	3rd Quartile 0.82,0.88	4th Quartile 0.89,1.00
Age	Mean (SD)	65.4 (10.0)	65.3 (10.2)	65.7 (10.2)	65.3 (10.0)	65.3 (9.8)
Sex	Female	54.5	53.9	55.6	54	54.5
Race	White	80.7	71.4	78.7	82.5	87.3
	Black	11.7	13.1	13.7	11.7	9
	Other	7.7	15.5	7.5	5.9	3.7
Ethnicity	Hispanic	10.4	23.9	11.7	5.7	3.8
Marital status	Married	92.3	90.7	90.9	92.6	94.4
Education	< HS	12.9	19.7	14.4	10.5	8.9
	College +	31.2	27.6	29.3	35.4	31.5
Total wealth	Lowest quartile	19.2	27.5	21.1	16.5	14.3
	Highest quartile	31.6	27.3	29.7	33.3	34.6
Home ownership	Owns home	78.2	68.9	76.8	80.4	84.1
Labor force status	Retired	44.1	44.7	46	42.9	43.2
Urbanicity	Urban	68.6	82.3	68.8	66.2	60.5
	Suburban	31.4	17.7	31.2	33.8	39.5
Neighborhood level SES	Mean (SD)	-0.1 (1.0)	0.1 (1.1)	0 (1.0)	-0.2 (1.0)	-0.1 (0.9)
Climate	Temperate	44.2	28.3	43.4	49.7	51.3
	Tropical	2.4	3	3.6	1.8	1.5
	Arid	14.8	49.5	13	3.9	1.2
	Cold	38.6	19.2	40	44.6	46
Water landcover (%)	Mean (SD)	2.2 (6.9)	1.5 (6.2)	2.2 (7.3)	2.3 (6.6)	2.5 (7.3)
Annual days of sunlight (% of total)	Mean (SD)	60.0 (9.5)	68.0 (9.8)	60.8 (8.6)	57.6 (7.6)	55.7 (7.4)
Major depression (last 12-months)	Yes	7.7	8.8	8.0	7.5	6.9

Note: All proportions, means, and standard deviations calculated using cross-sectional analysis weights. Some levels of categorical variables are omitted from this table for improved readability. A similar table with all levels of categorical variables can be found in Table 2-4

Table 2-2: Estimated prevalence ratios per interquartile range higher NDVI (95% CI).

	Exposure			
Model	1km maximum NDVI	250m maximum NDVI	1km minimum NDVI	250m minimum NDVI
Crude	0.89 (0.83-0.95)	0.85 (0.78-0.92)	0.95 (0.90-0.99)	0.91 (0.84-0.98)
Adjusted	0.91 (0.84-0.98)	0.89 (0.81-0.97)	0.97 (0.92-1.03)	1.00 (0.91-1.11)
Adjusted results by climate				
Temperate	0.98 (0.86-1.11)	0.95 (0.81-1.11)	0.96 (0.89-1.03)	0.97 (0.84-1.12)
Tropical	0.69 (0.47-1.01)	0.64 (0.46-0.89)	1.22 (0.45-3.33)	0.99 (0.68-1.44)
Arid	0.99 (0.90-1.09)	0.88 (0.76-1.02)	1.06 (0.85-1.33)	1.08 (0.80-1.46)
Cold	0.83 (0.74-0.93)	0.86 (0.77-0.96)	0.98 (0.89-1.08)	1.06 (0.92-1.21)

Note: Adjusted models include age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, home ownership, climate, neighborhood-level socioeconomic status, open water landcover, state level annual days of sunshine, and spatial basis functions with 10 degrees of freedom.

Table 2-3: Model results with additional adjustment for potential confounding or mediating environmental hazards.

Adjustment set	Pooled	Arid	Cold	Temperate	Tropical
Primary*	0.91 (0.84-0.98)	0.99 (0.90-1.09)	0.83 (0.74-0.93)	0.98 (0.86-1.11)	0.69 (0.47-1.01)
+noise	0.94 (0.87-1.03)	1.01 (0.91-1.12)	0.87 (0.77-0.99)	1.01 (0.89-1.15)	0.70 (0.48-1.03)
+noise+light	0.95 (0.87-1.03)	1.02 (0.92-1.13)	0.89 (0.78-1.01)	1.00 (0.88-1.14)	0.67 (0.40-1.12)
+noise+light+air pollution†	0.96 (0.87-1.06)	0.98 (0.87-1.11)	0.91 (0.78-1.06)	1.03 (0.90-1.18)	0.77 (0.57-1.05)

Note: Estimates for specific climate regions from models with interaction term between NDVI and climate region.
*Primary model adjusted for age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, home ownership, climate, neighborhood-level socioeconomic status, open water landcover, state level annual days of sunshine, and spatial basis functions with 10 degrees of freedom.
†$PM_{2.5}$, $PM_{10-2.5}$, NO_2, and O_3

Table 2-4: Descriptive statistics of Health and Retirement Study participants (2008-2016) living in urban and suburban areas by quartiles of residential greenspace with all categories.

			1km Maximum NDVI			
		Total	1st Quartile -0.04,0.69	2nd Quartile 0.70,0.81	3rd Quartile 0.82,0.88	4th Quartile 0.89,1.00
Age	mean (sd)	65.4 (10.0)	65.3 (10.2)	65.7 (10.2)	65.3 (10.0)	65.3 (9.8)
Birth cohort	before 1924	19	19.7	20	18.6	18
	1924-1930	2.8	3	3.2	2.9	2.4
	1931-1941	6.6	6.6	7.2	6.4	6.3
	1942-1947	17.5	16.1	17.4	18.4	17.8
	1948-1953	24.1	23.3	23.8	24	25.2
	1954-1959	24	24.9	23.1	23.7	24.4
	1960-1965	5.9	6.3	5.4	6.1	6
Sex	Female	54.5	53.9	55.6	54	54.5
Race	White	80.7	71.4	78.7	82.5	87.3
	Black	11.7	13.1	13.7	11.7	9
	Other	7.7	15.5	7.5	5.9	3.7
Ethnicity	Hispanic	10.4	23.9	11.7	5.7	3.8
Marital status	Never married	7.7	9.3	9.1	7.4	5.6
	Married	92.3	90.7	90.9	92.6	94.4
Education	< HS	12.9	19.7	14.4	10.5	8.9
	GED	4.2	4	4	4.1	4.5
	HS graduate	25.1	21.6	25	24.6	28.2
	Some college	26.7	27.2	27.3	25.4	26.9
	College +	31.2	27.6	29.3	35.4	31.5
Total wealth	First quartile	19.2	27.5	21.1	16.5	14.3
	Second quartile	22.5	21.8	23.6	23	21.8
	Third quartile	26.7	23.5	25.5	27.3	29.3
	Fourth quartile	31.6	27.3	29.7	33.3	34.6
Home ownership	Owns home	78.2	68.9	76.8	80.4	84.1
Labor force status	Works FT	32.7	30.9	30.5	34.5	34.1
	Works PT	6.1	6.2	6.2	5.8	6.3
	Unemployed	2.8	3.2	3.2	2.7	2.4
	Partly retired	7.9	6.9	7.6	8.5	8.4
	Retired	44.1	44.7	46	42.9	43.2
	Disabled	2	2.9	2.1	2	1.5
	Not in labor force	4.3	5.2	4.4	3.6	4.1

Table 2-4 continued

			1km Maximum NDVI			
		Total	1st Quartile -0.04,0.69	2nd Quartile 0.70,0.81	3rd Quartile 0.82,0.88	4th Quartile 0.89,1.00
Urbanicity	Urban	68.6	82.3	68.8	66.2	60.5
	Suburban	31.4	17.7	31.2	33.8	39.5
Neighborhood level SES	mean (sd)	-0.1 (1.0)	0.1 (1.1)	0 (1.0)	-0.2 (1.0)	-0.1 (0.9)
Climate	Temperate	44.2	28.3	43.4	49.7	51.3
	Tropical	2.4	3	3.6	1.8	1.5
	Arid	14.8	49.5	13	3.9	1.2
	Cold	38.6	19.2	40	44.6	46
Water landcover (%)	mean (sd)	2.2 (6.9)	1.5 (6.2)	2.2 (7.3)	2.3 (6.6)	2.5 (7.3)
Annual days of sunlight (% of total)	mean (sd)	60.0 (9.5)	68.0 (9.8)	60.8 (8.6)	57.6 (7.6)	55.7 (7.4)

Note: All proportions, means, and standard deviations calculated using cross-sectional analysis weights.

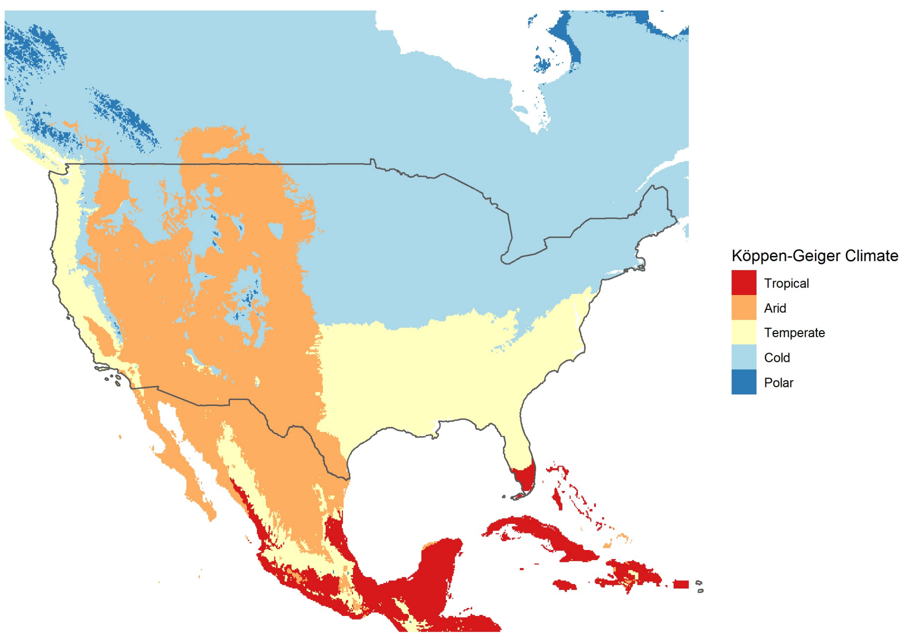

Figure 2-1: Distribution of Köppen-Geiger climate regions in North America.

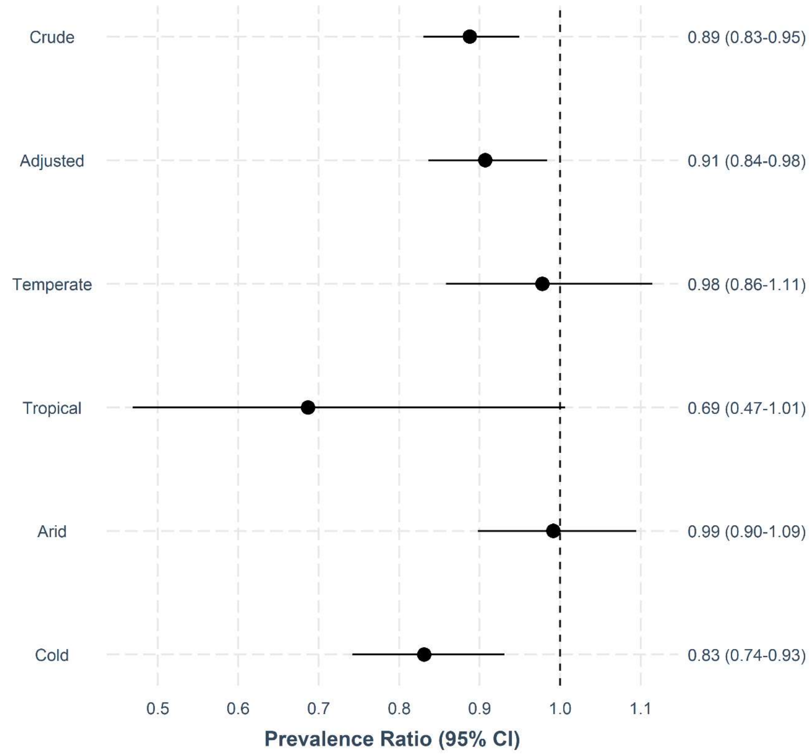

Figure 2-2: Estimated prevalence ratios (95% CI) from fully adjusted models of a major depressive episode per interquartile range difference in residential greenspace overall and by climate region.

Note: Adjusted models include age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, home ownership, climate, neighborhood-level socioeconomic status, open water landcover, state level annual days of sunshine, and spatial basis functions with 10 degrees of freedom.

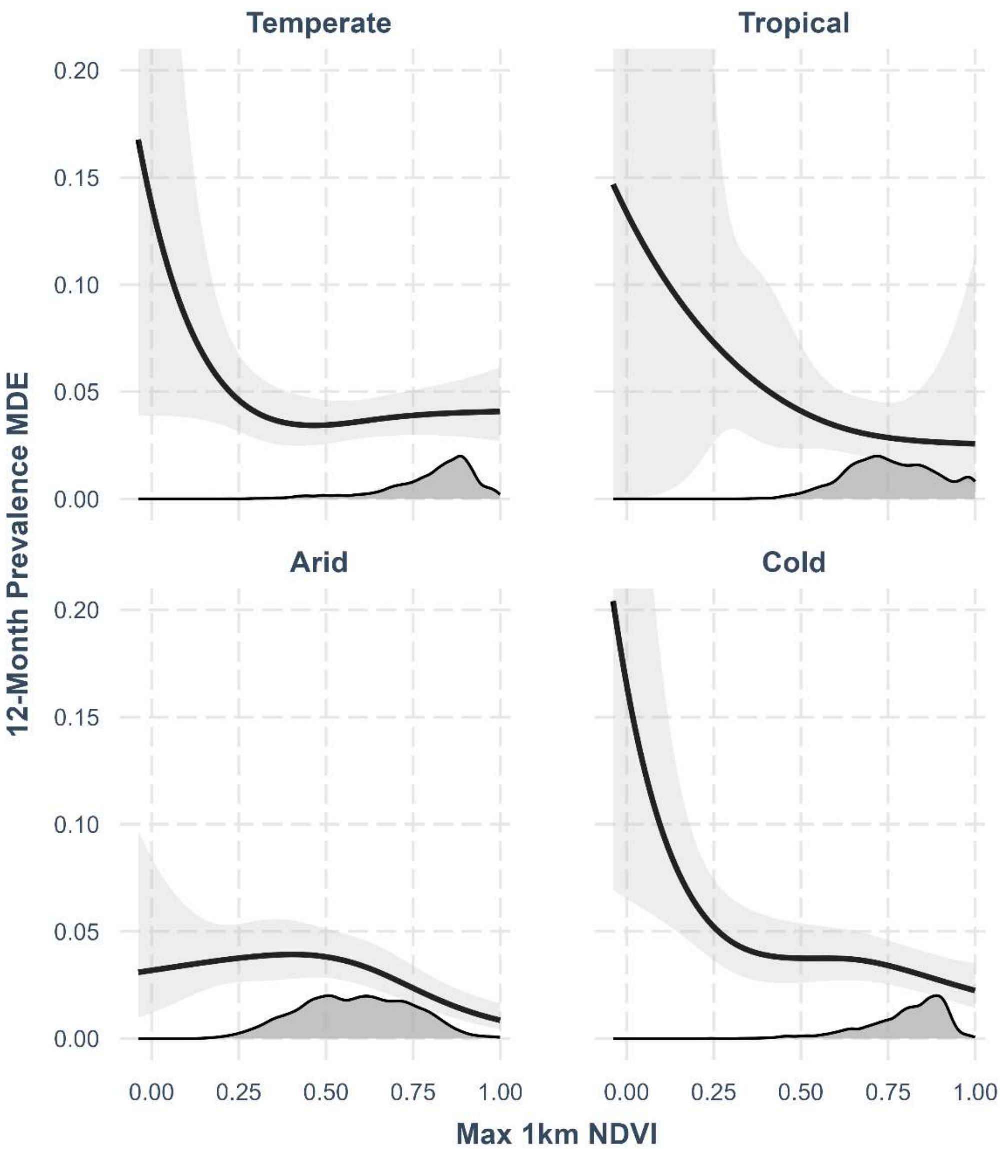

Figure 2-3: Predictions (95% CI) from fully adjusted model with interaction by climate and restricted cubic spline. Density distribution of NDVI is also shown.

Note: Adjusted models include age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, home ownership, climate, neighborhood-level socioeconomic status, open water landcover, state level annual days of sunshine, and spatial basis functions with 10 degrees of freedom.

Chapter 3 : Different Types of Greenspace Within Parks and Depressive Symptoms among Older U.S. Adults Living in Urban Areas

3.1 Introduction

Depression is a highly prevalent[14] and costly[17] mental health condition that can lead to a range of poor health outcomes and functional limitations.[60,61,103] It is characterized by depressed mood and/or anhedonia plus additional symptoms related to weight fluctuation, trouble concentrating, sleep disturbances, fatigue, feelings of worthlessness, abnormal physical functioning, and thoughts of death. Depending on the number and frequency of these symptoms, depression can be considered a clinically defined psychiatric disorder or a subclinical state. [104] The public health burden of depression underscores the need to prioritize research into determinants and preventive factors.

Engagement with nature is recognized by scientists and policymakers as an important environmental determinant of mental health.[3] Research from a myriad of disciplines informs this notion.[47] Equally diverse are the ways in which researchers conceptualize, measure, and parameterize nature in these studies.[105] Access to greenspace in the form of parks is frequently used to study the health benefits of nature.[106] Parks, however, can take many forms and provide resources that are unrelated to nature (e.g. basketball courts, event shelters, and playgrounds). Understanding the extent to which greenspace within parks underlies the mental health benefits of access to these spaces is important from a public health intervention standpoint.

Existing studies have investigated the association between the availability and characteristics of parks and depression using various methods.[10,55,106–109] In general, researchers have found that having access to parks is beneficial but the magnitude and robustness of these associations is sensitive to the way in which access to parks is parameterized. Studies that explicitly consider greenspace within parks are very few and to our knowledge no studies have examined how specific vegetation types (e.g., trees or grass) within parks may influence the mental health benefits of parks with respect to depression. Considering the relative benefits of the amount and type of vegetation could help inform funding allocation and park design.

In this study we aimed to investigate whether specific types of landcover within local parks is associated with depressive symptoms among older adults living in the United States. Our exposures of interest were the total area, tree covered area, grass covered area, and non-vegetated area of parks that are accessible to nearby residents for recreational use.

3.2 Methods

3.2.1 Study population

We used data from the Health and Retirement Study (HRS), a nationally representative cohort study of adults over the age of 50, and their spouses who live in the United States. HRS participants have provided interviews biennially since 1992 and new participants are recruited every six years. The HRS follows all participants from enrollment until death and collects a wide range of demographic, economic, health, familial, biological, and psychosocial measures.[66]

We restricted our study population to HRS participants living in urban areas who contributed biennial interviews between 2010 and 2016. We used the United States Department of Agriculture's urban-rural continuum codes to define urban residence.[110] We chose to limit our study population to those living in urban areas so that we could directly expand on our previous work which shows that parks in urban areas tend to have different types and amounts of greenspace depending on the sociodemographic characteristics of surrounding neighborhoods and parks likely play a unique role in promoting health within urban areas.[111] We selected interviews from 2010 thorough 2016 because we used a cross-sectional dataset from 2020 to measure park characteristics and wanted to limit the temporal difference to within the same decade and 2016 was the most recent year we had geocoded participant addresses.

3.2.2 Outcome assessment

The outcome of interest in our study was depressive symptomology as measured by the Center for Epidemiologic Studies Depression Scale 8 (CESD-8). The CESD-8 is widely used, and its validity and psychometric properties are described in detail elsewhere.[69] Briefly, the CESD-8 is an eight-item questionnaire that asks respondents whether they have experienced each of the following "much of the time" during the previous week: 1) felt depressed, 2) felt like everything was an effort, 3) sleep was restless, 4) felt happy, 5) felt lonely, 6) enjoyed life, 7) felt sad, 8) felt unmotivated and could not get going. Counting all of the reported symptoms results in scores that range from 0-8 with higher values indicating more depressive symptomology. This questionnaire is administered directly to all HRS participants during their biennial interviews.

3.2.3 Parks

We used the Parks and Protected Areas Database of the United States-AR (PADUS-AR) to identify parks for our analysis. The PADUS-AR is a curated version of the United States Geological Survey's national repository of public and private protected open spaces. Using metadata, a team of researchers and outdoor recreation experts identified all open spaces that are accessible to the public and whose primary purpose is recreation, which we focused on for our analyses. [112] The version of the PADUS-AR that we used in this study was created from V2.1 of the PADUS, published in September of 2020. It includes 248,871 recreational open spaces covering 1,866,564 km^2 across the entire United States.

3.2.4 Exposure assessment

For each study participant address, we identified all accessible parks whose boundaries fully or partially fell within 1km of a participant's residential address. We chose this buffer because 1km is a reasonable distance that respondents over the age of 50 years might walk in 10 minutes.[113] Ten minutes has been shown to be a normative duration of walking trips[73] and policymakers and non-profit organizations in the United States have used the 10-minute walk as an accessibility goal for parks.[114] Next, we characterized the type of vegetation within these parks using the WorldCover 2020 dataset, a global landcover dataset developed by the European Space Agency. Briefly, WorldCover 2020 classifies land at a 10m resolution into one of 11 classes and has an accuracy of 75%. Vegetation classifications include tree cover, shrubland, grassland, cropland, herbaceous wetland, mangroves, and moss/lichen.[115] We choose to only consider tree cover and grassland for this analysis because other vegetation types made up a negligible proportion of landcover within PADUS-AR parks (≤0.6%). To investigate the benefits of non-vegetated spaces like sports facilities and picnic shelters we also calculated the proportion of bare or built-up land, hereafter referred to as "non-vegetated", within parks using the same dataset.

To assign exposure for each participant, we calculated the total area of all parks within a 1km buffer around each respondent's residential address. We then calculated tree covered, grassy, and non-vegetated area by taking the product of the park area near their home and the proportion of the total park covered by trees, grass, and bare or built-up surfaces respectively. Because of the highly skewed distribution of exposure measures, we grouped exposures for each type of park area into five categories: no accessible park area of that type nearby and quartiles of area otherwise. A schematic of our exposure assessment process is shown in Figure 3-1.

3.2.5 Covariates

We used data collected as part of HRS interviews for all individual-level covariates. Specifically, we leveraged self-reported demographic data on age, birth cohort, sex, race, Hispanic/Latinx ethnicity, marital status, educational attainment, total wealth, labor force status, home ownership, and self-reported history of a psychiatric disorder. For ecologic-level covariates, we focused on climate as defined by the Köppen-Geiger classification system[74] and neighborhood socioeconomic status at participant addresses using a composite score constructed via Principal Component Analysis of census tract level American Community Survey 2011 5-year estimates.[75] We assigned environmental noise from National Parks Service models[78], artificial light at night from the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellites[79], and air pollution ($PM_{2.5}$, $PM_{10\text{-}2.5}$, NO_2, and O_3) from high-resolution spatiotemporal models.[80] We also used spatial basis functions with 10 degrees of freedom as further adjustment for geography.[81]

3.2.6 Statistical analysis

First, we calculated descriptive statistics for the outcome, exposures, and all covariates. We then examined the distribution of all covariates stratified by whether participants had any accessible park area. To estimate the association between the CESD-8 score and our exposures of interest we used Poisson regression with adjusted standard errors to accommodate repeated measures and the complex sampling design of HRS.[116] We fit separate models for total accessible park area and models with the separate park area types (tree, grass, and non-vegetated) together. Those with no accessible park area of a given type were used as the reference group in all models. Our primary models included adjustment for all aforementioned covariates. We modeled CESD-8 as continuous and all covariates as categorical except for age, wealth, and neighborhood socioeconomic status. For ease of interpretation, we expressed our model results as a percent change in CESD-8.

3.2.7 Sensitivity analysis

As a sensitivity analysis, we fit primary models with additional adjustment for covariates that may act as confounders or potential intermediates between park area and depression including one-year averages of environmental noise, artificial light at night, and air pollution ($PM_{2.5}$, $PM_{10-2.5}$, NO_2, and O_3).Additionally, to explore effect modification by climate, we fit primary models with an interaction term between all park exposures and climate.

3.3 Results

With nearly complete data capture on our outcome, exposures, and covariates (98%), we conducted a complete case analysis. There were 14,548 unique participants contributing 40,947 observations to our analysis. As shown in Table 3-1, our study population was 65 ±10 years old on average, 78% were White, 13% were Black, 10% were Hispanic/Latino, 34% had a college degree, and 42% were retired. The overall mean CESD-8 score was 1.3 ±2.0. The majority of participants (81%) had a park within 1km of their home. The distribution of covariates was generally similar between those who had a park within 1km of their residence and those who did not. The most substantive differences were Black race, Hispanic/Latino ethnicity, being in the lowest quartile of wealth, and living in a cold climate, all of which were more common among those who had a park within 1km.

Among those who had an accessible park, the average total park area was 59 ±616 km^2. On average, trees were the most dominant land-cover, making up 44 ±30% of total park area followed by grass (mean: 31 ±24%) and non-vegetated space (mean: 18 ±20%). Total area, grass, and non-vegetated area were strongly correlated (0.81-0.96) with much lower correlations with tree canopy (0.01-0.46) (Table 3-2).

As shown in Figure 3-2 and Table 3-3, neither total accessible park area nor tree covered park area were associated with depressive symptoms. In contrast, grassy park area near the home was associated with fewer depressive symptoms. This relationship followed a dose-response pattern with 17.2% (95% CI: 29.2, 3.1) fewer symptoms for participants in the lowest quartile of grassy park area to 25.2% (95% CI: 39.8, 7.2) fewer symptoms in the highest quartile as compared to individuals with no accessible grassy park area nearby. Non-vegetated area was associated with between 27.7% (95% CI: 1.0, 61.5) and 54.3 (95% CI: 19.3,99.7) more depressive symptoms with the largest impact for the highest quartile. Relationships between grassy and non-vegetative areas were largely robust to adjustment for noise, artificial light at night, and air pollution although there was much statistical uncertainty in models including all environmental hazards.

In sensitivity analyses, we observed some evidence of effect modification by climate although no interaction terms were statistically significant (p-values for interaction: 0.25-0.53[*]). The most notable difference from the primary models was that in temperate climates more tree area was associated with fewer depressive symptoms while the opposite appeared to be true in

[*] Tropical climates excluded from likelihood-ratio tests because some terms were could not be estimated.

cold climates. Results were otherwise generally consistent with the exception of cold climates where non-vegetated area was not associated with depressive symptoms and total park was associated with more depressive symptoms. (Figure 3-3)

3.4 Discussion

In a national cohort of older adults living in urban areas of the United States we found that the total area of parks within 1km of one's home address was not associated with depression. However, there was evidence that having grassy park area near one's home reduces depressive symptoms and non-vegetated spaces may increase depressive symptoms. These results were largely robust to adjustment for common environmental hazards including noise, artificial light at night, and air pollution suggesting access to parks may affect depression through mechanisms other than reducing harmful exposures. Overall, this study adds to our understanding of the role of neighborhood greenspace by documenting that the association between accessible park area and depression depends on landcover.

A key contribution of our study was our novel characterization of the amount and type of vegetation within parks. This allowed us to glean more nuanced information about parks as resources with variable types of natural spaces. With these data, we found that grassy park area was associated with less depressive symptoms, but tree covered area was not. This is surprising given that studies of residential greenspace have suggested that tree canopy is particularly beneficial for mental health.[117,118] In addition, tree canopy is most predictive of perceived neighborhood greenspace.[91] While these are true for residential areas, however, it may not be the case for parks. Perhaps grassy parks strike an appropriate balance between natural and manicured space for the older adults in our study population, providing natural spaces that are more inviting and accessible than forested areas.

Another interesting finding of this work is that greater areas of non-vegetated park were associated with more depressive symptoms. If this non-vegetative space is being used for features like basketball courts and playgrounds[119], this could detract from the utility of parks for older adults. Having more hardscape features within parks may shift the demographic of park users, which could discourage some older adults from utilizing parks. For example, a study by Moore et al. found that older adults living in neighborhoods with a younger age distribution were less likely to use local parks when compared to older adult living among peers.[120] Feeling unwelcome in local parks could contribute to social isolation for older adults especially in urban areas where parks are important spaces for social interaction and physical activity.[121] Our findings of some evidence of effect modification by climate may similarly support our conclusions that the health benefits of parks are dependent on factors that vary by place such as accessibility due to weather, urban design, and plant species.

In spite of interesting findings with specific types of natural spaces, our finding that total park area was not associated with depression is somewhat at odds with existing studies of urban populations. For example, Mukherjee et al. found that those living in areas within the lowest tertile of nearest park area had 3 times the odds of major depression as compared to people with greater areas of nearby park space among adults with chronic disease (average age over 54 years) in New Delhi, India.[109] Similarly, in a study of women living in Tijuana, Mexico; Bojorquez and Ojeda-Revah found that having a park near one's home was associated with fewer depressive symptoms, especially those with less vegetation,[107] but these parks were more beneficial for younger participants. This would support our hypothesis that non-vegetative spaces in parks promote physical activity and social cohesion in younger people. Another recent study by Bustamante et al. demonstrated that having a park within one's zip code area was associated with less depression among older adults residing in urban areas of the United States.[106] This investigation did not distinguish the type of vegetation present and it was conducted during the COVID-19 pandemic (April-May 2020), a time when outdoor recreational spaces may have played a particularly important role in promoting mental health.

Our study has several strengths. First, we used a newly published version of the PADUS, PADUS-AR, that has been curated by experts with accessibility and recreation in mind. PADUS-AR builds upon previous work in that it reflects the most comprehensive national data available on recreational open spaces in the Unites States, which allowed us to study the mental health benefits of parks in a national cohort. Second, we had a wide range of sociodemographic, neighborhood, and regional information for our study population, which allowed us to go beyond adjusting for a limited set of individual-level confounders as has been done in the past. We also leveraged a newer high resolution global landcover dataset to investigate the relative benefits of different types of landcover within parks. Lastly, we were able to adjust for several environmental hazards that may act as either confounders or intermediates between park area and depression but this had little impact on the conclusions of our study.

In spite of these many strengths, there were several note-worthy limitations of our study. First, we used radial buffers to measure accessibility. Yet parks may not be accessible from all points along their boundaries and the distance participants need to walk along roads to access parks is also likely longer than our methods suggest. While we selected 1km to reflect a common walking distance, ultimately the distance of 1km was somewhat arbitrary and may not capture all of the parks used by residents. Our analysis also assumed that landcover is homogenously distributed within parks yet certain types of landcover may be clustered within parks affecting the accessibility of these spaces. Additionally, we have assumed that the quality of each type of landcover is similar across parks even though not all parks may be equally as pleasant to use. These limitations could be especially important in a study of older adults as they tend to have a higher standard for perceived accessibility of parks.[122] The cross-sectional nature of the WorldCover 2020 dataset may have led to some exposure misclassification of landcover types if there were rapid changes in vegetation in parks over time. We attempted to mitigate this potential source of bias by limiting our study to within a decade of 2020. Lastly, our results may not be generalizable to a younger population because of different preferences in park design across age.[123,124]

3.5 Conclusions

In a large cohort of older adults living in urban areas across the United States, we found that parks may influence the mental health of nearby residents, but the benefits of parks appear to depend on the type of vegetation present. This study suggests that decision making around park design and improvement, particularly in urban neighborhoods with a large proportion of older residents, needs to be mindful of the types of spaces provided to the community. Future research might further explore the exact features of parks that confer benefits, thus providing greater insight as to the likely complex mechanisms by which different landcover types within parks affect depression.

3.6 Tables and Figures

Table 3-1: Descriptive statistics of Health and Retirement Study participants (2010-2016) living in urban areas by whether they have a park within 1km of their home.

		Total n: 40,947	No park within 1km n: 6,658 (18.8%)	Park within 1km n=34,289 (81.2%)
Age	mean (sd)	64.7 (10.0)	64.5 (9.6)	64.8 (10.0)
Sex	Female	54.1	51.4	54.7
Race	White	77.9	84.9	76.3
	Black	13.2	9.3	14.1
	Other	8.9	5.8	9.6
Ethnicity	Hispanic	10.0	6.9	10.7
Marital status	Married	91.1	94.8	90.2
Educational attainment	< HS	11.4	9.2	11.9
	College +	33.8	34.8	33.6
Total wealth	Lowest quartile	17.9	12.5	19.1
	Highest quartile	33.8	35.5	33.4
Labor force status	Works full-time	34.1	35.8	33.7
	Retired	7.6	8.2	7.5
Hx of psychiatric disorder (self-report)	Yes	17.6	15.9	18.0
Neighborhood level SES	mean (sd)	-0.16 (1.0)	-0.01 (1.0)	-0.2 (1.0)
Climate	Temperate	42.6	58.0	39.0
	Tropical	3.1	3.4	3.0
	Arid	14.5	9.3	15.7
	Cold	39.8	29.3	42.3
CESD-8	mean (sd)	1.3 (2.0)	1.2 (1.9)	1.4 (2.0)

Note: All proportions, means, and standard deviations calculated using cross-sectional analysis weights. Some levels of categorical variables are omitted from this table for readability. The frequencies are unweighted.

Table 3-2: Pearson correlations between different types of accessible park area and environmental hazards.

	Total park area	Tree	Grass	Non-vegetated	Noise	Light	$PM_{2.5}$	$PM_{10-2.5}$	O_3	NO_2
Total park area	1	0.24	0.87	0.97	-0.13	-0.12	-0.1	0.08	0.17	-0.06
Tree	0.24	1	0.39	0.08	-0.19	-0.21	-0.15	-0.05	0.15	-0.1
Grass	0.87	0.39	1	0.83	-0.15	-0.14	-0.12	0.04	0.17	-0.06
Non-vegetated	0.97	0.08	0.83	1	-0.1	-0.08	-0.08	0.08	0.14	-0.04
Noise	-0.13	-0.19	-0.15	-0.1	1	0.68	0.39	0.12	-0.56	0.54
Light	-0.12	-0.21	-0.14	-0.08	0.68	1	0.28	0.13	-0.37	0.42
$PM_{2.5}$	-0.1	-0.15	-0.12	-0.08	0.39	0.28	1	0.18	-0.33	0.55
$PM_{10-2.5}$	0.08	-0.05	0.04	0.08	0.12	0.13	0.18	1	0.17	0.28
O_3	0.17	0.15	0.17	0.14	-0.56	-0.37	-0.33	0.17	1	-0.52
NO_2	-0.06	-0.1	-0.06	-0.04	0.54	0.42	0.55	0.28	-0.52	1

Table 3-3: Percent change in CESD-8 (95% CI) from primary models and models with environmental hazards.

		Crude	Primary	Primary +noise	Primary +noise +light	Primary +noise +light +air pollution*
Total park area	1st quartile	26.7 (15.8,38.7)	5.2 (-4.2,15.4)	0.7 (-8.3,10.6)	0.5 (-8.7,10.7)	1.6 (-9.3,13.9)
	2nd quartile	23.2 (12,35.4)	5.3 (-3.8,15.2)	0.1 (-9,10.1)	-0.1 (-9.5,10.4)	0.5 (-10.4,12.8)
	3rd quartile	4.7 (-5.7,16.3)	-1.0 (-9.7,8.6)	-4.9 (-13.2,4.2)	-5.4 (-14,4.2)	-4.5 (-14.3,6.4)
	4th quartile	9.8 (-1.7,22.5)	7.7 (-0.7,16.8)	4.8 (-3.4,13.7)	4.4 (-4.2,13.7)	3.8 (-7.0,16)
Tree	1st quartile	7.2 (-18,40.2)	1.9 (-14.2,21.2)	0.7 (-15.3,19.8)	0.7 (-15.6,20.2)	2.5 (-27.3,44.7)
	2nd quartile	5 (-20.1,37.8)	0.7 (-14.6,18.7)	0.2 (-15.2,18.4)	0 (-15.8,18.7)	2.4 (-27.8,45.2)
	3rd quartile	-6.9 (-28.5,21.2)	-3.8 (-18.5,13.7)	-3.9 (-18.6,13.5)	-4 (-19.1,13.9)	-3 (-31.2,36.8)
	4th quartile	-11.5 (-34.1,18.9)	-5.2 (-21.7,14.7)	-3.6 (-20.1,16.4)	-3.5 (-20.5,17.1)	-0.6 (-31.8,44.7)
Grass	1st quartile	-22.3 (-40.9,2.1)	-17.2 (-29.2,-3.1)	-16.4 (-28.8,-1.9)	-16.6 (-29.1,-1.7)	-15.9 (-38.5,15.2)
	2nd quartile	-29.2 (-46.9,-5.5)	-19.8 (-32.9,-4.1)	-18.1 (-31.9,-1.6)	-18.2 (-32.3,-1.2)	-16.6 (-43.5,23.2)
	3rd quartile	-34 (-50.3,-12.4)	-23.5 (-37,-7.1)	-21.5 (-35.8,-4.1)	-21.9 (-36.5,-4.1)	-20.3 (-46.2,18)
	4th quartile	-40.6 (-55.9,-19.8)	-25.2 (-39.8,-7.2)	-21.7 (-37.6,-1.8)	-22.4 (-38.5,-2.1)	-18.8 (-47.2,25)
Non-vegetated	1st quartile	53.5 (9.9,114.3)	27.7 (1,61.5)	23.6 (-2.8,57.2)	23.7 (-3.3,58.2)	20.7 (-25.3,95.2)
	2nd quartile	55.2 (10.9,117.2)	28.1 (0.9,62.6)	21.7 (-4.6,55.3)	21.8 (-4.9,56.1)	19 (-27.1,94.2)
	3rd quartile	76.1 (24.3,149.5)	34 (5.3,70.5)	24.6 (-3.1,60.4)	25.1 (-3.3,62)	21.9 (-27,103.4)
	4th quartile	110.4 (51.5,192.1)	54.3 (19.3,99.7)	41.4 (8.8,83.6)	42 (8.5,85.7)	30.4 (-23.7,122.8)

Note: No accessible park area used as reference. Primary models adjusted for age, birth cohort, sex, race, ethnicity, marital status, educational attainment, total wealth, labor force status, home ownership, history of psychiatric illness, climate, neighborhood SES, and spatial basis functions (10df).

*$PM_{2.5}$, $PM_{10-2.5}$, NO_2, O_3

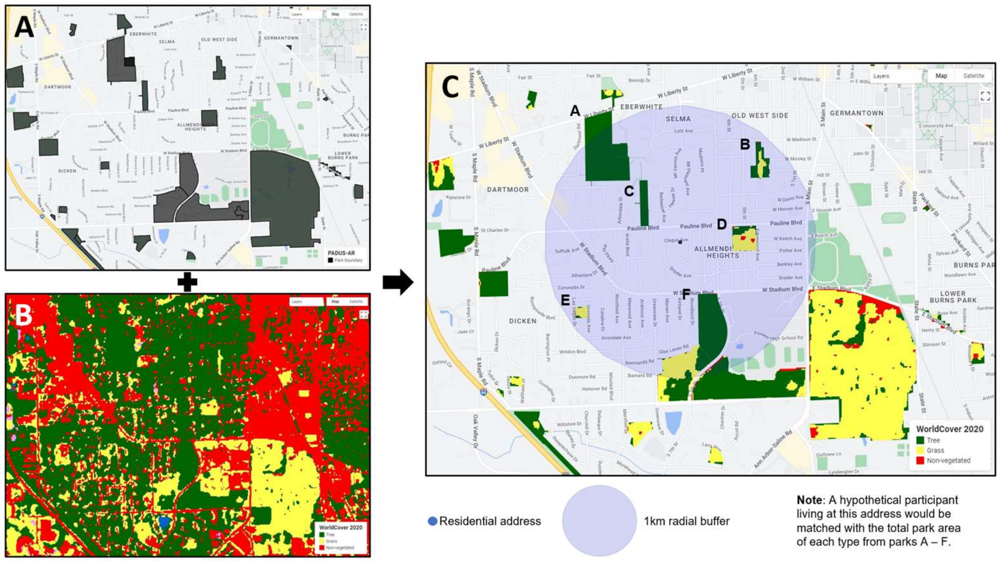

Figure 3-1: Schematic of accessible park area exposure assessment. Panel A shows park boundaries from PADUS-AR. Panel B shows landcover within the same area from WorldCover 2020. Panel C is a hypothetical participant's address (not an actual HRS participant) with a 1km buffer.

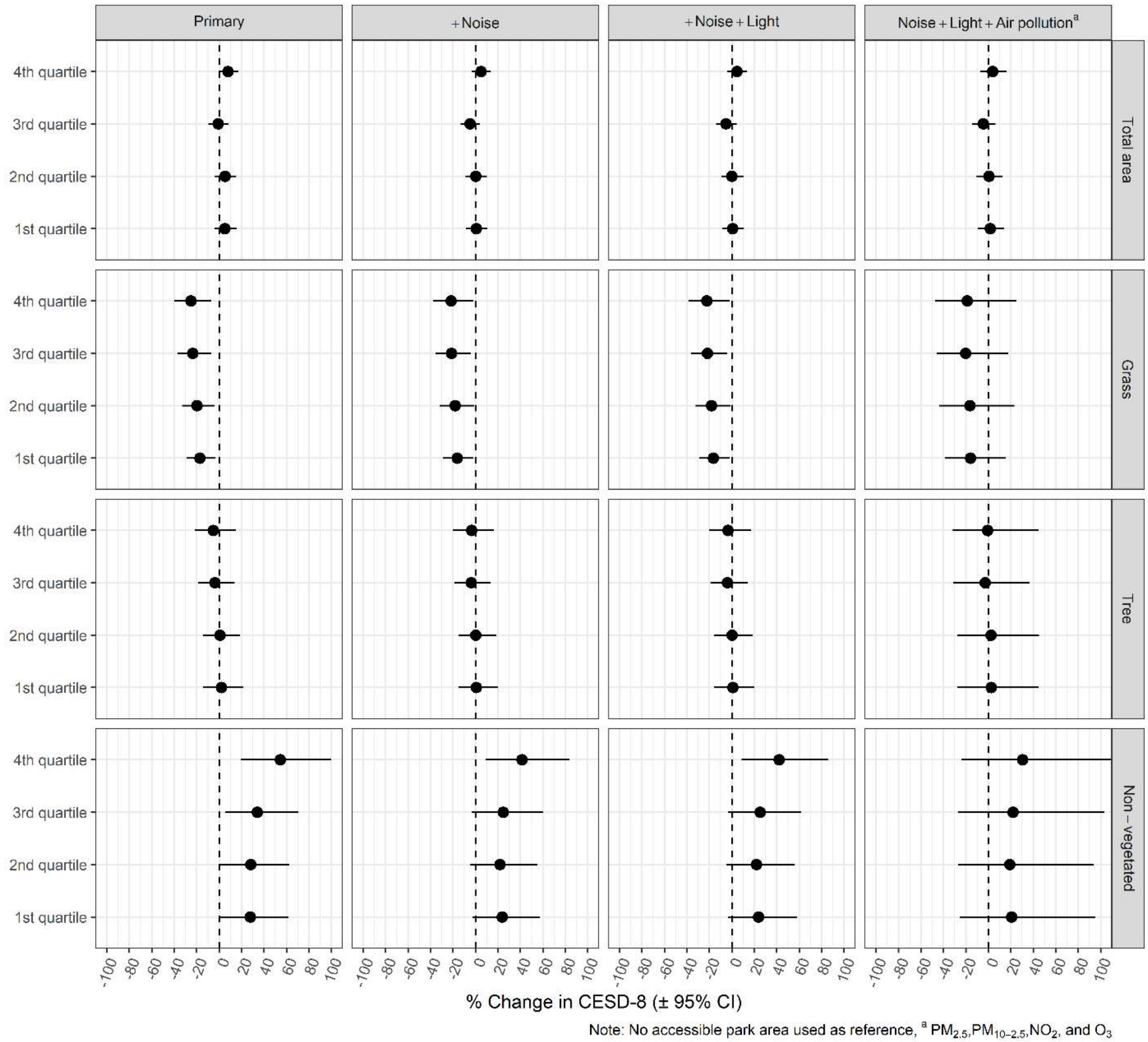

Figure 3-2: Percent change in CESD-8 (95% CI) from primary models and models with environmental hazards. Note: No accessible park area used as reference. Primary models adjusted for age, birth cohort, sex, race, ethnicity, marital status, educational attainment, total wealth, labor force status, home-ownership, history of psychiatric illness, climate, neighborhood SES, and spatial basis functions (10df).

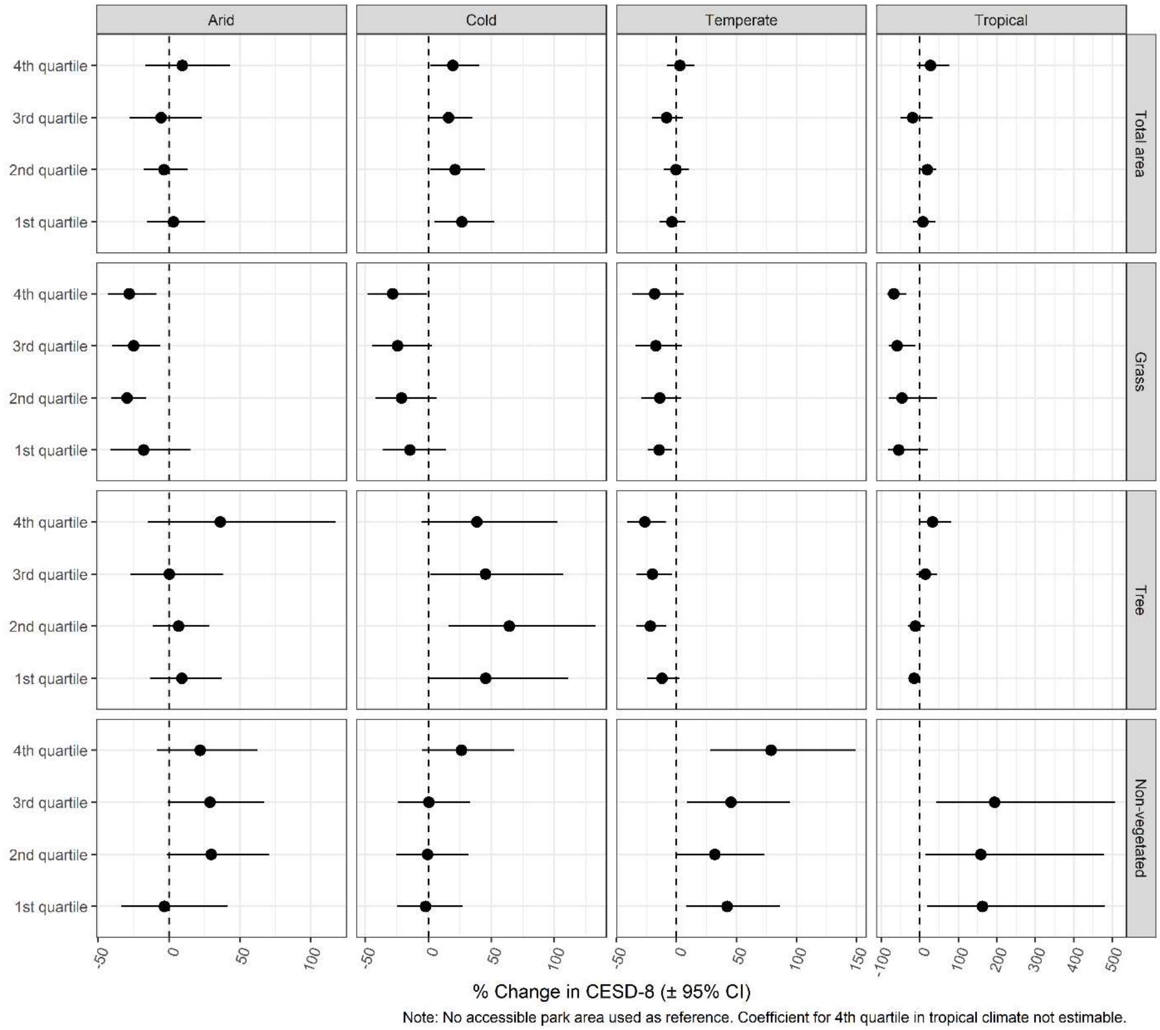

Figure 3-3: Percent change in CESD-8 (95% CI) from primary models with interaction by climate.

Note: No accessible park area used as reference. Primary models adjusted for age, birth cohort, sex, race, ethnicity, marital status, educational attainment, total wealth, labor force status, home-ownership, history of psychiatric illness, climate, neighborhood SES, and spatial basis functions (10df).

Chapter 4 : Sociodemographic Determinants of Greenspace within Public Parks in Three U.S. Cities

4.1 Introduction

Equitable access to urban vegetation (also known as greenspace) is an important environmental justice issue because marginalized populations bear a disproportionate burden of environmental stressors including air pollution[75], environmental noise[125], and extreme heat[126] that greenspace may assuage.[5,11] Researchers often presume parks provide greenspace for urban populations. Previous studies have explored how sociodemographic characteristics influence park accessibility and overall quality with mixed results.[45,127–130] However, there is a lack of research explicitly investigating how greenspace within parks compares to surrounding neighborhoods and the sociodemographic determinants of greenspace within parks, especially concerning specific types of vegetation. This study aimed to explore the relationship between park and neighborhood greenspace and identify sociodemographic determinants of greenspace within urban public parks. We focused our analysis on three of the most populous cities in the United States - one in the East, one in the Midwest, and one in the West.

4.2 Methods

We considered all properties under the jurisdiction of the Chicago Parks District, the City of Los Angeles Department of Recreation and Parks, and the New York City Department of Parks and Recreation on record as of August 2021 as the public parks in our study. To focus on public parks that primarily serve surrounding neighborhoods, we included only parks which fell below the 90th percentile for park areas (<19.7 acres) in our analysis (Figure 4-1). We used publicly available geospatial datasets to delineate park boundaries and, as illustrated in Figure 4-2, defined the neighborhood associated with each park as the collection of 2010 United States census tracts with centroids that fell within 1km of park boundaries. In Figure 4-2 the dashed line is a park boundary. The shaded area in A identifies all census tracks with centroids within a 1km buffer. The shaded area in B was used to calculate neighborhood greenspace. The park pictured was assigned sociodemographic characteristics from census tracts 8429, 8412, and 3106-3109.

To quantify greenspace, we calculated percent tree canopy and percent grass separately within park and neighborhood boundaries using Meter-Scale Urban Land Cover (MULC), a high resolution ($1m^2$) dataset developed for the United States Environmental Protection Agency's EnviroAtlas.[65] Using the same dataset, we also calculated percent impervious surface or soil to characterize potential tradeoffs in park resources e.g., playgrounds or basketball courts rather than fields or urban forests. Data used to construct MULC spanned the years 2010 through 2016.[65] To avoid duplication of park values when measuring neighborhood greenspace, we removed data within park boundaries from MULC rasters when extracting neighborhood values.

To characterize the community that each park serves, we used census tract-level data on Black race, Hispanic/Latino ethnicity, and several measures of socioeconomic status (SES) including educational attainment, income, home ownership, poverty, and unemployment rate from the 2015 American Community Survey 5-year estimates. We chose these sociodemographic characteristics because previous studies have shown that minority race, Hispanic/Latino ethnicity, and lower SES is associated with less greenspace within urban areas in general.[43,45] We used principal components analysis to reduce the dimensionality of highly correlated socioeconomic indicators and retained only one principal component to summarize the construct of SES. This single principal component, which explained 62% of the variance in SES indicators, was negatively correlated with educational attainment, income, and home ownership and positively correlated with poverty and unemployment rate. (Table 4-1) As such, we refer to this principal component as depravation score. We assigned each park a population weighted average of sociodemographic characteristics from those census tracts which comprised the surrounding neighborhood.

To allow for the observation of city specific results, we stratified all analyses by city. To reduce the influence of areas with an abundance of very small parks, we weighted all analyses by park area. We calculated means and standard deviations for all landcover measures for parks and their surrounding neighborhoods. We also calculated the difference in landcover for each park-neighborhood pair and correlation between these measures. To investigate differences in landcover by sociodemographic characteristics we fit a series of bivariate log-linear binomial models regressing each landcover type (% tree canopy, % grass, and % impervious surface or soil) on each sociodemographic characteristic. For interpretability, we present the percent change in landcover per interquartile range higher Black race, Hispanic/Latino ethnicity, and deprivation score and produced graphical displays of predicted landcover across the range of each sociodemographic characteristic. Finally, we conducted a sensitivity analysis which included all parks regardless of area and did not weight by park area.

4.3 Results

A total of 2,833 parks were included in our analysis, 559 in Chicago, IL; 406 in Los Angeles, CA; and 1,868 in New York, NY. Of these, 2,803 (99%) had complete data. As shown in Table 4-2, park and neighborhood greenspace had weak positive correlations with each other in all three cities. Parks had substantially more greenspace than surrounding neighborhoods in terms of both tree canopy and grass. This difference was most pronounced for tree canopy in New York, NY where parks had, on average, 24% more tree canopy than surrounding neighborhoods. In all cases, the average difference between park and neighborhood greenspace was greater than one standard deviation of neighborhood greenspace. Conversely, parks had substantially less impervious surface or soil than surrounding neighborhoods.

Table 4-3 and Figure 4-3 show the difference in each landcover type by sociodemographic characteristics. These models show that the sociodemographic characteristics considered were moderate predictors of landcover within parks, but the magnitude of these associations varied substantially by city. In general, neighborhood level Black race, Hispanic/Latino ethnicity, and socioeconomic deprivation was associated with less tree canopy and more grass and impervious surface or soil within parks. Results from our unweighted sensitivity analysis including all parks regardless of size were very similar.

4.4 Discussion

In three large cities in the United States, public parks were substantially greener than surrounding neighborhoods, confirming public parks are key contributors to urban greenspace. The sociodemographic characteristics we considered were moderate predictors of greenspace within parks. Parks quite consistently had less tree canopy and more grass as the population of Black, Hispanic/Latino, or low SES residents in surrounding neighborhoods increased. In some instances, similar sociodemographic characteristics were also associated with increases in impervious surfaces or soil. Results differed between cities, raising questions about how city-specific factors such as the extent and spatial structure of residential segregation impact investigations of access to urban greenspace and subsequent health effects.

Our study contributes to the literature on sociodemographic determinants of urban greenspace by explicitly exploring greenspace within public parks and the landcover types that contribute to that greenspace. Previous studies have focused on measures of park accessibility and overall quality, or greenspace within urban areas in general whereas we have added information on the percent tree canopy, grass, and impervious surface or soil within urban public parks. Our findings suggest that when studying the health effects of urban greenspace, the use of exposure measures such as NDVI or proximity to parks may lead to information bias since they do not distinguish between vegetation types or simply assume that parks have greenspace. This error will be particularly important in cases where the health outcome of interest is affected by a specific type of vegetation. For example, trees that provide shade may lower the risk of heat related mortality while grass fields may increase physical activity by providing a place to play sports and games.

Our results also highlight opportunities for public health interventions in that they suggest that marginalized and under resourced populations may have less access to tree canopy within their local public parks. This is important since some studies have shown that tree canopy may be particularly beneficial to human health.[57,70,91,131] Nonetheless, it is important to note that parks provide many benefits other than exposure to vegetation. Public pools, playgrounds, sport facilities, and sheltered picnic areas are resources that may be particularly important for certain populations.[53] As such, our observations may be the result of deliberate decisions by municipalities to meet the needs of communities.

4.5 Conclusions

Public parks are indeed an important source of greenspace for urban populations, but different populations have access to varying types of vegetation in those spaces. Researchers and policy makers would do well to consider both the type and amount of vegetation within parks in future studies and interventions.

4.6 Tables and Figures

Table 4-1:Factor loadings from principal components analysis of neighborhood socioeconomic status indicators.

	PC1 (62% variance explained)	PC2 (16% variance explained)	PC3 (12% variance explained)
% Population >25 with a high school education	-0.42	0.18	-0.49
% Population >25 with a 4-year college degree	-0.42	0.52	-0.22
Median income	-0.47	-0.04	-0.05
% Population living in poverty	0.46	0.24	-0.14
% Owner occupied housing	-0.33	-0.76	-0.05
Unemployment rate	0.33	-0.24	-0.83

Note: PC1 was used as deprivation score.

Table 4-2: Park and surrounding neighborhood landcover in three large American cities.

		Chicago, IL (n=559)	Los Angeles, CA (n=406)	New York, NY (n=1,868)
Percent Tree Canopy				
Park	mean ± SD	30.8 ± 15.5	28.3 ± 15.4	38 ± 25.3
Neighborhood	mean ± SD	18.8 ± 8.1	19.6 ± 8.0	14.2 ± 6.6
Difference between park and neighborhood[a]	mean ± SD	11.8 ± 14.7	8.3 ± 14.4	24.0 ± 23.6
Park and neighborhood correlation	R	0.36	0.34	0.36
Percent Grass				
Park	mean ± SD	43.7 ± 14.5	31 ± 18.6	21.0 ± 21.1
Neighborhood	mean ± SD	20.5 ± 5.2	13.2 ± 5.5	9.2 ± 6.4
Difference between park and neighborhood[a]	mean ± SD	23.2 ± 14.6	18.4 ± 17.6	11.3 ± 20.0
Park and neighborhood correlation	R	0.17	0.19	0.24
Percent Impervious Surface or Soil				
Park	mean ± SD	24.5 ± 14.8	37.9 ± 19.5	33.6 ± 25.2
Neighborhood	mean ± SD	57.3 ± 11.9	64.6 ± 12.6	63.1 ± 16.6
Difference between park and neighborhood[a]	mean ± SD	-32.6 ± 16.7	-26.5 ± 20.9	-29.4 ± 27.0
Park and neighborhood correlation	R	0.23	0.23	0.21

[a]Difference calculated as park landcover minus neighborhood landcover.

Table 4-3: Difference in landcover (95% CI) per interquartile range higher Black race, Hispanic/Latino ethnicity, and deprivation score.

City	Sociodemographic characteristic	Landcover type (%)		
		Tree canopy	Grass	Impervious surface/soil
Chicago, IL	% Black	0.3 (-10.4,12.3)	4.5 (-3.4,13)	-10.4 (-22.3,3.4)
	% Hispanic/Latino	-11.4 (-17.1,-5.4)	2.1 (-2.4,6.9)	12.3 (1.8,23.8)
	Deprivation score	-16.9 (-25.2,-7.6)	6.7 (-1.3,15.3)	9.7 (-4.5,26)
Los Angeles, CA	% Black	-2.9 (-6.5,0.9)	4.1 (1.8,6.5)	-0.7 (-3.6,2.3)
	% Hispanic/Latino	-9.6 (-20.1,2.3)	0.6 (-13.5,17)	14.7 (1.2,30.1)
	Deprivation score	-6.7 (-17.8,6)	-1.2 (-15.7,15.7)	15.1 (1.2,30.9)
New York, NY	% Black	-9.6 (-17.7,-0.6)	16.7 (5.1,29.5)	12.5 (3.2,22.6)
	% Hispanic/Latino	-4.8 (-13.2,4.4)	14.7 (1.6,29.5)	1 (-7.5,10.3)
	Deprivation score	-15.3 (-22.9,-6.8)	20.9 (6.9,36.7)	19.2 (8,31.6)

Note: Percent change calculated as $(\exp(\beta_1 * IQR)-1)*100\%$. Estimates of β_1 obtained from log-linear models.

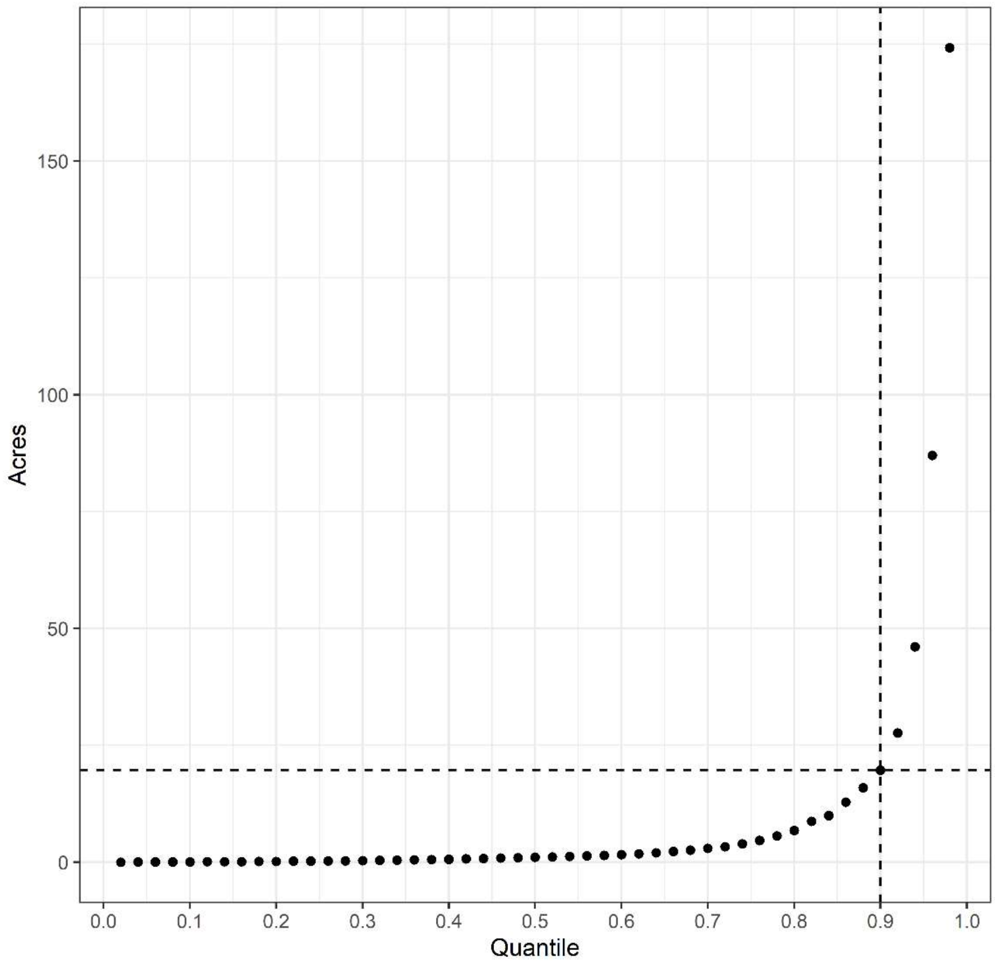

Figure 4-1: Plot of park acreage and corresponding quantiles.

Note: Intersection of dashed lines indicates acreage cut-off used in primary analysis.

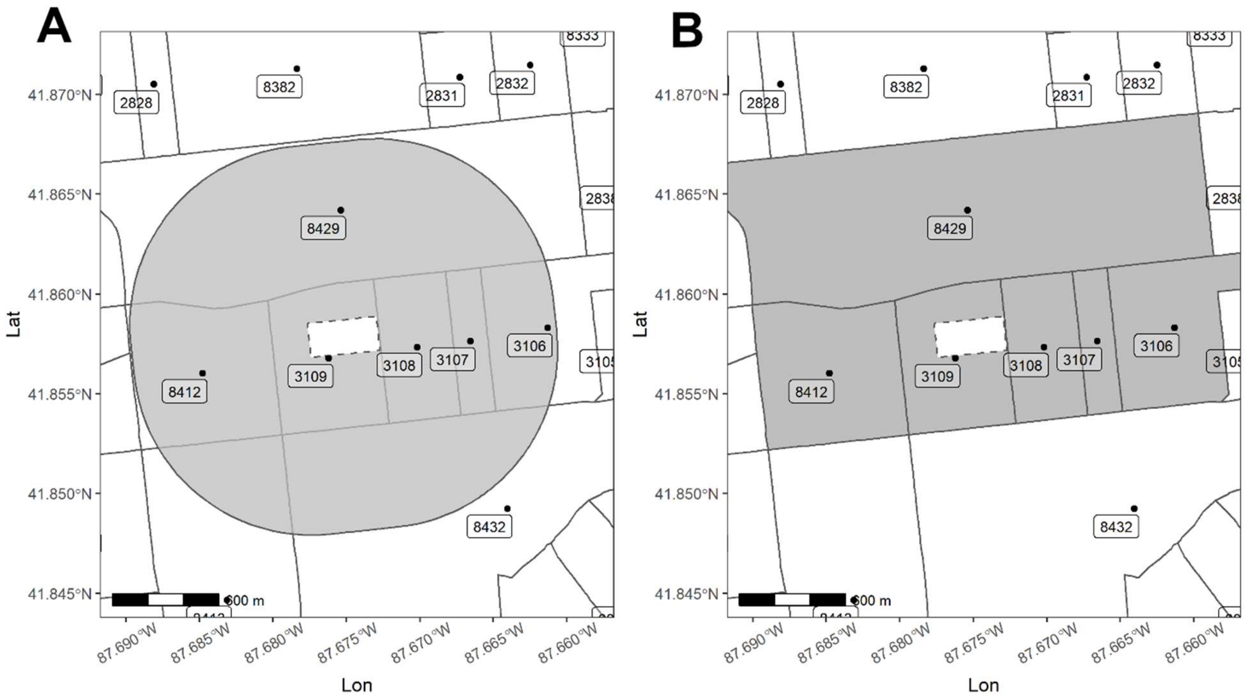

Figure 4-2: An example of the spatial analysis used to define the neighborhood associated with each park. The dashed line is a park boundary. The shaded area in A identifies all census tracks with centroids within a 1km buffer. The shaded area in B was used to calculate neighborhood greenspace. The park pictured was assigned sociodemographic characteristics from census tracts 8429, 8412, and 3106-3109.

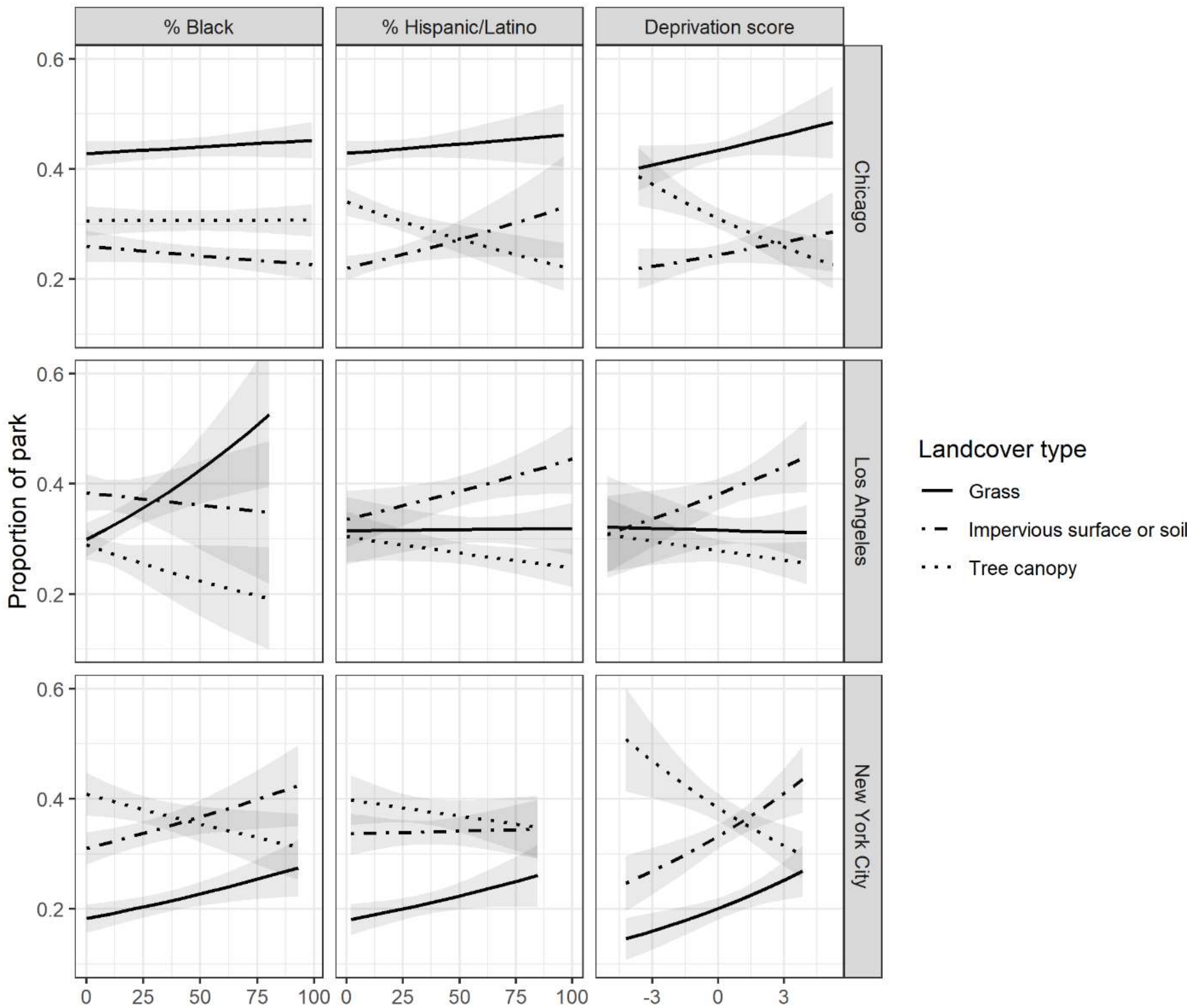

Figure 4-3: Predictions from models regressing landcover type on sociodemographic characteristics by city.

Chapter 5 : Discussion

5.1 Summary and Implications of Findings

Depression is a highly prevalent mental health condition and a leading cause of disability globally.[13,132] Greenspace is increasingly being recognized as a feature of the physical environment that may relieve depression.[23] The goal of this dissertation was to deepen our understanding of how greenspace affects depression in older adults residing in urban spaces and expand on previous research regarding the equitable distribution of greenspace across race, ethnicity, and socioeconomic status. Given that there is growing interest in identifying which types of greenspace are most beneficial to human health,[3] we considered access at the home and in parks, effect modification by climate, and, specific types of vegetation present within neighborhood greenspaces.

One key finding of this dissertation is that climate may play an important role in the relationship between greenspace and mental health. In Aim 1 we found that more total vegetation in residential areas as measured by satellite observed greenspace was associated with a modestly lower prevalence of major depression. However, we also observed that this association depended on the climate region. Greenspace appeared to be beneficial in cold and tropical climates, not beneficial in temperate climates and not beneficial in arid climates, except at the highest levels. Similarly, in Aim 2 we found that climate may influence how people benefit from greenspace within their local public parks. Most notably, we observed that tree covered area was associated with fewer depressive symptoms in temperate climates but the opposite was true in cold climates.

The effect modification by climate that we observed in Aims 1 and 2 could be a result of many different factors such as weather or plant species composition. Weather is one logical explanation as it is known to impact utilization of greenspaces for physical activity. For example, a study by Lanza et al. in Austin, Texas found that use of an urban greenspace trail for walking and cycling decreased with higher ambient temperatures in the spring, summer, and fall.[133] Conversely, studies in more temperate locations have generally found that higher temperatures encourage outdoor physical activity in both adolescents and older adults.[134,135] Observed differences in the way temperature and seasonality affect the use of greenspaces for physical activity may help explain some of our findings of effect modification by climate.

Varying plant species and landscapes may also explain why climate matters when studying the mental health benefits of greenspace. Numerous studies and theories in human evolution and environmental psychology propose that humans prefer environments with more green vegetation as compared to more brown-less vegetated places.[136] Yet this is an oversimplification of innate human preferences. One useful example in the context of this dissertation is a study by Balling and Falk in which a demographically diverse study population was shown a series of photographs representing different biomes and asked about their preferences for living in or visiting these places. While they found that participants generally preferred mesic[2] landscapes as opposed to arid ones, the most preferred landscapes were less dense forests or open savannas whereas dense tropical forests rated similarly to deserts and dryer savannas.[137] Much of the work in this dissertation is motivated by the fact that increasing neighborhood greenspace through interventions like planting street trees or rewilding vacant lots could facilitate much needed human-nature connections in an increasingly urbanized society.

[2] An environment with moderate amounts of moisture.

However, thinking of greenspace only as green vegetation, as is commonly done, may not encompass all aspects of the natural environment. All types of biomes including deserts, tundra, grasslands, coniferous forests, deciduous forests, and tropical forests can be thought of as natural landscapes even though they differ substantially in their vegetation abundance and composition. This framework can help us understand how climate and different vegetation types influence how people benefit from greenspace. For instance, the results of Aim 1 suggest that greenspace in arid climates may not be beneficial except at the highest levels potentially owing to the fact that greenspace as measured by NDVI is not able to fully capture natural landscapes in these places.

In addition to differing innate aesthetic appeal, individual plant species also have varying capacities to deliver ecosystem services to humans. For example conifers which can be planted in high density may be better at reducing environmental noise pollution from roadways when compared to hardwood deciduous trees.[138] Conversely, trees with canopies and broad leaves are likely better at mitigating urban heat islands.[139] While we were unable to examine these mechanisms in great detail in this dissertation, we observed varying sensitivity of our associations with residential and park greenness to adjustment for environmental hazards that are plausible confounders or mediators of the association between greenspace and depression. Our results were generally robust to adjustment for noise pollution, artificial light at night, and air pollution, though estimates from Aim 1 were slightly more attenuated compared to Aim 2. These results suggest that greenspace in residential areas may play more of a role in protecting individuals from harmful environmental exposures while greenspace within parks may promote mental health via more nuanced psychosocial mechanisms like promoting social cohesion and increasing connectedness with nature.

While our observations in Aims 1 and 2 suggest, as many other studies do, that greenspace in certain forms and contexts may reduce depression[11], the magnitude of these associations is very modest when compared to other potentially modifiable risk factors such as uncontrolled type II diabetes which has been shown to increase the risk of major depression by up to 50%.[140] For example, we estimated that, even in cold climates where we observed the strongest associations, one interquartile range higher NDVI reduces the prevalence of major depression by 17%. Given the approximately 8% prevalence in the older adult population of the Health and Retirement Study, such a reduction translates to a small absolute difference. Nonetheless, because greenspace is so common, increasing greenspace in residential areas may prevent a large number of major depressive events when aggregated over an entire population. Additionally, increasing access to greenspace could have positive impacts on a number of health outcomes besides depression across populations of all ages including birthweight, community violence, cognitive functioning, and mortality.[6,38,141,142] Therefore, while increasing access and exposure to greenspace is not a magic bullet for addressing mental health issues at the population scale, it should be considered as one of many social and environmental changes that must occur to elicit meaningful changes in public health.

Improving landscapes within public parks is a logical way for municipalities to increase and optimize access to greenspace. In Aim 3 we confirmed that public parks are important for providing greenspace to urban populations as they have substantially more vegetation than surrounding neighborhoods. Aim 2, however, suggested that simply having access to parks was not associated with fewer depressive symptoms. Rather, when we disaggregated different types of vegetation in parks, we found that grass covered park area was associated with fewer depressive symptoms, the opposite was true for non-vegetated spaces, and tree covered area was not associated with depressive symptoms. This suggests that some level of thoughtfulness is needed in selecting plants for parks when trying to leverage the mental health benefits of these spaces.

The varying health benefits with plant type especially interesting since we observed that the type of vegetation comprising greenspace within parks can vary across populations. Specifically, we found that Black, Hispanic/Latino, and lower socioeconomic status neighborhoods in the cities studied have parks with more grass, more non-vegetated space, and less tree canopy when compared to parks in more affluent communities. This suggests that neighborhoods may be well served by local parks with plentiful grassy space and cautions us from assuming that park characteristics experienced by less privileged neighborhoods are, by default, undesirable or deleterious. That said, it is challenging to conclude the health benefits of those parks since having more non-vegetated area appears to be harmful among this older population. Furthermore, even though we did not find that tree canopy was protective of mental health, it may provide benefits that grassy areas do not like shade during periods of extreme heat[131], an ecosystem service that will be increasingly important with climate change.

Finally, it is worth noting that the findings of Aims 1 and 2 may not be generalizable, especially to younger, non-White, or lower socioeconomic status populations. The specific needs and preferences of communities should always be considered when translating research findings into public health action. For example, multiple studies have shown that the presence of facilities like basketball courts, baseball field, and shelters in parks promote usage in low socioeconomic status communities.[143] This may be less true, however, for older populations like the one followed in HRS. Older adults have very specific preferences when it comes to their local parks; they tend to prioritize safety, accessibility, interaction with peers, opportunities for walking, and greenspace that offers engagement with nature but are easily navigable.[123] As such, it is essential for planners to be considering their populations in selecting greening interventions.

5.2 Strengths and Limitations

The quality of Health and Retirement Study (HRS) data is a strength of this dissertation. In Aim 1 we were able to use a validated instrument for detecting major depression that is based on Diagnostic and Statistical Manual of Mental Disorders criteria and administered to all study participants uniformly. This is expected to have less measurement error as compared to previous studies that have largely relied on self-report or medical claims. In Aim 2, we had multiple measurements of CESD-8 score per person, which provided better precision and adjustment for between-person differences. Additionally, we were able to adjust for a wide variety of potential individual, neighborhood, and geographic confounders which improved confidence in our effect estimates in both aims.

Detailed information about residential locations for each respondent was also an important strength of this work that allowed us to estimate person-specific access to greenspace for Aims 1 and 2. Similarly, our use of remote sensing data to objectively measure greenspace is a strength of all three aims. In Aim 1 we used NDVI from the MODIS-Terra satellite. This allowed us to capture exposures specific to the location of the respondent and the year of outcome assessment. In Aims 2 and 3 we employed the higher-resolution (1m-10m) landcover datasets WorldCover 2020 and Meter-scale Urban Landcover which allowed us to disaggregate trees from grass within urban areas and further still within urban parks. Lastly, a notable and unique strength of Aim 2 was our use of the PADUS-AR, a newly published comprehensive database of accessible and recreational open spaces all over the United States. This builds upon previous work in the field that has relied on municipality-based catalogs of parks or small de novo field studies to investigate the health benefits of parks within smaller geographies.

While NDVI has been justifiably criticized for not capturing aspects of greenspace such as accessibility and vegetation types,[99] it is one of the few measures of greenspace that can be feasible linked to a cohort study as large and long running as HRS. In Aim 1 we attempted to overcome some of the limitations of NDVI by using climate to glean information about how specific types of vegetation that are highly subject to climatic conditions differ with respect to their mental health benefits. While the use of the high-resolution datasets WorldCover 2020 and Meter-scale Urban Landcover in Aims 2 and 3 allowed us to distinguish between vegetation types and other spaces within urban areas and further still, within parks, these datasets come with drawbacks in that they are limited in temporal resolution. This could create some temporal ambiguity in the relationships studied. We do not expect this to be highly problematic since vegetation abundance is generally stable over the time periods considered in our studies.[43] In addition , we were not able to characterize park facilities that may be indicated by the presence of non-vegetated spaces. As such, we are unable to distinguish between features like playgrounds and parking lots, which likely have very different health implications and associations with neighborhood sociodemographic characteristics. The same goes for specific attributes of vegetated spaces that influence usability for older adults such as the presence of park benches near grassy fields or accessible walking paths under tree canopies. Additionally, our use of straight lines distances to park boundaries, lack of information about park access points, and data on which parks our participants actually used is a limitation.

Another limitation specific to Aims 1 and 2 is the potential for residual confounding by neighborhood self-selection. The propensity for healthier individuals to elect to live in neighborhoods with more salubrious features, like more greenspace, is a persistent concern in studies of the built environment's influence on health.[144,145] Some studies have attempted to explore the existence, direction, and magnitude of this potential source of bias. For example, a recent study by Gailey found that the association between pre-move health status indicators and post-move residential NDVI was weak or non-existent among mothers in California.[146] While this is a younger population than our cohort, their findings indicate that neighborhood self-selection bias, if present, is likely small.

5.3 Future Research

The collective findings of this dissertation point to several avenues of future research. Since we found that not all greenspaces may be equally beneficial, future studies could find better ways to characterize vegetation. Unfortunately, however, even high resolution landcover datasets like the ones we used in Aims 2 and 3 tend not to identify individual species of plants. Yet this may be important when studying the health benefits of vegetation. For example, a study by Zhang found that certain species of shrubs are better than others at reducing surface temperature in urban areas.[51] Similarly, a study by Wang et al. found that there was substantial heterogeneity in the ability of nine different tree species to reduce ultrafine particulates from diesel exhaust fumes.[52] Characterization of this granularity may not be feasible in large scale epidemiologic studies and need to be carried out in situations where horticultural data is tracked at the municipal level, or study populations are small, and the infrastructure exists to collect data de novo. There are also efforts to study the health benefits of specific types of vegetation at larger scales using machine learning to classify vegetation in Google Street View images.[101] This work is still ongoing, however, and to our knowledge it has yet to be used to identify specific plant species.

Another interesting finding of our work was that climate appeared to influence how people benefit from greenspace. Since the climates studied in this investigation have very different seasonal patterns that influence vegetation and use of natural spaces, future studies might consider the role of seasons. For example, in Aim 1 we speculated that vegetation might be particularly important for mental health in places with harsh winters because of fall foliage and spring flowers. This assumption could be tested by comparing the impacts of deciduous vs. evergreen vegetation within cold regions or integrating information on vegetation types with temporally specific outcomes that are likely to be affected by surrounding greenspace close to the time of onset.

Lastly, future research might delve deeper into how the composition of parks influences their health benefits. The findings of Aims 2 suggest that grassy park area may be most useful for relieving depression among older adults. Approaches that characterize usage and preferences with regard to different park spaces could be illuminative.

5.4 Conclusions

This dissertation contributes to our scientific understanding of the mental health benefits and equitable distribution of greenspace in parks and residential areas. We leveraged cohort data from older adults living all over the United States, high resolution landcover datasets, and newly available national data on accessible and recreational parks to accomplish three aims that add to this rapidly growing field of research. Our findings indicate that the relationship between greenspace and depression is highly complex and depends on contextual factors like climate, where greenspace is located (residential areas versus parks), and the types of vegetation present in those spaces. This work underscores the importance of continued research into the nuanced landscape of greenspace equity. Lastly, this dissertation informs future research regarding the mental health benefits of greenspace and can be used to motivate and design effective policies and interventions that leverage greenspace as a tool to improve population health.

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