EFFECT OF GREEN SPACE EXPOSURE ON THE RELATIONSHIP BETWEEN SOCIOECONOMIC STATUS AND MENTAL HEALTH AMONG OLDER CANADIANS

by

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Dalhousie University is located in Mi'kma'ki,
the ancestral and unceded territory of the Mi'kmaq People.
We are all Treaty people.

DEDICATION

To my Nanny, Joyce Fay Irvin.

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ABSTRACT

Green space is considered to be a health-promoting feature of both natural and built environments and has the potential to influence mental health outcomes at both an individual and population level. Green space interventions, such as incorporating grass and trees into built environments, have been suggested as a strategy to improve population-level mental health outcomes and reduce socioeconomic-related inequalities in mental health. However, most green space research to date has neglected to address whether green space exposure differentially affects mental health outcomes for individuals with different levels of socioeconomic status. Our study explored the relationship between green space, socioeconomic status, and mental health outcomes in Canada using multivariate regression models, as well as the association between green space and socioeconomic-related mental health inequalities measured using the concentration index. We found a significant moderating effect of green space exposure on depression score when using self-rated social standing as a measure of socioeconomic status, but did not measure any statistically significant associations between green space exposure and socioeconomic-related mental health inequalities. Our results suggest there is a relationship between green space exposure and mental health in Canada, however further research is warranted using more descriptive measures of green space as well as more geographically defined populations when measuring mental health inequalities.

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Chapter One: Introduction

Understanding how the natural environment shapes mental health outcomes and mental health inequalities is crucial for improving population health and has important implications for urban planning and public health interventions. Over the last decade, multiple cross-sectional studies have indicated that green space exposure influences mental health by reducing stress and improving attention, which decreases the risk of depression and anxiety (1–4). These findings have led to the suggestion that green space interventions, such as increasing vegetation in urban areas and improving the quality of parks may lead to better population-level mental health outcomes. However, most green space research to date has neglected to address how green space exposure affects mental health outcomes for individuals with different characteristics, such as socioeconomic status. Given the strong associations between socioeconomic status and mental health outcomes, as well as potential systematic differences in green space exposure based on socioeconomic status, we believe that it is important to understand the interplay between socioeconomic status, green space, and mental health in order to fully realize the mental health benefits of green space through thoughtful, evidence-based interventions.

Socioeconomic status (SES) is an important social determinant of health and affects mental health by modifying psychosocial, material, and behavioural factors (5). For example, individuals with low SES are more likely to experience chronic stress, negative life events, and often have lower levels of social support (5). From a material perspective, individuals with low SES are more likely to live in crowded conditions and poor-quality housing, and from a behavioural perspective, individuals with low SES are less likely to engage in physical activity and have higher rates of substance use compared to individuals with high SES (5). Although these factors are wide ranging in scope, they are all influenced by SES and are associated with poor mental health outcomes.

Depression, self-rated mental health, anxiety, and stress all have strong social gradients and individuals with low SES are disproportionately affected compared to individuals with high SES (5,6). Although green space is an environmental feature, exposure to green space may be determined by factors related to SES such as income, occupation, and health status. For example, more affluent neighbourhoods often have higher levels of green space compared to less affluent neighbourhoods (7), and healthier people may choose to live in neighbourhoods that support healthy behaviours, which in turn may be greener due to parks and other outdoor recreation facilities (8). Therefore, it is important to consider how green space exposure varies based on SES to understand systematic differences that may underlie mental health inequalities.

Despite potential socioeconomic differences in green space exposure, researchers are beginning to consider if the effects of green space exposure on mental health could be equigenic, meaning that individuals with low SES may benefit the most (9). The rationale behind this hypothesis is that green space exposure modifies psychosocial and behavioural factors that are strongly associated with low SES, such as stress, low social cohesion, and low levels of physical exercise (9). It has also been suggested that communities with more green space may have lower levels of mental health inequalities because everyone is subject to the mental health promoting effects of green space regardless of SES (1). As green space research progresses, it will be important to explore potential interactions between SES and green space when considering how both factors influence mental health outcomes at an individual and community level.

The purposes of this study were to determine if green space exposure is a moderating factor in the relationship between SES and mental health outcomes at an individual level, as well as to determine if environmental green space exposure is associated with mental health inequalities using data from the Canadian Longitudinal Study on Aging (CLSA). The results of this study help fill a gap in the literature by determining how green space affects individuals with different demographic characteristics, as well as provide evidence of if, and if so, how green space exposure shapes mental health outcomes and mental health inequalities within a Canadian context. Ultimately, this research may help inform public policy surrounding green space interventions as an approach to improving mental health outcomes in Canada.

Chapter Two: Background

2.1 Green Space Research

In the last two decades there has been a significant increase in green space research from a diverse range of scientific fields including epidemiology, urban planning, and other social sciences (10). The speed of urbanization, along with the removal of natural vegetation from human habitats, has prompted researchers to explore the beneficial effects that green space has on human health in an attempt to improve various health outcomes and promote greener urban environments. Although green space research varies in scope and context across disciplines, the consensus is that exposure to green spaces and other natural environments has positive effects on human health and wellbeing. As a result, green space interventions aimed at increasing green space exposure have been proposed as a low-cost alternative to improve population health and may be used as upstream interventions to address specific health inequalities within societies (11).

Most epidemiological studies measuring the association between green space, health, and wellbeing use vegetation indices to quantify the density of vegetation within a specified geographic area. The most used vegetation index in green space research is the Normalized Difference Vegetation Index (NDVI), which uses satellite imaging to capture reflectance from vegetation, soil, pavement, and other surfaces and assigns scores based on vegetation density (12). NDVI scores are measured on a scale from -1 to +1, with 0 corresponding with barren land or pavement and +1 corresponding with lush green vegetation. Negative values usually correspond with standing bodies of water (not vegetation). Generally, NDVI scores between 0.2 and 0.3 are considered moderate green space (e.g., shrubs, grassland), and scores between 0.6 and 0.8 are considered high green space (e.g., temperate forests) (13).

Vegetation indices produced from satellite imaging techniques, including NDVI, are considered the "gold standard" to objectively classify environmental conditions due to their precise spatial and temporal resolution (14). The main satellite sensor used to produce NDVI is Landsat, which has a 30m spatial resolution (15). However, when using NDVI in epidemiological studies as a measure of individuals' green space exposure it is usually linked to postal code data and reported as a mean value of NDVI scores within a specific buffer area of postal code locations (50m, 100m, 250m, 500m, or 1km) (16,17). Temporally, NDVI can be reported as an annual or growing season mean, or maximum (16).

Green space exposure influences a variety of health outcomes across the life course that begin during pregnancy and persist until the end of life. During pregnancy, mothers with higher levels of green space exposure may have better outcomes including higher birth weight and lower infant mortality. A cross-sectional study in California used NDVI to measure the association between residential green space exposure and birth outcomes, and found that for every interquartile range increase in NDVI within a 50m buffer area surrounding pregnant mothers' homes, mean birth weight increased by 6.09 grams (p<0.01) (18). Other research in France found that high-risk clusters of infant deaths in Lyon, France were rendered statistically insignificant (p=0.12) after adjusting for greenness at the census block-level (19).

Children and adolescents also benefit from green space exposure, and it has been proposed that children who are not exposed to green space may suffer from a type of "nature-deficit disorder" which affects many aspects of physical and mental health (20). For example, green space exposure may mediate physical activity therefore influencing the prevalence of obesity among children and adolescents. Cross-sectional research in Spain addressing the association between residential green space and health outcomes in children found that for every interquartile range increase in NDVI, school-aged children were 13-19% less likely to be overweight or obese compared to children with less residential green space exposure (21). As people age, higher levels of green space exposure are associated with lower risk of stroke, diabetes, cardiovascular mortality and all-cause mortality (20). These health outcomes are all associated with physical activity and stress, and green space exposure may reduce the risk of these outcomes by promoting physical activity and reducing stress (20).

Green space exposure is also inversely associated with various mental health outcomes, including depression, anxiety, and stress, and positively associated with self-rated mental health (2–4,17,22). For example, a cross-sectional study in Wisconsin found that among participants in both urban and rural areas, a 25% increase in green space exposure measured using a combination of NDVI and percent tree canopy was associated with lower depression, anxiety, and stress scores measured using the 42-item Depression Anxiety and Stress Scales (DASS). The authors used the DASS instrument as a continuous measure of depression, anxiety, and stress symptoms, with higher scores indicating worse mental health states (2). Individuals with 25% more green space exposure scored on average 1.4 points lower for depression, 0.4 points lower for anxiety, and 0.7 points lower for stress, which were statistically significant decreases in DASS scores compared to individuals with less green space exposure ($p<0.05$ for depression, anxiety, and stress) (2). These results are supported by many other studies, including research conducted in Canada. For example, in 2019, Hystad et al. determined that among adults living in urban areas in Quebec, a 0.1 increase in NDVI within a 500m buffer area surrounding their home significantly reduced the odds of clinically diagnosed depression (OR= 0.85), as well as the odds of experiencing anxiety (OR= 0.81) (17).

Despite general consensus that green space exposure improves health, “green space” is not clearly defined across disciplines and is therefore measured in different ways. This limits studies’ generalizability and may lead to discrepancies in results when determining how green space affects health (1,10). In urban areas, green space is often the product of intentional urban planning initiatives to make cities more natural by increasing vegetation within a built environment (1). Examples of these initiatives include grassy roadway medians instead of gravel or pavement, planting flowers and trees along sidewalks, and building parks. However, current green space research also defines green space as agricultural land or natural landscapes (10), which are more likely to be in rural areas, and in contrast with urban green space, are not specifically designed with the intention of increasing green space exposure or providing natural environments for recreation (10). It is important to consider the definition of green space when comparing results between studies because there may be implications for how people interact with and use the green space in question. This is especially relevant when comparing green space studies conducted in rural versus urban environments because of potential systemic differences in types of green space exposure between these environments (1,10).

2.2 Pathways linking Green Space and Health

Medical geographers who study the relationship between health and place have noted the shared importance of natural features including landscapes, topography, and water sources, among locations that have been considered places of healing throughout history (e.g., Lourdes in France, Denali in Alaska, and Epidauros in Greece) (23). As urbanization progressed in the 19th and 20th centuries, cities around the world recognized the importance of including urban green spaces to provide recreational spaces to conduct leisure activities, which was viewed as important for maintaining physical and mental wellbeing (24). The early perception of natural, green environments being beneficial to physical and mental health is also reflected in the choice of location for hospitals and asylums in the 19th century, as they were usually built in rural locations with lots of surrounding green space, clean air, and low population density (23).

Although green space has been valued for hundreds of years, researchers have only recently begun to explore the specific pathways and mechanisms by which it improves health especially in urban environments. Green space exposure is thought to influence health and wellbeing through three main pathways: mitigation, restoration, and instoration. The mitigation pathway focuses on how green space improves environmental conditions beneficial to health and wellbeing, including reducing noise and air pollution. The restoration pathway explores the underlying biological mechanisms that green space acts on to help restore attention and reduce the stress response, and the instoration pathway is related to how green space promotes healthy behaviours such as physical activity and encourages social cohesion (1,12). Figure 1 illustrates these pathways and provides examples of changes in health and wellbeing associated with green space exposure.

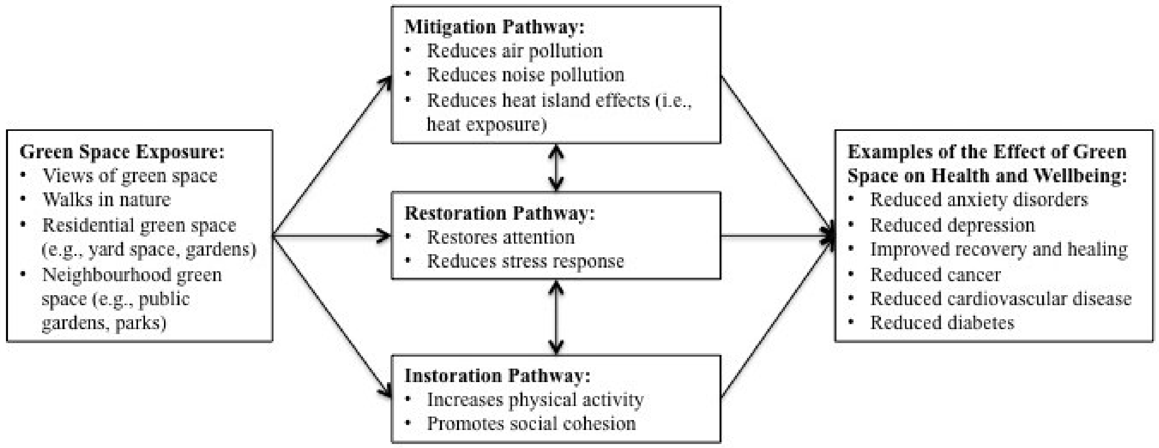

Figure 1. Examples of types of green space exposure, and the pathways through which it affects health and wellbeing. Adapted from Markevych et al(1).

The ability for green space to promote healthy behaviours and improve environmental conditions largely depends on the type and quality of the green space in question. For example, in order for green space to promote healthy behaviours such as physical activity and social connectedness, it must be accessible (e.g., a park within walking distance of a community) and intended for physical activity (e.g., a walking trail, not a field used for agriculture) (1). Similarly, for green space to improve environmental conditions, it must meet certain requirements such as density of trees and other plants required to reduce air pollution, or land cover requirements required to reduce heat island effects (25).

In contrast, the stress-reduction properties of green space seem to stem from the physical presence of green space in an individual's environment, and not necessarily their use of that green space. For example, a randomized control study found students in classrooms with window views of green space recovered faster from stressful experiences and had 14.33 percent higher attention capacity than students in classrooms with views of built environments, even when the students did not get to spend time outside and therefore were not physically exposed to green space (26). Other cross-sectional research has demonstrated that views of green space improve recovery for stationary patients (i.e., patients who are unable to go outside). An early study conducted with cholecystectomy patients in the 1980s found that patients with window views of natural spaces spent an average of 7.96 days in hospital post-operation compared to 8.70 days for patients with views of brick walls (27). Views of natural green space also improves self-rated wellbeing at work (28). The most widely accepted theory for this phenomenon is the Attention Restoration Theory proposed in 2001 by Kaplan and Kaplan, which posits that exposure to natural environments, including viewing these environments, passively captures attention and attenuates the stress response (29,30).

2.3 Green Space Exposure and Mental Health Outcomes

There is a strong positive association between green space exposure and desirable mental health outcomes. Green space exposure reduces the risk of depression, stress, anxiety (2–4,17,22), and loneliness, and improves self-rated mental health and feelings of social support (31). In addition to green space mediating the stress response, a functional magnetic resonance imaging (fMRI) study has demonstrated that exposure to green environments decreases blood flow in the prefrontal cortex (32), which may reduce ruminative brooding, a psychological state where people constantly compare themselves to an unachievable standard. Reduction in ruminative brooding may reduce social stress and lower the risk of mental health outcomes such as anxiety (30).

Green space exposure primarily affects mental health outcomes through the restoration (i.e., stress-reduction) pathway, although this pathway can be mediated by factors related to the mitigation and instoration pathways as well. For example, healthy behaviours and better environmental conditions facilitated by green environments can also reduce stress and improve mental health outcomes (3,33). There is also a contemporaneous relationship between green space exposure and cortisol levels, which indicates that green space exposure has the ability to immediately attenuate the stress response and may lead to better mental health outcomes over time (34,35). For example, the practice of forest bathing (shinrin-yoku) in Japan has long been considered to have therapeutic effects on mental health and reduce stress (36). An experimental study conducted with 348 men in Japan measured salivary cortisol concentration immediately after a 15 minute exposure to either a forest (i.e., green) or urban environment and found that the mean salivary cortisol concentration for all participants was 0.90 nmol/L lower after exposure to the forest environment compared to the urban environment ($p<0.001$) (37). Another experimental study in Sweden used virtual reality technology to expose participants to multisensory environments depicting a forest, park, or urban landscape and measured attenuation of the stress response using skin conductance levels measured during and after the induction of physiological stress from mild electric shocks. Participants in the forest and park groups had significantly lower skin conductance levels compared to the urban group ($p<0.001$ for both) during the induction of the stress response, as well as during the recovery period ($p=0.003$ for forest, $p<0.001$ for park) (35). The mean skin conductance (measured in siemens) for the forest, park, and urban groups during the induction of the stress response (i.e., while the electric shocks were being administered) were 0.65, 0.50, and 1.14 respectively, and 0.35, 0.33, and 1.05 during the recovery period (35). This suggests that being in a green environment not only attenuates the stress response during a stressful experience, as indicated by the lower mean skin conductance levels for the forest and park groups, it may also help people recover from those experiences as illustrated by the larger decreases in mean skin conductance between the induction and recovery periods for the forest and park groups compared to the urban group (-0.30 for forest, -0.17 for park, and -0.09 for urban). Because green space exerts immediate effects on the stress response, it can promote psychological restoration and may improve individuals' ability to reflect and process their emotions, which in turn may reduce the risk of experiencing negative mental health outcomes (34).

Continuous green space exposure (e.g., living in an environment with surrounding green space) can also reduce chronic stress. A study conducted in the UK used hair cortisol concentrations from 132 healthy adults to determine the effect of natural spaces on chronic stress (38). Hair cortisol concentration is a unique biomarker for stress because it captures cortisol secretions over time (up to three months when measuring cortisol in a hair sample taken from 3cm of scalp hair) (38). The authors measured the percentage of area within 400m of study participants' residences that consisted of natural features (e.g., fields, parks, and gardens), and created tertiles of natural environment (55.5%, 67.4%, and 77.0% natural environment, respectively). The overall mean hair cortisol concentration for all study participants was 10.8 pg/mg, however those in the lowest natural environment tertile had statistically significant ($p<0.05$) higher mean hair cortisol concentration (approximately 14 pg/mg) compared to those in the second and third tertiles (10 pg/mg and 9 pg/mg). A separate analysis determined that income deprivation was also significantly associated with higher hair cortisol concentration ($p<0.05$). When income deprivation and the natural features of the environment were combined in a multivariate regression model, both coefficients were rendered insignificant, which is likely due to a high degree of collinearity between the variables (38). While this is a limitation of the study, it does highlight that both income and natural features (i.e., green space) affect chronic stress, and that it is important to improve our understanding of not only the physiological effects of green space on stress and mental health but also how green space interplays with socioeconomic status to produce mental health outcomes.

Green space exposure is also associated with subjective measures of mental health such as perceived stress and self-rated mental health (33,39). A nationally representative longitudinal study among older adults in the United States found a direct negative association between green space exposure and perceived stress (33). While the relationship between green space and perceived stress was statistically significant for the entire study population ($p<0.05$), race, social support, and education significantly modified the effect. This highlights potential socio-demographic differences in the relationship between green space and perceived stress (33). In Canada, a study conducted using 397,900 participants from the Canadian Community Health Survey found that the odds of having low self-rated mental health decreased by 6% for every interquartile range increase in NDVI, which corresponded to an NDVI increase of 0.12 (40).

Green space exposure can also be used as therapy to improve subjective mental health outcomes. A study in Serbia found that psychiatric patients with depression disorders reported an average decrease of ~1.25 points in self-rated stress using the Depression Anxiety Stress Scale (DASS) after participating in horticulture therapy. In comparison, patients who did not participate in the horticulture therapy only reported an average decrease of ~0.25 points in self-rated stress after receiving their conventional therapy, and there was a statistically significant interaction in pre and post intervention DASS scores between the horticulture therapy group and conventional therapy group ($p<0.05$) (22).

Green space research consistently highlights the beneficial effects of green space exposure on mental health outcomes. Although the scopes of individual green space studies vary by target population, type of green space exposure (i.e., horticulture therapy vs. viewing an image), and mental health outcomes, the results of these and other related studies have led to 8 systematic reviews published between 2015 and 2021 supporting the conclusion that green space exposure improves mental health (4,12,41–46). Building on the results of these studies, there is increasing interest in intentionally incorporating green space into the built environment to improve mental health outcomes for populations. Urban green space interventions are gaining traction as a way to improve mental health outcomes, while simultaneously providing opportunities to increase biodiversity and improve environmental conditions (47). Examples of urban green space interventions include park-based interventions (i.e., building or improving the quality of parks), creating greenways and trails, greening unused areas (e.g., roadway medians or vacant lots), and more specific interventions such as green roofs and rain gardens (47). Natural green spaces, urban green space interventions, and nature-based therapies may be effective population mental health strategies (4), as well as play a role in improving environmental conditions and mitigating the effects of climate change (47). Undoubtedly, increasing and improving quality and access to green space is a worthy investment for our collective future.

2.4 Socioeconomic Status and Measuring Health Inequalities

Socioeconomic status (SES) is a complex construct that measures an individual's position in a social hierarchy, as well as their ability to obtain health-promoting resources (48). It is typically measured using one or a combination of income, education, and occupation indicators, which are all associated with social gradients in mental health outcomes. Income, education, and occupation are objective indicators that reflect the three main mechanisms by which SES is theorized to influence health outcomes (material, behavioural, and psychosocial pathways), and specific indicators are often chosen to help illustrate these pathways (49).

Across contexts, individuals with lower SES have worse health outcomes than individuals with higher SES due to a combination of material, behavioural, and psychosocial factors, which creates social gradients in health and drives socioeconomic-related health inequalities (50). The Whitehall studies by Marmot et al. conducted on British civil servants beginning in the 1960s were critical in establishing the inverse gradient between social class (measured using grade of employment, income, and education) and health (51), and have widened our view of risk factors for disease beyond those included in biomedical models of health. This has led to a shift in epidemiological models from controlling for social class and SES in an attempt to understand the "true" relationship between other more traditional risk factors (e.g., obesity, smoking) and health outcomes (e.g., heart disease), to including SES as an important determinant of health and driver of health inequalities (52).

Income is one of the most objective measures of SES and is therefore widely used to measure and explain socioeconomic-related health inequalities. Individual-level income has a strong positive association with general mental health measures using psychological distress scales (e.g., Mental Health Inventory-5) (53) as well as specific mental health outcomes including depression (54). Income affects the psychosocial pathway linking SES and mental health because individuals with low income may experience more psychosocial stress related to financial hardship than individuals with high income (55). Income also impacts the material and behavioural pathways by contributing to an individual's ability to obtain material resources (e.g., quality housing) as well as their ability and likelihood to participate in health promoting behaviours (e.g., physical exercise, healthy diet).

Because SES is a complex construct involving position in a social hierarchy, it is important to also consider subjective measures of SES to understand how individuals rank themselves compared to others. Subjective social standing, also called self-rated social standing, is measured by asking individuals where they fit on a ten rung ladder representing the social hierarchy in their community, with people at the top being the most advantaged (56). Self-rated social standing is strongly associated with multiple health outcomes including depression and self-rated health (56) and is a strong predictor of health status and health decline especially among older adults (57).

Quantifying the degree of socioeconomic-related mental health inequalities is important for developing policy aimed at improving mental health outcomes. Over time a variety of methods have been used to measure inequalities in health, including range, the Gini coefficient, the Lorenz curve, the index of dissimilarity, the slope index of inequality, and the concentration index (58). The seminal paper in 1991 by Wagstaff et al. (58) highlighted the importance of health inequality measures capturing the socioeconomic dimension of health inequalities across the whole population, not just between the least and most advantaged individuals (e.g., inequality captured by range). They also suggested that measures should be sensitive to changes in how the population is distributed across socioeconomic groups. They proposed that the best health inequality measures are the slope index of inequality and the concentration index because both measures meet these criteria (58). Since the publication of the paper by Wagstaff et al., the concentration index and the slope index of inequality have become two of the most widely used methods of measuring health inequalities (59,60).

The concentration index is based off the concentration curve, which plots the cumulative percentage of individuals in a population ranked according to a socioeconomic variable against the cumulative percentage of the health outcome. In a population with perfect equality the concentration curve would be a straight diagonal (a 45 degree line), and populations with inequality have concentration curves that deviate from the diagonal (61,62). The concentration index is defined algebraically as $C=2cov(x,h)/\mu$, where $cov(x,h)$ is the covariance between the relative rank, x, and health, h, and μ is mean level of health. It can also be defined graphically as twice the area between the concentration curve and the diagonal (63). To make the concentration index more relevant for policy decisions, it is often standardized through direct or indirect methods which allows for the measurement of avoidable inequalities in health by controlling for policy-irrelevant variables (e.g., age and sex) while considering the impact of policy-relevant variables (e.g., income and education) on health inequalities (63–65).

The slope index of inequality also measures the relationship between SES and health, however, instead of utilizing cumulative percentages of individuals and health outcomes, it groups individuals into socioeconomic groups and measures the relationship between socioeconomic rank and mean health status of each group using regression analysis (58). The value of the slope index of inequality is equal to the slope of the regression line relating mean health status to socioeconomic rank (58).

Although both the concentration index and the slope index of inequality are sensitive to changes in health status across socioeconomic groups, the concentration index has several advantages over the slope index of inequality when comparing socioeconomic health inequalities between separate populations (58). The primary advantage is that the concentration index is a relative measure (compared to the slope index of inequality, which is an absolute measure), which facilitates comparisons of inequalities between different measures of health (58). This is particularly useful when developing and evaluating strategies to reduce socioeconomic-related mental health inequalities because it allows for evaluations of effectiveness of the strategies for different measurements of mental health (66). Another key difference between the two methods is in their graphical representation. Because the slope index of inequality relies on grouped data (i.e., socioeconomic groups), the graphical representation of the data will vary based on the size of the groups which makes straightforward interpretation across populations and time more challenging if the size of the socioeconomic groups vary (58). In contrast, the graphical representation of the concentration index, should individual-level data be available, does not visually group data because it plots the cumulative percentage of individuals according to the socioeconomic variable of interest. This results in a consistent visual representation of inequality for each population being studied and allows for easier comparisons (58).

2.5 Inequalities in Green Space Exposure in Canada

When considering the beneficial effects of green space exposure on mental health, it is important to recognize existing inequalities in green space exposure and address these inequalities when designing green space interventions aimed at improving population-level mental health. Across both urban and rural contexts, disadvantaged individuals often live in poorer quality environments, which may result in less access and exposure to green space compared to more advantaged individuals (67,68). This differential green space exposure across social classes may cause disadvantaged individuals to miss out on the mental health-promoting effects of green space, and further exacerbate existing mental health inequalities.

Multiple cohort and cross-sectional studies conducted in Canada have concluded that disadvantaged Canadians have less green space exposure compared to more advantaged Canadians. A cohort study by Crouse et al. found gradients in green space exposure among Canadians living in cities (67), where individuals with the lowest income and educational attainment had the lowest residential green space exposure (measured using average NDVI score within a 250m buffer from their residential address). For example, individuals in the lowest income quintile had a mean NDVI of 0.55, and those in the highest income quintile had a mean NDVI of 0.60 (67). While a difference in mean NDVI of 0.05 is only a modest increase, it highlights the gradients of greenness experienced by individuals across the socioeconomic distribution (67).

In Montréal, a study conducted by Pham et al. found that individuals with low income and those who are visible minorities were more likely to live on streets with less vegetation (68). The authors determined there was a statistically significant negative association (p<0.001) between the percentage of low-income population and total vegetation by city block, and that the magnitude of the association increased when only including public lands in the analysis (versus also including private yards). For models measuring vegetation in private yards, a 10% increase in low-income population was associated with a 6.3% decrease in total vegetation, but when private yards were excluded the decrease in total vegetation was 13.2%. This may indicate that there is less investment in public vegetation in low income areas, which may be related to having fewer community actors advocating for increased green space in these neighbourhoods (68). Similar patterns exist in other large Canadian cities including Vancouver and Toronto (69), which suggests that there are differences in green space exposure between socioeconomic groups across Canada and warrants further exploration into the underlying causes of green space inequality especially in Canadian cities.

Socioeconomic differences in green space exposure raise questions about health equity and environmental justice. Health equity can be defined as "the state where everyone has the opportunity to attain their full health potential, and no one is disadvantaged in attaining this potential" (70). In other words, if green space exposure improves mental health outcomes and individuals with low SES are systematically disadvantaged in their level of green space exposure through mechanisms outside of their control (e.g., municipalities do not invest in parks in low-income neighbourhoods), then individuals with low SES are denied the fair opportunity to attain their full mental health potential.

Environmental justice is related to the concept of health equity in that it argues for the universal right to health, specifically regarding environmental exposures. The environmental justice movement started in the 1970s in the United States, when it was acknowledged that poor, predominantly Black individuals were unfairly exposed to environmental hazards through processes of racial discrimination (e.g., the construction of toxic waste landfills in predominantly Black communities) (71). In Canada, historically the discourse surrounding environmental justice has primarily focused on differential exposure to environmental hazards based on social class and has largely ignored racial differences in exposure (72). However, the distribution of environmental hazards in Canada, including open dumps, waste facilities, and other toxic sites, are often unfairly concentrated in close proximity to Indigenous and Black communities (72). One of the most blatant examples is in Pictou Landing First Nation, Nova Scotia, a Mi'kmaw community whose sacred burial ground was contaminated from the 1960s until 2020 by toxic wastewater from the Northern Pulp paper mill. Despite Mi'kmaq People never ceding their land, and a Crown grant to protect 34 acres of land containing the burial grounds, Northern Pulp pumped approximately 25 million gallons of toxic wastewater per day into the estuary known as A'Se'K, or Boat Harbour, exposing residents to dangerous levels of heavy metals and contaminating the sacred site (72).

When addressing issues of environmental justice in Canada it is imperative to recognize the role that colonialism and racism have played in shaping exposure to environmental hazards, as well as recognize how racial discrimination, and discrimination on the basis of other characteristics, may influence policies surrounding environmental exposures in the present and future. Green space exposure is quickly becoming an environmental justice issue because urban green space initiatives (e.g., building parks) more often occur in predominantly white communities, and benefit individuals with higher income (73). To move forward in an equitable and unbiased way we must address racial and economic inequalities in green space exposure and interventions.

2.6 Green Space Interventions to Reduce Mental Health Inequalities

Given the evidence that green space is associated with better mental health outcomes, green space interventions such as building parks and increasing vegetation levels in cities through urban greening initiatives have been proposed as upstream approaches to reduce socioeconomic-related mental health inequalities within populations (1,34,73). Socioeconomic-related mental health inequalities are systematic differences in mental health status by SES and are an important public health concern because they represent potentially unfair differences in health status and increase burden on individuals, communities, and healthcare systems (74).

The underlying principle of green space interventions is that in general, green space exposure improves mental health outcomes. However, individuals with low SES may have less access to green space exposure in their communities and therefore are unable to reap the mental health benefits, which puts them at a disadvantage compared to individuals and communities with high SES. Increasing green space exposure for individuals and communities with low SES may improve mental health outcomes and reduce socioeconomic-related mental health inequalities (7,47). In order for green space interventions to be effective, it is important to first understand the complex relationship between green space exposure, SES, and mental health outcomes, specifically how green space exposure modifies the relationship between SES and mental health. This will inform policy makers and public health practitioners about the potential benefits of green space exposure on mental health outcomes for individuals and communities across the socioeconomic distribution.

2.7 Summary

Although there is a body of evidence to support the benefits of green space exposure on mental health outcomes, there remain significant gaps in the literature that we hoped our study would address. First, there has been limited research addressing the relationship between green space exposure and mental health outcomes in Canada. Second, most green space research has neglected to address if green space exposure differentially affects individuals based on demographic characteristics such as SES. Finally, green space interventions (e.g., neighbourhood greening initiatives) have been proposed as an upstream approach to reducing mental health inequalities (11), however there has been limited research quantifying the effects of green space exposure on these inequalities. Measuring mental health inequalities with respect to green space exposure is a critical step in determining the potential effectiveness of green space interventions, and is important evidence to consider when directing resources towards different strategies such as urban green space initiatives or other public health interventions.

Chapter Three: Study Objectives

The purpose of this study is to explore the relationship between green space, socioeconomic indicators, and mental health outcomes using data from the Canadian Longitudinal Study on Aging (CLSA). The results of this study will help fill gaps in the literature by determining how green space affects individuals with different demographic characteristics, as well as provide evidence of how green space exposure shapes mental health outcomes and mental health inequalities within a Canadian context.

The specific objectives of this study are as follows:

1. Examine the distribution of green space as represented by NDVI in Canada across urban/rural environments and socioeconomic indicators.
2. Determine if the relationship between SES and mental health varies by green space at residential location.
3. Determine if socioeconomic-related mental health inequalities are associated with green space exposure at the provincial level in urban and rural populations.

We hypothesized that green space exposure, measured by NDVI, would vary across urban/rural environments and that rural environments would have higher levels of green space exposure than urban environments due to inherent differences between the two (e.g., urban environments have more roads, sidewalks, buildings, etc.). We also hypothesized that there would be differences in NDVI across socioeconomic indicators, in particular, income. Other studies conducted in Canada have determined that individuals with lower income have lower green space exposure (67,68) and we expected to see a similar pattern in our study population.

For our second objective, we hypothesized that there would be variation in the relationship between SES and mental health outcomes based on green space exposure at residential location. Having low SES is associated with worse mental health (5,6), however increased green space exposure may mitigate the effects of psychosocial stress associated with low SES by attenuating the stress response (38).

Finally, we hypothesized that provincial sub-populations with higher green space exposure would have lower socioeconomic-related mental health inequalities. Similar to our second objective, we expected that the negative effects of low SES on mental health would be attenuated in greener areas and that green space exposure would act as an equalizer in terms of mental health outcomes between individuals with low and high SES.

Chapter Four: Methods

4.1 Overview

We used a cross-sectional design to compare mental health outcomes between individuals with different levels of SES and green space exposure. Our study used data from the CLSA collected at baseline to examine the distribution of green space in Canada, determine if there is an interaction effect between green space exposure and SES on specific mental health outcomes, and determine the degree of association between green space exposure and socioeconomic-related mental health inequalities.

To understand the relationship between SES and green space exposure on mental health outcomes, we need to know how each affects mental health outcomes separately, as well as how they intersect. Previous work on the social determinants of health has demonstrated that SES affects mental health outcomes through three explanatory pathways: psychosocial factors, material factors, and behavioural factors (75). Emerging evidence from green space exposure research indicates that green space also affects mental health by modifying psychosocial and behavioural factors, such as stress and activity levels. Although green space exposure does not directly determine material factors (e.g., living conditions), material factors related to SES may influence green space exposure (e.g., individuals with higher SES may live in higher quality neighbourhoods with more parks). Therefore, it is also important to consider material factors when evaluating the complex relationship between variables.

We drew on existing theoretical frameworks from research on the social determinants of health (5), as well as green space research (76) to develop a conceptual framework illustrating the potential mechanisms by which green space acts as an effect modifier in the relationship between SES and mental health (Figure 2). This conceptual framework helped guide our research by highlighting important variables and potential effect modification.

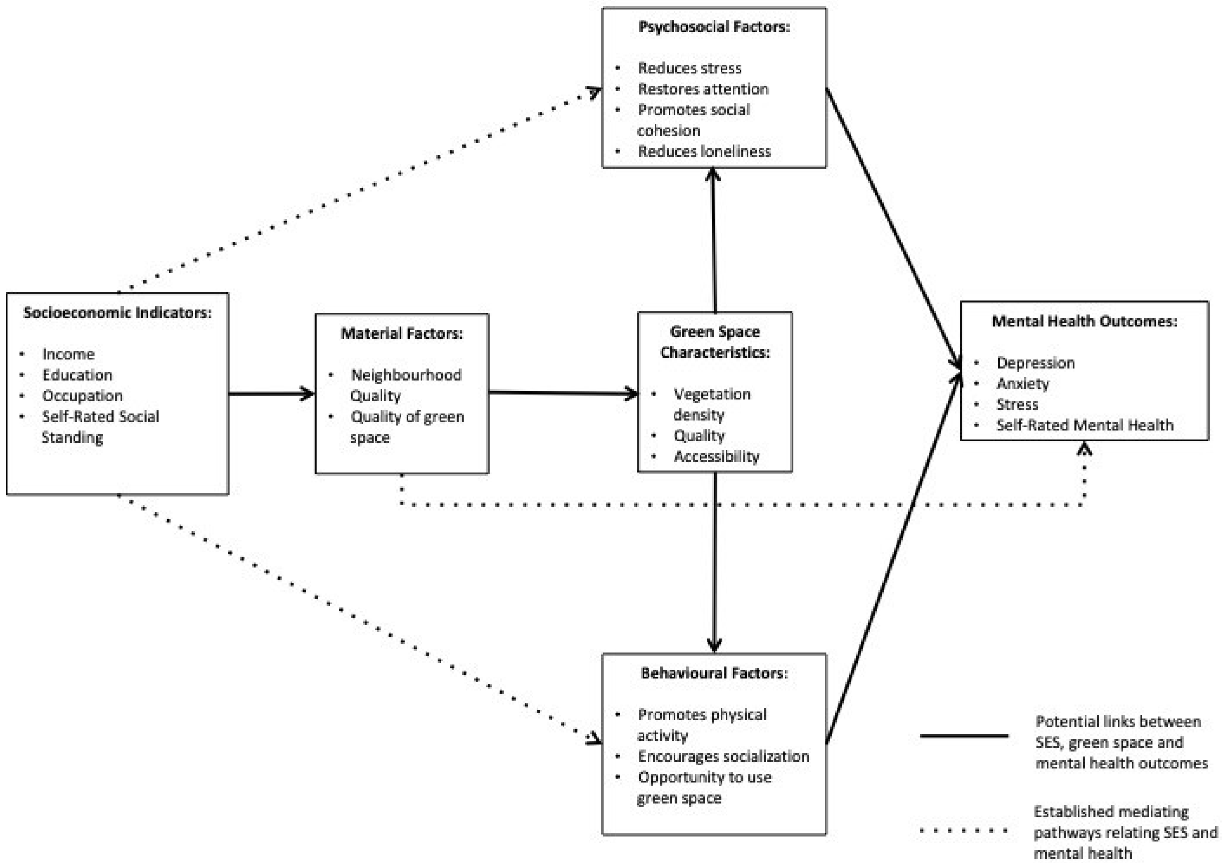

Figure 2. Socioeconomic status (SES) and green space both affect mental health outcomes. Our conceptual framework illustrates how factors associated with SES are related to green space characteristics, and how SES and green space might be related in the production of mental health outcomes.

After a comprehensive review of current literature, we chose to include two socioeconomic indicators (income and self-rated social standing) and two mental health outcomes (depression and self-rated mental health) in our study. We chose to use income as our objective measure of SES because there is a large body of evidence that individuals with lower income have worse mental health outcomes, and that many population-level mental health inequalities can be explained by income inequalities (53,66,77). Self-rated social standing is a subjective measure of SES that has been proven to have high construct validity and can predict mental health outcomes independently from other, more objective, measures of SES (56,78). Additionally, self-rated social standing has been used as a measure of SES in older populations where objective measures of SES (such as income or occupation) may be less relevant due to retirement (56). We chose to use depression as a clinically-relevant measure of mental health because of its high prevalence in Canada (over 12% of Canadians report a lifetime prevalence of depression) (6), as well as the association between green space and depression established in other studies (2,12,79). Finally, we chose to also include self-rated mental health because it provides a more holistic measure than simply measuring specific mental health disorders (e.g., depression) (80) and will allow us to capture a continuum of mental health states within our study population.

All four variables are well-suited to the cross-sectional nature of our study because they are representative of the study participants' SES and mental health at the time of data collection (e.g., the instrument used to measure depression, Centre for Epidemiological Studies Depression Scale [CESD-10], is reflective of a participant's depressive symptoms within the past week, where "ever diagnosed with depression" could reflect a depression diagnosis at any point in the participant's lifetime). This reduces the risk of misclassification bias and allows us to measure the contemporaneous relationship between green space exposure, socioeconomic indicators and mental health outcomes at the time of data collection. We chose to conduct a cross-sectional study because we were limited by the availability of green space data, which was only available at baseline. Although we acknowledge that long-term green space exposure is beneficial to mental health (33,38), a longitudinal analysis of green space exposure on mental health outcomes was not feasible for our study because we would have been unable to determine participants' green space exposure throughout the entire duration of the study (i.e., between baseline and follow-up). Despite this data limitation, we thought that measuring the contemporaneous relationship between green space exposure and mental health at baseline was important because we know that green space exposure exerts immediate effects on mental health by attenuating the acute stress response and providing a restorative environment (34,35,37).

Figure 3 illustrates the relationships between the variables in our study and helped guide our specific study objectives and analysis plan.

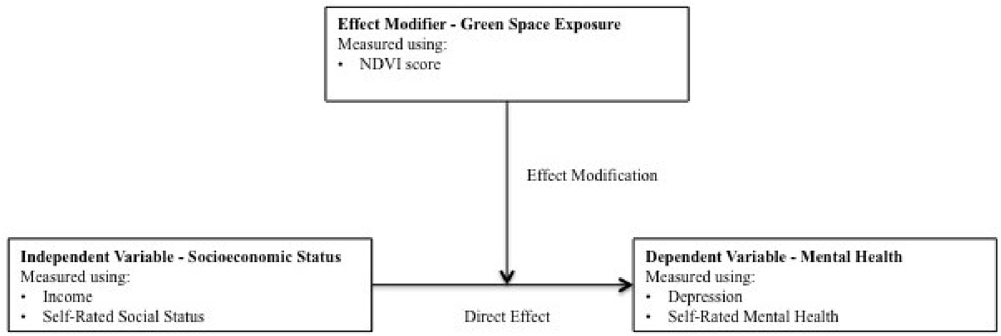

Figure 3. SES has a direct effect on mental health outcomes. One of the objectives of our study is to determine if green space exposure modifies the effects of SES on mental health outcomes by determining if there is a significant interaction between socioeconomic indicators and green space when modelling mental health outcomes.

4.2 Data Source

The Canadian Longitudinal Study on Aging (CLSA) is a population-based cohort study designed to investigate biological, clinical, psychosocial, societal, and environmental factors that contribute to healthy aging. It includes socioeconomic, environmental, and mental health indicators, which will allow us to broaden our understanding of the complex relationship between SES, green space and mental health in Canada.

The CLSA cohort consists of a stratified sample of 51,338 Canadians between the ages of 45 and 85 at baseline. Individuals included in the CLSA underwent baseline interviews and provided written, informed consent. Baseline data was collected from 2011 - 2015, and the first follow-up was completed in 2018. All participants will continue to provide follow-up data every three years until 2033 or until death (81). Due to the complex survey design, the CLSA provides analytic and inflation sample weights that we used in our statistical analyses to ensure that the results are representative of the Canadian population. A detailed description of the calculation of CLSA sample weights is provided in the CLSA Technical Document (82).

The CLSA cohort is split into two complementary cohorts, Tracking and Comprehensive. The Tracking cohort consists of 21,241 participants from all 10 Canadian provinces, and data is collected via computer-assisted telephone interviews (CATIs). Participants in the Tracking cohort were primarily recruited from Statistic Canada's Canadian Community Health Survey on Healthy Aging, as well as provincial healthcare registration databases, and random digit dialling. The Comprehensive cohort consists of 30,097 participants who live within 25-50km of 11 data collection sites in seven provinces (British Columbia, Alberta, Manitoba, Ontario, Québec, Nova Scotia, and Newfoundland). Data is collected from the Comprehensive cohort using computer-assisted personal interviews (CAPIs), as well as physical assessments and biospecimen collection at the data collection sites. Participants in the Comprehensive cohort were recruited from provincial healthcare registration databases and random digit dialling. Both cohorts complete the same core questionnaire that covers a broad range of social, health, and lifestyle measures (81).

Green space data is provided to the CLSA from the Canadian Urban Environmental Health Research Consortium (CANUE) (16). CANUE provides environmental data to the CLSA to help further our understanding of how environmental conditions affect health and aging. CANUE data, including green space data, is linked to CLSA data using Desktop Mapping Technologies Incorporated (DMTI) single link postal code coordinates and is available for CLSA participants in both the Tracking and Comprehensive cohorts.

Data access for this study was granted by the CLSA in June 2021, and the study received ethics approval from Dalhousie University's Research Ethics Board.

4.3 Inclusion/Exclusion Criteria

The CLSA's inclusion criteria is people 45 years or older who live in households or transitional housing environments (e.g., seniors' residences with minimal care) in the ten provinces. Participants must be able to communicate in either English or French. The CLSA excludes residents of the three territories, individuals who live on federal First Nations reserves, full-time members of the Canadian Armed Forces, and individuals living in institutions at baseline. It also excludes individuals with cognitive impairment at baseline (83).

Our inclusion criterion was to include all CLSA participants (from both the Tracking and Comprehensive cohorts) that had green space data. In 2012 there was an interruption in NDVI data collection (due to the decommissioning of Landsat 5 in advance of the launch of Landsat 8, which began capturing NDVI in 2013 (84)). Therefore, all CLSA participants with baseline data collection in 2012 did not have NDVI data and were excluded from our study. Our study population included 35,176 of the original 51,338 CLSA participants. We compared the distribution of age, sex, socioeconomic, and mental health variables between the included and excluded participants, and did not find any meaningful differences between the two groups. Therefore, we were not concerned about introducing bias by excluding participants who were missing green space data.

4.4 Description of Variables

4.4.1 Green Space Exposure: Normalized Difference Vegetation Index

Green space exposure data in the CLSA is provided by the Canadian Urban Environmental Health Research Consortium (CANUE) and is linked to individual participants based on 6-digit residential postal codes. Green space exposure is reported as a Normalized Difference Vegetation Index (NDVI) score, which measures vegetation density. NDVI scores are a well-validated measure of green space exposure (15,85) and have been used in numerous epidemiological studies measuring the association between green space and various health outcomes (85,86).

NDVI scores are calculated using satellite sensors that measure near infrared and red light reflectance from the earth's surface. Chlorophyll in green vegetation absorbs red light and reflects near-infrared light, while soil and dead vegetation reflect more red light than green vegetation because they do not have chlorophyll. NDVI scores are measured on a scale from -1 to +1, with +1 representing lush green vegetation and 0 representing pavement or bare soil. NDVI scores less than 0 usually represent reflectance from standing bodies of water. Although NDVI scores alone cannot indicate specific types of plants present in the environment, many NDVI studies use the generalization that scores between 0.2 and 0.3 represent moderately green environments and may include plants like shrubs and grass, and scores between 0.6 and 0.8 represent highly green environments and therefore may include darker and denser vegetation such as temperate forests (13).

NDVI score is recorded in the CLSA as a continuous variable with values between -1 and +1. Our study will only include NDVI scores between 0 and +1, because these are the scores that represent land and green space in the environment. Although there is evidence that “blue space exposure” (i.e., living in environments with natural water features) may also affect mental health outcomes (87), we are specifically interested in measuring the association between green space exposure and mental health. NDVI scores less than zero will be coded as “missing” and will be deleted in order to avoid potential confounding. To help contextualize “change in NDVI score” in our regression analyses, we converted NDVI score into a four level categorical variable using NDVI score quartiles.

NDVI scores in the CLSA are available at four different spatial resolutions representing the average NDVI score of the geographic area within a circular buffer of 100, 250, 500, and 1000m from each postal code location. Previous green space research has demonstrated that NDVI scores with larger buffer areas are more strongly associated with health outcomes because they capture participants’ environmental exposure as they live and move around their neighbourhood (86,88). Therefore, our study used the annual maximum NDVI score within a 1000m buffer area to ensure that we were fully capturing participants’ environmental exposure.

4.4.2 Socioeconomic Indicators: Income and Self-Rated Social Status

Our study used income and self-rated social status as socioeconomic indicators. Both measures have high construct validity and have been used in previous research to measure socioeconomic gradients in mental health outcomes (49,56). We decided to include both objective (income) and subjective (self-rated social standing) socioeconomic indicators in order to capture different dimensions of SES.

We used the variable “Total Household Income” to measure income. It is a categorical variable with five levels (1= Less than \$20,000, 2= \$20,000 or more, but less than \$50,000, 3= \$50,000 or more, but less than \$100,000, 4= \$100,000 or more, but less than \$150,000, 5= \$150,000 or more). To simplify the interpretation of interaction terms in our regression models, we dichotomized income into “less than $50,000” and “$50,000 or more”. We ran separate analyses using income as a five level variable to ensure we were not losing valuable information about the green space gradient by income category. While there was a gradient in NDVI score across the five income categories, using the five level variable compared to the dichotomized variable did not change the outcomes of our regression models, therefore we decided to use dichotomized income in our reported results.

Self-rated social standing is a commonly used socioeconomic indicator and captures how individuals view themselves in their social hierarchy. Participants were asked to picture a ladder with 10 steps representing where people stand in their communities, and to place themselves on the ladder. Self-rated social standing is a categorical variable with 10 categories (1= individuals who consider themselves to have the lowest social standing in their community, and 10= individuals who consider they have the highest social standing in their community). We collapsed self-rated social standing into three categories, “Low” (scores of 1-3 on the ladder), “Medium” (scores of 4-7 on the ladder), and “High” (scores of 8-10 on the ladder), which is consistent with other studies using self-rated social standing as a measure of SES (89).

4.4.3 Mental Health Outcomes: Depression and Self-Rated Mental Health

We used depression and self-rated mental health as outcomes. Previous studies have shown that both outcomes have strong social gradients (6,80) and are affected by green space exposure (2,31).

Depression was measured using the 10-item clinical screening tool Centre for Epidemiological Studies Depression Scale (CESD-10). It was recorded as both a continuous and binary variable in the CLSA. Raw CESD-10 scores were recorded on a continuous scale from 0-30. Depression was also recorded as a binary variable where 1= “Positive screen for depression” and 0= “Negative screen for depression”. The cut-off point for a positive depression screening was a raw CESD-10 score of 10 or more. We used both the continuous and binary depression variables in our study. An advantage of using both continuous and categorical measures of depression was that the continuous measure captured depressive symptoms on a well being to depression continuum (90), while the categorical measure provided a clinically relevant measure of depression screening status.

Self-rated mental health was recorded as a categorical variable with 5 levels (1= Excellent, 2= Very good, 3= Good, 4= Fair, 5= Poor). Participants were asked, “In general, would you say your mental health is excellent, very good, good, fair, or poor?”. Self-rated mental health was used as a categorical variable with 5 levels in Objectives 1 and 2, and was dichotomized into “low” and “high” (“low”= self-rated mental health reported as “poor” or “fair”, “high”= self-rated mental health reported as “excellent”, “very good”, or “good”) for the purpose of Objective 3 because the concentration index inequality measure can only be used for continuous or binary outcomes.

4.4.4 Other Covariates

NDVI score measures vegetation density within a specified buffer area at a specific postal code location and is a well-validated measure when assessing the association between green space and mental health outcomes. However, it is important to acknowledge that other aspects of green space, such as access, also influence mental health outcomes and are not captured by NDVI score. In order to improve our understanding of CLSA participants’ green space exposure we needed to consider how participants interacted with the natural environment. To do this, we included Life Space Index (LSI) as a covariate, which provides a general measure of participants’ mobility within their home and surrounding community. LSI was measured as a continuous variable on a scale from 0-120 (0= totally bed bound, 120= travelled out of town every day without assistance) and helped us determine if participants’ green space exposure was via viewing (e.g., looking out a window) or in-person (e.g., participant has the necessary mobility to go outside). Although there is evidence that simply viewing green space from a window is sufficient to improve mental health outcomes (26,28), green space exposure also improves mental health outcomes through other mechanisms such as increasing social cohesion and promoting exercise (1). Neglecting to account for different types of green space exposure (i.e., viewing vs. in-person) may lead to confounding if there are systematic differences in mental health between participants based on their mobility level (i.e., if participants who are house-bound have worse mental health compared to participants who have more mobility).

We used the urban/rural classification variable to control for degree of rurality. We thought that this was important due to potential differences in types of green space between urban and rural environments that may influence participants' level of green space exposure (e.g., rural participants may have higher green space exposure due to agricultural land, but may not interact with green space in the same way as urban participants who live near a park). Although we expected that rural areas would have higher green space exposure and should therefore have better mental health outcomes, we were cognizant of urban/rural health inequities in Canada due to limited access to health care services in rural populations. Therefore, we thought that it was important to control for degree of rurality to avoid potential confounding (91). The urban/rural classification variable in the CLSA was a categorical variable with five levels (0= Rural, 1= Urban Core, 2= Urban Fringe, 4= Urban population centre outside census metropolitan areas and census agglomerations, 6= Secondary Core). For our regression analyses, we collapsed the variable into three levels, "Urban", which included participants classified as "urban core", "Rural", which included participants classified as "rural", and "Other", which included participants classified as "urban fringe", "urban population centres outside of census metropolitan areas and census agglomerations", and "secondary core". This allowed us to control for confounding based on potential differences in green space across urban/rural environments. We also dichotomized the urban/rural classification variable into "Urban" and "Rural/Other" for descriptive purposes, as well as creating provincial urban/rural sub-populations large enough to calculate concentration index values in Objective 3.

Other covariates included in our models were based on the literature on green space and mental health, as well as mental health in older adults. They included age, sex, race, marital status, social support measures, and physical activity (2,31,33).

4.5 Statistical Analyses

4.5.1 Overview

The specific objectives and analyses conducted were as follows:

1. Examine the distribution of green space in Canada in terms of urban/rural environment and socioeconomic indicators

We used descriptive statistics to describe our study population in terms of green space exposure, socioeconomic indicators, and mental health outcomes (Table 1 and 2). We used independent sample t tests and one-way ANOVAs to test for significant differences in mean NDVI scores between provinces, urban and rural populations, income categories, self-rated social standing categories, and groups of individuals with and without the mental health outcomes of interest (depression and low self-rated mental health). This exploratory analysis helped us understand the distribution of green space among CLSA participants.

2. Determine if the relationship between SES and mental health varies based on green space exposure by identifying significant interactions between socioeconomic indicators and green space exposure in regression models for mental health outcomes

We conducted separate regression analyses with depression and self-rated mental health at an individual level as the dependent variables and tested for significant interaction effects between socioeconomic indicators (income and self-rated social standing) and green space exposure (NDVI score by quartile) (Tables 3-8). Significant interaction terms in these models indicated that the relationship between socioeconomic indicators and mental health outcomes varied based on green space exposure. Our regression analyses helped us further our understanding of the interplay between socioeconomic and environmental factors in producing mental health outcomes.

We used linear regression to model depression measured as a continuous variable (using raw CESD-10 scores) and logistic regression to model depression measured as a binary variable. We believed that it was important to measure depression as both a continuous and binary outcome variable because the continuous measure captured depressive symptoms on a well being to depression continuum, while the binary measure provided a clinically relevant measure of depression screening status. Self-rated mental health was modelled using an ordinal logistic regression model. The simplified regression models were:

Linear:	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + e$	*Where:* *Y = depression as a continuous outcome variable* X_1 *= socioeconomic indicator* X_2 *= NDVI quartile*
Logistic:	$logit\ (Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + e$	*Where:* *Y = depression as a binary outcome variable* X_1 *= socioeconomic indicator* X_2 *= NDVI quartile*
Ordinal Logistic:	$ologit\ (Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + e$	*Where:* *Y = self-rated mental health as a categorical outcome variable* X_1 *= socioeconomic indicator* X_2 *= NDVI quartile*

In words, our regression models describe the following scenarios:

1. Depression score is modelled by income, NDVI, and their interaction
2. Depression status is modelled by income, NDVI, and their interaction
3. Depression score is modelled by self-rated social standing, NDVI, and their interaction
4. Depression status is modelled by self-rated social standing, NDVI, and their interaction
5. Self-Rated Mental Health is modelled by income, NDVI, and their interaction
6. Self-Rated Mental Health is modelled by self-rated social standing, NDVI, and their interaction

Missing socioeconomic data is a common issue when examining the relationship between SES and health outcomes, and can lead to biased results depending on the pattern of missing data (92). In our study population, 6.06% of participants were missing income, and 8.76% were missing self-rated social standing. Missing income and self-rated social standing were both significantly associated with being female, over the age of 65, and being depressed, and having lower educational attainment. We used the Multiple

Imputation by Chained Equations (MICE) method to impute missing income and self-rated social standing data using sex, age group, depression status, and educational attainment, and used the imputed data in our regression analyses.

We controlled for age and sex to account for potential age and sex differences in mental health outcomes. Life Space Index score was included as a covariate to adjust for individuals' mobility within their home and community. This helped avoid confounding by including a measure of exposure to green space not captured by NDVI scores (e.g., participants' ability to go outside to exercise in a park versus viewing green space from a window). Other covariates included in the analysis were race (Caucasian and non-Caucasian), marital status, physical activity, social support measures, and urban/rural status.

3. Determine if differences in provincial-level socioeconomic-related mental health inequalities are associated with provincial-level green space exposure for both urban and rural populations

For this objective, we divided the CLSA population by province and then further divided each provincial population according to the urban/rural binary classification variable. This generated 20 sub-populations (one urban and one rural for each of the ten provinces). We then used the concentration index to calculate socioeconomic-related mental health inequality for each sub-population and calculated a mean NDVI score for each sub-population. Finally, we measured the degree of association between green space exposure (measured using the mean NDVI score for each sub-population) and mental health inequality (measured using the concentration index) across the 20 sub-populations by Spearman's rank correlation coefficient to determine the relationship between green space exposure and mental health inequality at the provincial-level for urban and rural populations.

4.5.2 Measuring Mental Health Inequalities using the Concentration Index

We used the concentration index to measure socioeconomic-related mental health inequalities in each urban and rural sub-population in all 10 provinces. We calculated concentration indices for four different socioeconomic-related mental health inequalities, which ensured that we were capturing both socioeconomic variables (income and self-rated social status) and both mental health outcomes (depression status and dichotomized self-rated mental health). The four mental health inequalities are as follows, and are represented in Figure 4:

1. Income-related inequality in depression
2. Income-related inequality in self-rated mental health
3. Self-rated social status-related inequality in depression
4. Self-rated social status-related inequality in self-rated mental health

		Socioeconomic Indicators	
		Income	Self-rated social status
Mental Health Outcomes	Depression	Income inequality in depression	Self-rated social status inequality in depression
	Self-rated mental health	Income inequality in self-rated mental health	Self-rated social status inequality in self-rated mental health

Figure 4. 2x2 table representing the four different mental health inequalities. We calculated a concentration index for each urban and rural sub-population in all 10 provinces for each of the four inequalities (2 concentration indexes per province, per inequality*10 provinces = 20 concentration indexes per inequality).

Concentration index values are based off the concentration curve, which plots the cumulative percentage of the individuals in a population ranked according to a socioeconomic variable (income and self-rated social status) against the cumulative percentage of the health outcome (depression and self-rated mental health). In a population with perfect equality, the concentration curve would be a straight diagonal (a 45 degree line) (61,62). Concentration curves below the diagonal correspond to positive concentration index values and indicate that the health outcome is concentrated in individuals with higher socioeconomic rank (i.e., better-off individuals have worse health). In contrast, concentration curves above the diagonal correspond to negative concentration index values and indicate that the health outcome is concentrated in individuals with lower socioeconomic rank (i.e., worse-off individuals have worse health). (61,62).

For continuous health outcome variables, the concentration index is bounded between -1 and +1. When calculating the concentration index for binary outcome variables (e.g., depression status and binary self-rated mental health), the minimum is defined as μ-1 and the maximum is defined as 1-μ, however, the concentration index and its standard deviation can be normalized using Wagstaff's normalization by multiplying both by a factor of 1/1- μ which results in the range remaining -1 to +1 (93). Among different approaches to normalizing the concentration index for binary variables, Wagstaff's approach is one of the most commonly used methods.

4.5.3 Mean NDVI Score by Provincial Sub-Population

To determine provincial-level green space exposure by urban and rural sub-populations we calculated a mean NDVI score for each provincial sub-population. To do this, we divided the CLSA population as described above (by province and then by urban/rural classification). We then summed the individual NDVI scores for the participants in a particular sub-population, and divided by the number of participants in that sub-population.

4.5.4 Measuring the Association Between Green Space Exposure and Mental Health Inequality

We used Spearman's rank correlation coefficient to determine the degree of association between green space exposure (measured using mean NDVI score for each provincial sub-population [urban and rural]) and each of the four mental health inequalities (measured using the concentration index) across the 20 provincial sub-populations.

All statistical analyses were conducted using Stata and were weighted using the inflation and analytic sampling weights provided by the CLSA. We used inflation weights when estimating means and proportions for the entire Canadian population, and analytic weights in our regression analyses. Analytic weights are inverse variance sampling weights that are rescaled from the inflation weights, and are used to ensure that participants from the larger provinces do not dominate the statistical models. In all of our analyses, we considered p-values less than or equal to 0.05 as statistically significant.

Chapter Five: Results

5.1 Objective 1: Examine the distribution of green space as represented by NDVI in Canada across urban/rural environments and socioeconomic indicators

Our study population included 35,176 participants from the Tracking and Comprehensive CLSA cohorts who had NDVI data at baseline data collection. The study population was close to evenly split between males and females (55.17% were male and 44.83% were female), predominantly Caucasian (94.83%), and the majority of participants were between the ages of 45-64 (72.68% of participants were ages 45-64, and 27.32% were 65 years or older). Most study participants included in our sample lived in urban environments (71.79%), were married (76.22%), participated in physical activity at least once a week (39.56%), had higher income (65.97% had a total household income greater than $50,000), and had medium self-rated social standing (65.38%). Nearly a fifth (18.46%) of study participants had a positive screening for depression on the CESD-10, and 6.38% had poor or fair Self-Rated Mental Health (Table 1).

The mean NDVI for our study population, measured as the maximum annual NDVI within 1000m of postal code locations, was 0.792, with a standard deviation of 0.039 and a range of 0.901 (minimum= 0.099, maximum= 1.000).

There was statistically significant variability in mean NDVI between provinces (F (9, 35,166)= 791.82, $p< 0.001$). Tukey's HSD Test for multiple comparisons determined significant differences ($p< 0.05$) in mean NDVI scores between all provinces except Ontario and British Columbia ($p= 1.000$) and Quebec and Prince Edward Island ($p= 0.999$). The range of mean NDVI scores was 0.051, with Manitoba having the lowest (0.761) and Newfoundland having the highest (0.812). Geographically, Prairie Provinces had the lowest NDVI scores (Manitoba, Saskatchewan, and Alberta) and coastal provinces had the highest NDVI scores (British Columbia and Newfoundland) (Table 2).

Across provinces, urban environments had slightly lower NDVI scores than rural environments, with Newfoundland and Nova Scotia as the only exceptions (t (7105.17)= 12.46, $p<0.001$) (Table 2). The overall mean NDVI score for urban environments was 0.791, and the mean NDVI score for rural environments was 0.799 (Table 2).

As income increased, mean NDVI score increased as well, with statistically significant differences in mean NDVI scores between income groups (F (4, 33,037)= 30.88, p<0.001) (Table 1). Individuals in the lowest income group ("less than $20,000") had a mean NDVI score of 0.785, compared to 0.795 for people in the highest income group ("more than $150,000"). Tukey's HSD Test for multiple comparisons determined significant differences (p< 0.05) in mean NDVI scores between all income groups except between "$20,000-$50,000" and "$50,000-$100,000". (p=0.059), "$50,000-$100,000" and "$100,000-$150,000" (p=0.051), and "$100,000-$150,000"-"more than $150,000" ($p$= 0.096).

We divided the ten levels of self-rated social standing into three categories, "Low" (self-rated social standing values of 1-3), "Medium" (self-rated social standing values of 4-7), and "High" (self-rated social standing values of 8-10) to streamline our analyses and provide meaningful categories (89). Difference in mean NDVI between the three groups was not significant (F (2, 32,092)= 2.13, p=0.119) (Table 1), however Tukey's HSD Test for multiple comparisons determined that mean NDVI between "Low" and "High" self-rated social standing categories was significant (p= 0.020). Participants in the "Low" self-rated social standing group had a mean NDVI score of 0.791, and participants in the "High" self-rated social standing group had a mean NDVI score of 0.792.

In terms of mental health outcomes, participants with a positive screen for depression on the CESD-10 had a significantly lower mean NDVI score than participants with a negative screen for depression on the CESD-10 (t (8150.5)= 4.424, p< 0.001). The mean NDVI score for participants who screened positive for depression was 0.790, and 0.792 for participants who screened negative for depression (Table 1). Self-Rated Mental Health (SRMH) also had an NDVI gradient. As self-rated mental health increased, mean NDVI score increased as well and there were significant differences in mean NDVI between groups (F (4, 35,142)= 11.81, p< 0.001). Individuals with poor self-rated mental health had a mean NDVI score of 0.789, and individuals with excellent self-rated mental health had a mean NDVI score of 0.793 (Table 1).

NDVI captures the amount of greenness in a given environment, however actual types of green space (i.e., types of vegetation) and use of green space may differ between urban and rural environments. Many rural environments are naturally greener than urban environments due to their inherent characteristics (e.g., more natural vegetation, more agricultural land), and may have more uniform green space exposure across socioeconomic gradients (i.e., all neighbourhoods are green, not just neighbourhoods with higher income). In contrast, individuals living in urban environments may have more variability in green space exposure based on factors such as income (67,68). Additionally, most green space interventions (i.e., greening of neighbourhoods by implementing vegetation into built environments) aimed at improving health outcomes are implemented in urban environments (47). In our study, there was a significant difference in mean NDVI between urban and rural environments (0.791 in urban compared to 0.799 in rural, $p<0.001$, Table 2). To account for potential differences in the association between green space and mental health in urban and rural populations, we chose to run sensitivity analyses for urban only participants to determine if the pattern between NDVI scores, socioeconomic characteristics, and mental health remained consistent. The pattern of results for urban participants was identical to the whole population. Mean NDVI scores were higher among those with higher income, higher self-rated social standing, a negative screen for depression, and better self-rated mental health. Results of these analyses can be found in Appendix A.

Table 1. Descriptive characteristics and NDVI scores for CLSA participants

		Participants		Max Annual NDVI measured within 1000m of postal code location	
Characteristic:		*n*	*Sample Weighted %*	*Mean*	*SD*
Sex	Male	18,406	55.17	0.793**	0.038
	Female	16,770	44.83	0.791**	0.040
Age Group	45-64	20,870	72.68	0.791**	0.041
	≥ 65	14,306	27.32	0.793**	0.038
Race	Caucasian	33,662	94.83	0.792**	0.040
	Other	1,514	5.17	0.785**	0.046
Urban/Rural	Urban	27,847	71.79	0.790**	0.036
	Rural	3,731	18.04	0.802**	0.053
	Other	2,108	10.17	0.799**	0.048
Marital Status	Single	3,016	7.80	0.786**	0.051
	Married	24,359	76.22	0.793**	0.039
	Widowed	3,307	6.19	0.791**	0.038
	Divorced	3,536	7.11	0.789**	0.042
	Separated	950	2.68	0.790**	0.032
Physical Activity	Daily	2,958	7.83	0.794**	0.036
	Weekly	15,575	39.56	0.793**	0.038
	Monthly	6,163	16.50	0.793**	0.035
	Yearly	2,789	8.69	0.791**	0.038
	Never	7,638	27.42	0.788**	0.049
Income	<$20,000	1,966	5.59	0.785**	0.057
	$20,000-$50,000	7,873	22.38	0.791**	0.041
	$50,000-$100,000	11,477	32.63	0.792**	0.041
	$100,000-$150,000	6,264	17.81	0.794**	0.035
	>$150,000	5,462	15.53	0.795**	0.031
Self-Rated Social Standing	Low (1-3)	3,245	13.34	0.791	0.041
	Medium (4-7)	20,570	65.38	0.792	0.038
	High (8-10)	8,280	21.27	0.792	0.039
Depression Status	Positive Screening	5,695	18.46	0.790**	0.040
	Negative Screening	29,362	81.54	0.792**	0.040
Self-Rated Mental Health	Poor	247	0.93	0.789**	0.035
	Fair	1,725	5.45	0.787**	0.058
	Good	8,887	27.56	0.791**	0.039
	Very Good	14,438	38.52	0.792**	0.039
	Excellent	9,850	27.53	0.793**	0.037

**$p<0.001$ on tests for differences in means between groups

Table 2. NDVI scores by province, and urban/rural environments within provinces

	Max Annual NDVI measured within 1000m of postal code location					
	Whole Province		**Urban Only**		**Rural Only**	
Province:	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Manitoba	0.761	0.036	0.759	0.034	0.786	0.039
Alberta	0.774	0.036	0.774	0.035	0.786	0.036
Saskatchewan	0.765	0.040	0.766	0.034	0.767	0.032
P.E.I.	0.782	0.144	0.774	0.139	0.808	0.093
Nova Scotia	0.783	0.050	0.786	0.043	0.776	0.086
Quebec	0.792	0.032	0.789	0.031	0.809	0.030
New Brunswick	0.799	0.028	0.794	0.026	0.804	0.028
Ontario	0.805	0.027	0.803	0.025	0.823	0.028
British Columbia	0.806	0.025	0.804	0.026	0.815	0.027
Newfoundland	0.812	0.029	0.818	0.024	0.799	0.033
Overall:	**0.792****	**0.039**	**0.791****	**0.037**	**0.799****	**0.048**

**$p<0.001$ on tests for differences in means between groups

5.2 Objective 2: Determine if the relationship between SES and mental health varies based on green space exposure by identifying significant interactions between socioeconomic indicators and green space exposure in regression models of mental health outcomes

5.2.1. Overview of Regression Results

We used six scenarios to model mental health outcomes using SES indicators and NDVI using regression analyses. The scenarios were:

1. Depression score modelled by income and NDVI
2. Depression status modelled by income and NDVI
3. Depression score modelled by self-rated social standing and NDVI
4. Depression status modelled by self-rated social standing and NDVI
5. Self-rated mental health modelled by income and NDVI
6. Self-rated mental health modelled by self-rated social standing and NDVI

In each scenario our baseline model (Model 1) was adjusted for age and sex, Model 2 was adjusted for other relevant covariates, and Model 3 added an interaction term between NDVI and the socioeconomic indicator (income or self-rated social standing). There were significant interactions between levels of self-rated social standing and NDVI quartile when modelling depression score (scenario 3), which indicates that the relationship between self-rated social standing and depression score varies based on green space exposure (Table 5, Model 3). None of the other scenarios had significant interaction terms. In those situations, Model 2 was the final model (adjusted for all covariates).

Overall, SES had more statistically significant main effects on mental health outcomes than NDVI. In baseline models adjusted for age and sex NDVI was significantly associated with better mental health outcomes but that association was attenuated beyond significance after adjusting for other covariates. The only exceptions were modelling depression score and depression status using income and NDVI. In those scenarios, NDVI was still statistically significant, however the coefficients for NDVI were positive (Table 3, Model 2) and the odds ratio was greater than one (Table 4, Model 2) indicating that higher NDVI was associated with higher depression score and the odds of a positive screen for depression after adjusting for other covariates.

5.2.2 Effect of Income and NDVI on Depression

Table 3. Results of regression analysis modelling depression score by income and NDVI

	Model 1: Adjusted for Age and Sex			**Model 2: Adjusted for all covariates**			**Model 3: Interaction between NDVI and Income**		
Main Effects:	*Coeff.*	*p*	*[95%]*	*Coeff.*	*p*	*[95%]*	*Coeff.*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	-0.030	0.674	[-0.171, 0.110]	0.020	0.794	[-0.132, 0.173]	-0.188	0.206	[-0.480, 0.134]
3rd quartile	-0.087	0.229	[-0.288, 0.055]	0.060	0.439	[-0.093, 0.214]	0.016	0.919	[-0.301, 0.334]
4th quartile	-0.199	<0.001*	[-0.341, -0.058]	0.161	0.048*	[0.001, 0.321]	0.201	0.215	[-0.117, 0.519]
Income (ref: Low, <$50,000)									
High, >$50,000	-2.261	<0.001*	[-2.383, -2.138]	-0.998	<0.001*	[-1.151, -0.845]	-1.083	<0.001*	[-1.369, -0.796]
Sex (ref: male)									
Female	0.768	<0.001*	[0.667, 0.869]	0.863	<0.001*	[0.752, 0.975]	0.864	<0.001*	[0.752, 0.975]
Age Group (ref: 45-64)									
65+	-1.040	<0.001*	[-1.157, -0.923]	-1.128	<0.001*	[-1.260, -0.995]	-1.129	<0.001*	[-1.261, -0.997]
Race (ref: not Caucasian)									
Caucasian				0.191	0.142	[-0.064, 0.446]	0.192	0.140	[-0.063, 0.447]
Marital Status (ref: single)									
Married				0.298	0.008*	[0.079, 0.517]	0.294	0.008*	[0.075, 0.513]
Widowed				0.031	0.844	[-0.274, 0.335]	0.030	0.847	[-0.274, 0.334]
Divorced				-0.237	0.088	[-0.509, 0.035	-0.242	0.082	[-0.514, 0.030]
Separated				0.903	<0.001*	[0.512, 1.294]	0.900	<0.001*	[0.509, 1.291]
Physical Activity (ref: daily)									
Weekly				0.061	0.547	[-0.138, 0.260]	0.061	0.549	[-0.138, 0.260]
Monthly				0.493	<0.001*	[0.273, 0.714]	0.493	<0.001*	[0.272, 0.713]
Yearly				0.735	<0.001*	[0.473, 0.997]	0.735	<0.001*	[0.473, 0.997]
Never				1.096	<0.001*	[0.869, 1.322]	1.095	<0.001*	[0.869, 1.322]
Life Space Index				-0.030	<0.001*	[-0.034, -0.027]	-0.030	<0.001*	[-0.034, -0.027]
Overall Social Support				-0.097	<0.001*	[-0.100, -0.093]	-0.097	<0.001*	[-0.100, -0.093]
Urban/Rural (ref: rural)									
Urban				0.100	0.339	[-0.105, 0.304]	0.100	0.338	[-0.104, 0.304]
Other				0.030	0.862	[-0.307, 0.367]	0.031	0.855	[-0.306, 0.368]
NDVI*Income (ref: 1st NDVI quartile*Low income)									
2nd*High income							0.300	0.104	[-0.062, 0.662]
3rd*High income							0.067	0.736	[-0.328, 0.462]
4th*High income							-0.047	0.814	[-0.440, 0.346]

Table 4. Results of regression analysis modelling depression status by income and NDVI

	Model 1: Adjusted for Age and Sex			Model 2: Adjusted for all covariates			Model 3: Interaction between NDVI and Income		
Main Effects:	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	1.038	0.335	[0.962, 1.121]	1.059	0.242	[0.962, 1.167]	0.968	0.688	[0.826, 1.135]
3rd quartile	0.952	0.224	[0.81, 1.030]	1.007	0.891	[0.912, 1.111]	1.085	0.336	[0.918, 1.283]
4th quartile	0.945	0.155	[0.874, 1.022]	1.110	0.046*	[1.002, 1.231]	1.176	0.070	[0.987, 1.401]
Income (ref: Low, <$50,000)									
High, >$50,000	0.350	<0.001*	[0.328, 0.373]	0.564	<0.001*	[0.510, 0.623]	0.567	<0.001*	[0.478, 0.679]
Sex (ref: male)									
Female	1.391	<0.001*	[1.316, 1.472]	1.531	<0.001*	[1.424, 1.646]	1.531	<0.001*	[1.424, 1.646]
Age Group (ref: 45-64)									
65+	0.634	<0.001*	[0.593, 0.678]	0.590	<0.001*	[0.540, 0.645]	0.589	<0.001*	[0.539, 0.643]
Income (ref: Low, <$50,000)									
High, >$50,000	0.350	<0.001*	[0.328, 0.373]	0.564	<0.001*	[0.510, 0.623]	0.570	<0.001*	[0.478, 0.679]
Race (ref: not Caucasian)									
Caucasian				1.135	0.112	[0.971, 1.326]	1.133	0.116	[0.970, 1.325]
Marital Status (ref: single)									
Married				1.160	0.022*	[1.021, 1.317]	1.155	0.027*	[1.017, 1.311]
Widowed				0.979	0.812	[0.821, 1.167]	0.976	0.788	[0.819, 1.164]
Divorced				0.870	0.076	[0.745, 1.015]	0.864	0.064	[0.741, 1.009]
Separated				1.470	<0.001*	[1.189, 1.819]	1.465	<0.001*	[1.185, 1.813]
Physical Activity (ref: daily)									
Weekly				1.029	0.697	[0.891, 1.188]	1.029	0.694	[0.894, 1.189]
Monthly				1.306	0.001*	[1.120, 1.523]	1.305	0.001*	[1.119, 1.522]
Yearly				1.323	0.002*	[1.111, 1.575]	1.324	0.002*	[1.112, 1.577]
Never				1.577	<0.001*	[1.355, 1.837]	1.581	<0.001*	[1.357, 1.841]
Life Space Index				0.985	<0.001*	[0.983, 0.987]	0.985	<0.001*	[0.983, 0.987]
Overall Social Support				0.963	<0.001*	[0.961, 0.965]	0.963	<0.001*	[0.961, 0.965
Urban/Rural (ref: rural)									
Urban				1.058	0.420	[0.923, 1.212]	1.060	0.404	[0.925, 1.214]
Other				1.151	0.208	[0.925, 1.433]	1.156	0.195	[0.928, 1.440]
NDVI*Income (ref: 1st NDVI quartile*Low income)									
2nd*High income							1.159	0.176	[0.936, 1.436]
3rd*High income							0.888	0.302	[0.709, 1.113]
4th*High income							0.912	0.450	[0.717, 1.160]

Income was significantly associated with depression score and depression status in baseline and adjusted models (Models 1 and 2 in Tables 3 and 4). After adjusting for covariates, individuals with high income scored on average 0.99 points lower on the CESD-10 compared to individuals with low income (p<0.001) (Model 2, Table 3). Having high income also significantly lowered the odds of having depression (OR= 0.56, p<0.001) (Model 2, Table 4), which is defined as a score of 10 or higher on the CESD-10.

Higher NDVI was significantly associated with lower depression score in the baseline model adjusted for age and sex (Model 1, Table 3). Individuals in the highest NDVI quartile scored on average 0.2 points lower on the CESD-10 than individuals in the lowest NDVI quartile ($p<0.001$). NDVI was not significantly associated with depression status in the baseline model (Model 1, Table 4). After adjusting for covariates in Model 2 the direction of association between NDVI and depression changed (Model 2 in Tables 3 and 4). Individuals in the highest NDVI quartile scored on average 0.16 points higher on the CESD-10 than individuals in the lowest NDVI quartile (Model 2, Table 3), and had significantly higher odds of depression (OR= 1.11, p=0.046) (Model 2, Table 4).

There were no significant interaction terms between income and NDVI when modelling depression score or depression status (Model 3, Tables 3 and 4).

5.2.3 Effect of Self-Rated Social Standing and NDVI on Depression

Table 5. Results of regression analysis modelling depression score by self-rated social standing and NDVI

	Model 1: Adjusted for Age and Sex			**Model 2: Adjusted for all covariates**			**Model 3: Interaction between NDVI and Income**		
Main Effects:	*Coeff.*	*p*	*[95%]*	*Coeff.*	*p*	*[95%]*	*Coeff.*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	-0.088	0.233	[-0.229, 0.053]	<-0.001	0.997	[-0.153, 0.152]	0.339	0.232	[-0.221, 0.900]
3rd quartile	-0.196	0.007*	[-0.338, -0.053]	0.009	0.904	[-0.144, 0.162]	0.194	0.461	[-0.323, 0.713]
4th quartile	-0.269	<0.001*	[-0.411, -0.127]	0.141	0.084	[-0.019, 0.300]	0.838	0.006*	[0.250, 1.426]
SRSS (ref: Low)									
Medium	-2.051	<0.001*	[-2.254, -1.848]	-1.209	<0.001*	[-1.436, -0.982]	-0.943	<0.001*	[-1.409, -0.474]
High	-3.135	<0.001*	[-3.338, -2.932]	-1.800	<0.001*	[-2.035, -1.565]	-1.323	<0.001*	[-1.838, -0.808]
Sex (ref: male)									
Female	0.935	<0.001*	[0.833, 1.036]	0.893	<0.001*	[0.781, 1.004]	0.890	<0.001*	0.778, 1.001]
Age Group (ref: 45-64)									
65+	-0.381	<0.001*	[-0.493, -0.269]	-0.881	<0.001*	[-1.009, -0.753]	-0.883	<0.001*	[-1.011, -0.755]
Race (ref: not Caucasian)									
Caucasian				0.008	0.952	[-0.247, 0.262]	0.018	0.891	[-0.237, 0.272]
Marital Status (ref: single)									
Married				-0.053	0627	[-0.265, 0.160]	-0.057	0.599	[-0.270, 0.156]
Widowed				-0.016	0.920	[-0.319, 0.289]	-0.020	0.895	[-0.325, 0.284
Divorced				-0.239	0.085	[-0.511, 0.033]	-0.250	0.071	[-0.522, 0.022]
Separated				0.838	<0.001*	[0.447, 1.228]	0.825	<0.001*	[0.434, 1.215]
Physical Activity (ref: daily)									
Weekly				0.054	0.594	[-0.145, 0.253]	0.058	0.569	[-0.141, 0.257]
Monthly				0.496	<0.001*	[0.276, 0.716]	0.492	<0.001*	[0.272, 0.713]
Yearly				0.657	<0.001*	[0.394, 0.917]	0.656	<0.001*	[0.394, 0.918]
Never				1.091	<0.001*	[0.865, 1.317]	1.093	<0.001*	[0.866, 1.319]
Life Space Index				-0.031	<0.001*	[-0.034, -0.028]	-0.031	<0.001*	[-0.035, -0.028]
Overall Social Support				-0.094	<0.001*	[-0.098, -0.091]	-0.095	<0.001*	[-0.098, -0.091]
Urban/Rural (ref: rural)									
Urban				0.070	0.498	[-0.134, 0.275]	0.069	0.508	[-0.135, 0.273]
Other				0.038	0.825	[-0.299, 0.375]	0.030	0.864	[-0.307, 0.366]
NDVI*SRSS (ref: 1st NDVI quartile*Low SRSS)									
2nd*Medium SRSS							-0.326	0.291	[-0.934, 0.283]
2nd*High SRSS							-0.532	0.135	[-1.234, 0.170]
3rd*Medium SRSS							-0.148	0.607	[-0.715, 0.419]
3rd*High SRSS							-0.362	0.253	[-0.984, 0.261]
4th* Medium SRSS							-0.661	0.041*	[-1.293, -0.028]
4th*High SRSS							-1.088	0.004*	[-1.820, -0.355]

Table 6. Results of regression analysis modelling depression status by self-rated social standing and NDVI

	Model 1: Adjusted for Age and Sex			Model 2: Adjusted for all covariates			Model 3: Interaction between NDVI and Income		
Main Effects:	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	1.008	0.835	[0.934, 1.087]	1.047	0.345	[0.951, 1.154]	1.141	0.380	[0.848, 1.537]
3rd quartile	0.900	0.008*	[0.833, 0.973]	0.973	0.591	[0.882, 1.074]	0.950	0.704	[0.727, 1.240]
4th quartile	0.911	0.018*	[0.843, 0.984]	1.098	0.075	[0.991, 1.217]	1.268	0.141	[0.923, 1.742]
SRSS (ref: Low)									
Medium	0.456	<0.001*	[0.417, 0.499]	0.607	<0.001*	[0.536, 0.688]	0.637	<0.001*	[0.510, 0.795]
High	0.293	<0.001*	[0.265, 0.326]	0.417	<0.001*	[0.413, 0.538]	0.512	<0.001*	[0.394, 0.666]
Sex (ref: male)									
Female	1.496	<0.001*	[1.416, 1.581]	1.559	<0.001*	[1.450, 1.676]	1.559	<0.001*	[1.450, 1.676]
Age Group (ref: 45-64)									
65+	0.890	<0.001*	[0.837, 0.947]	0.685	<0.001*	[0.629, 0.745]	0.684	<0.001*	[0.628, 0.745]
Race (ref: not Caucasian)									
Caucasian				1.030	0.708	[0.882, 1.203]	1.032	0.688	[0.884, 1.206]
Marital Status (ref: single)									
Married				0.937	0.291	[0.830, 1.058]	0.936	0.286	[0.829, 1.057]
Widowed				0.940	0.491	[0.789, 1.121]	0.940	0.486	[0.788, 1.120]
Divorced				0.866	0.066	[0.742, 1.010]	0.863	0.061	[0.740, 1.007]
Separated				1.405	0.002*	[1.136, 1.737]	1.399	0.002*	[1.131, 1.731]
Physical Activity (ref: daily)									
Weekly				1.031	0.682	[0.892, 1.190]	1.032	0.670	[0.893, 1.192]
Monthly				1.317	<0.001*	[1.129, 1.536]	1.318	<0.001*	[1.130, 1.537]
Yearly				1.288	0.004*	[1.082, 1.534]	1.290	0.004*	[1.083, 1.536]
Never				1.603	<0.001*	[1.376, 1.867]	1.605	<0.001*	[1.378, 1.870]
Life Space Index				0.984	<0.001*	[0.982, 0.986]	0.984	<0.001*	[0.982, 0.986]
Overall Social Support				0.963	<0.001*	[0.961, 0.965]	0.963	<0.001*	[0.961, 0.965]
Urban/Rural (ref: rural)									
Urban				1.033	0.643	[0.901, 1.183]	1.034	0.628	[0.903, 1.185]
Other				1.156	0.193	[0.929, 1.439]	1.158	0.190	[0.930, 1.441]
NDVI*SRSS (ref: 1st NDVI quartile*Low SRSS)									
2nd*Medium SRSS							0.910	0.576	[0.651, 1.271]
2nd*High SRSS							0.884	0.542	[0.592, 1.319]
3rd*Medium SRSS							1.059	0.707	[0.786, 1.427]
3rd*High SRSS							0.937	0.726	[0.652, 1.347]
4th*Medium SRSS							0.844	0.348	[0.590, 1.206]
4th*High SRSS							0.852	0.456	[0.557, 1.303]

Similar to income, self-rated social standing had significant main effects on depression score and depression status in baseline and adjusted models (Models 1 and 2 in Tables 5 and 6). When modelling depression score, individuals with medium self-rated social standing scored on average 2.05 points lower on the CESD-10 than individuals with low self-rated social standing (p<0.001), and individuals with high self-rated social standing scored on average 3.13 points lower on the CESD-10 than individuals with low self-rated social standing ($p<0.001$) (Model 1, Table 5). After adjusting for covariates in Model 2, individuals with medium self-rated social standing scored on average 1.21 points lower on the CESD-10 than individuals with low self-rated social standing ($p<0.001$), and individuals with high self-rated social standing scored on average 1.80 points lower ($p<0.001$) (Table 5).

When modelling depression status as a binary variable, the odds of having depression decreased as self-rated social standing increased. Medium and high self-rated social standing were associated with significantly lower odds of having depression (OR= 0.46, $p<0.001$ for individuals with medium self-rated social standing and OR= 0.29, $p<0001$ for individuals with high self-rated social standing) compared to low self-rated social standing in our baseline model (Model 1, Table 6). The effect of self-rated social standing on depression status was stronger in Model 2 after adjusting for covariates (OR= 0.61, $p<0.001$ for individuals with medium self-rated social standing, and OR= 0.42, $p<0.001$ for individuals with high self-rated social standing, using individuals with low self-rated social standing as the reference group) (Model 2, Table 6).

In models without the self-rated social standing-NDVI interaction, NDVI only had significant main effects on depression score and depression status in baseline models adjusted for age and sex (Model 1, Table 5). In these models, depression score and odds of depression decreased as NDVI increased. Individuals in the highest NDVI quartile scored on average 0.27 points lower on the CESD-10 than individuals in the lowest NDVI quartile ($p<0.001$) (Model 1, Table 5) and had lower odds of depression (OR= 0.91, $p=0.018$ for individuals in the highest NDVI quartile compared to the lowest NDVI quartile) (Model 1, Table 6). NDVI did not have a significant main effect after adjusting for other variables (Model 2, Tables 5 and 6).

There were significant interaction terms between self-rated social standing and NDVI when modelling depression score (Model 3 in Table 5), but not when modelling depression status (Model 3, Table 6). Figure 5 illustrates the interaction between self-rated social standing and NDVI on depression score. Overall, individuals with low and medium self-rated social standing have higher depression scores than individuals with high self-rated social standing, however as NDVI increases, depression scores for individuals with low and medium self-rated social standing decrease more compared to individuals with high self-rated social standing.

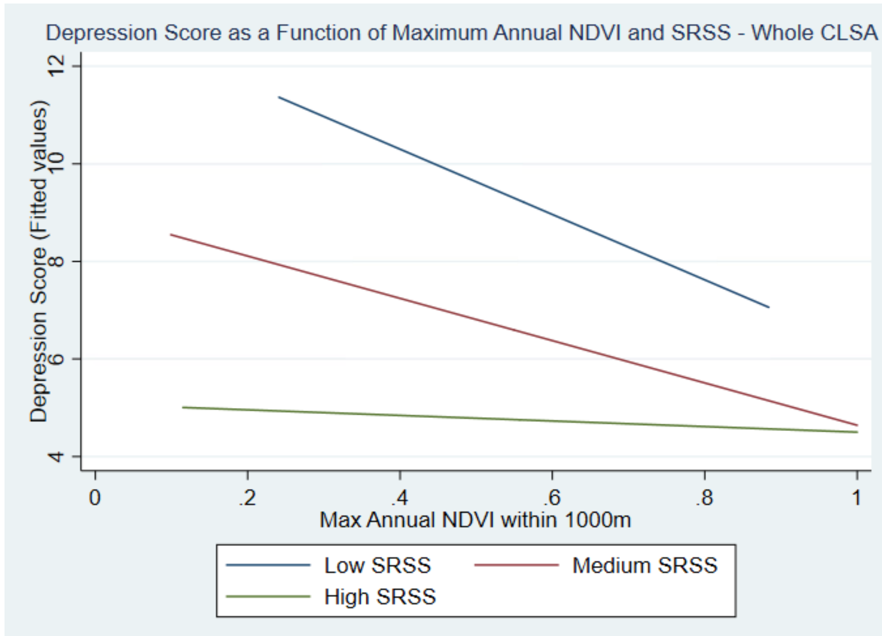

Figure 5. Interaction between self-rated social standing (SRSS) and NDVI on depression score. Increasing NDVI has a greater impact on depression score for participants with low and medium self-rated social standing compared to participants with high self-rated social standing.

5.2.4 Effect of Income and NDVI on Self-Rated Mental Health

Table 7. Results of regression analysis modelling self-rated mental health by income and NDVI

	Model 1: Adjusted for Age and Sex			Model 2: Adjusted for all covariates			Model 3: Interaction between NDVI and Income		
Main Effects:	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	0.963	0.165	[0.912, 1.016]	0.950	0.117	[0.890, 1.013]	0.888	0.056	[0.786, 1.003]
3rd quartile	0.968	0.247	[0.917, 1.022]	0.991	0.779	[0.928, 1.057]	0.944	0.374	[0.831, 1.072]
4th quartile	0.910	0.001*	[0.862, 0.961]	0.992	0.817	[0.927, 1.061]	0.898	0.105	[0.788, 1.023]
Income (ref: Low, <$50,000)									
High, >$50,000	0.494	<0.001*	[0.471, 0.518]	0.679	<0.001*	[0.638, 0.723]	0.630	<0.001*	[0.562, 0.707]
Sex (ref: male)									
Female	1.039	0.051	[1.000, 1.080]	1.044	0.075	[0.996, 1.095]	1.044	0.075	[0.996, 1.095]
Age Group (ref: 45-64)									
65+	0.755	<0.001*	[0.722, 0.790]	0.678	<0.001*	[0.641, 0.717]	0.679	<0.001*	[0.641, 0.718]
Race (ref: not Caucasian)									
Caucasian				1.289	<0.001*	[1.157, 1.436]	1.293	<0.001*	[1.160, 1.441]
Marital Status (ref: single)									
Married				1.150	0.003*	[1.047, 1.263]	1.152	0.003*	[1.049, 1.265]
Widowed				1.014	0.833	[0.891, 1.154]	1.016	0.806	[0.893, 1.157]
Divorced				0.938	0.282	[0.834, 1.054]	0.940	0.305	[0.836, 1.058]
Separated				1.345	0.001*	[1.136, 1.593]	1.348	0.001*	[1.138, 1.596]
Physical Activity (ref: daily)									
Weekly				1.211	<0.001*	[1.111, 1.319]	1.210	<0.001*	[1.111, 1.318]
Monthly				1.469	<0.001*	[1.337, 1.615]	1.471	<0.001*	[1.338, 1.617]
Yearly				1.757	<0.001*	[1.572, 1.965]	1.759	<0.001*	[1.573, 1.968]
Never				1.629	<0.001*	[1.477, 1.795]	1.627	<0.001*	[1.476, 1.794]
Life Space Index				0.988	<0.001*	[0.987, 0.989]	0.988	<0.001*	[0.987, 0.989]
Overall Social Support				0.973	<0.001*	[0.971, 0.974]	0.973	<0.001*	[0.971, 0.974]
Urban/Rural (ref: rural)									
Urban				1.097	0.036*	[1.006, 1.196]	1.095	0.038*	[1.005, 1.194]
Other				0.984	0.830	[0.854, 1.135]	0.986	0.842	[0.855, 1.136]
NDVI*Income (ref: 1st NDVI quartile*Low income)									
2nd*High income							1.102	0.198	[0.950, 1.278]
3rd*High income							1.074	0.364	[0.920, 1.253]
4th*High income							1.151	0.079	[0.984, 1.347]

Similar to other scenarios using income as the socioeconomic indicator, there was a significant main effect of high income on poor mental health. High income significantly reduced the odds of having poor self-rated mental health in baseline and adjusted models (Model 1 and 2 in Table 7). In Model 1, individuals with high income had ~51% lower odds of having poor self-rated mental health compared to individuals with low income (OR= 0.49, p<0.001). After adjusting for covariates in Model 2, the relationship between income and poor self-rated mental health was attenuated but still significant (OR= 0.68, $p<0.001$) (Model 2, Table 7).

NDVI only had a significant main effect on the odds of having poor self-rated mental health in our baseline model. As NDVI increased, the odds of having poor self-rated mental health were lower (OR= 0.91, $p<0.001$ for individuals in the highest NDVI quartile compared to the lowest NDVI quartile) (Model 1, Table 7). After adjusting for covariates in Model 2, NDVI was not associated with the odds of poor self-rated mental health (Model 2, Table 7).

There were no significant interaction terms between income and NDVI when modelling self-rated mental health (Model 3, Table 7).

5.2.5 *Effect of Self-Rated Social Standing and NDVI on Self-Rated Mental Health*

Table 8. Results of regression analysis modelling self-rated mental health by self-rated social standing and NDVI

	Model 1: Adjusted for Age and Sex			**Model 2: Adjusted for all covariates**			**Model 3: Interaction between NDVI and Income**		
Main Effects:	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*	*OR*	*p*	*[95%]*
NDVI Quartile (ref: 1st)									
2nd quartile	0.945	0.041*	[0.895, 0.998]	0.939	0.059	[0.880, 1.002]	0.854	0.208	[0.667, 1.094]
3rd quartile	0.937	0.020*	[0.888, 0.990]	0.968	0.327	[0.907, 1.033]	0.819	0.085	[0.652, 1.028]
4th quartile	0.893	<0.001*	[0.845, 0.943]	0.979	0.535	[0.914, 1.047]	0.829	0.123	[0.652, 1.052]
SRSS (ref: Low)									
Medium	0.523	<0.001*	[0.485, 0.564]	0.590	<0.001*	[0.540, 0.645]	0.508	<0.001*	[0.417, 0.620]
High	0.288	<0.001*	[0.266, 0.312]	0.365	<0.001*	[0.330, 0.404]	0.353	<0.001*	[0.283, 0.441]
Sex (ref: male)									
Female	1.098	<0.001*	[1.056, 1.141]	1.060	0.017*	[1.011, 1.111]	1.059	0.018*	[1.010, 1.111]
Age Group (ref: 45-64)									
65+	0.931	0.001*	[0.892, 0.972]	0.751	<0.001*	[0.711, 0.793]	0.750	<0.001*	[0.710, 0.793]
Race (ref: not Caucasian)									
Caucasian				1.178	0.003*	[1.056, 1.314]	1.180	0.003*	[1.058, 1.316]
Marital Status (ref: single)									
Married				1.007	0.876	[0.919, 1.104]	1.004	0.933	[0.916, 1.100]
Widowed				1.007	0.944	[0.885, 1.147]	1.003	0.968	[0.880, 1.142]
Divorced				0.943	0.326	[0.838, 1.060]	0.937	0.281	[0.833, 1.054]
Separated				1.308	0.002*	[1.105, 1.549]	1.308	0.002*	[1.105, 1.549]
Physical Activity (ref: daily)									
Weekly				1.217	<0.001*	[1.117, 1.326]	1.217	<0.001*	[1.117, 1.327]
Monthly				1.478	<0.001*	[1.345, 1.626]	1.477	<0.001*	[1.343, 1.624]
Yearly				1.688	<0.001*	[1.508, 1.888]	1.691	<0.001*	[1.511, 1.892]
Never				1.621	<0.001*	[1.470, 1.788]	1.618	<0.001*	[1.467, 1.785]
Life Space Index				0.988	<0.001*	[0.986, 0.989]	0.988	<0.001*	[0.986, 0.989]
Overall Social Support				0.974	<0.001*	[0.973, 0.976]	0.974	<0.001*	[0.973, 0.976]
Urban/Rural (ref: rural)									
Urban				1.085	0.065	[0.995, 1.183]	1.082	0.075	[0.992, 1.180]
Other				0.981	0.798	[0.851, 1.132]	0.976	0.742	[0.846, 1.126]
NDVI*SRSS (ref: 1st NDVI quartile*Low SRSS)									
2nd*Medium SRSS							1.166	0.264	[0.888, 1.530]
2nd*High SRSS							0.974	0.861	[0.723, 1.312]
3rd*Medium SRSS							1.218	0.119	[0.950, 1.561]
3rd*High SRSS							1.170	0.263	[0.888, 1.541]
4th*Medium SRSS							1.283	0.054	[0.996, 1.653]
4th*High SRSS							1.002	0.987	[0.746, 1.348]

The observed patterns between SES and mental health remained consistent when using self-rated social standing as our socioeconomic indicator. Self-rated social standing had a significant main effect on the odds of having poor self-rated mental health in baseline and adjusted models (Model 1 and 2 in Table 7). In Model 1, individuals with medium self-rated social standing had ~48% lower odds of having poor self-rated mental health compared to individuals with low self-rated social standing (OR= 0.52, $p<0.001$) and individuals with high self-rated social standing had ~71% lower odds of having poor self-rated mental health compared to individuals with low self-rated social standing (OR= 0.29, $p<0.001$) (Model 1, Table 8). After adjusting for covariates in Model 2, the effect of self-rated social standing on the odds of poor self-rated mental health was slightly attenuated but still significant (OR= 0.59, $p<0.001$ for individuals with medium self-rated social standing and OR= 0.36, $p<0.001$ for individuals with high self-rated social standing) (Model 2, Table 8).

Once again, NDVI only had a significant main effect on the odds of having poor self-rated mental health in our baseline model (Model 1, Table 8). As NDVI increased, the odds of having poor self-rated mental health were lower (OR= 0.89, $p<0.001$ for individuals in the highest NDVI quartile compared to the lowest NDVI quartile) (Model 1, Table 8). After adjusting for covariates in Model 2, NDVI was not associated with the odds of poor self-rated mental health (Model 2, Table 8).

There were no significant interaction terms between self-rated social standing and NDVI when modelling self-rated mental health (Model 3, Table 8).

5.3 Objective 3: Determine if differences in provincial-level socioeconomic-related mental health inequalities are associated with provincial-level green space exposure for both urban and rural populations

Mean NDVI scores for each urban and rural sub-population, as well as concentration index values for each socioeconomic-related mental health inequality are presented in Table 9. Concentration index values were negative for most provincial urban and rural sub-populations, which indicated that the burden of poor mental health (depression and poor self-rated mental health) was concentrated among individuals with lower income and self-rated social standing. In general, the largest concentration index values were for income and self-rated social standing-related inequalities in self-rated mental health, both of which had several sub-populations with concentration index values larger than -0.500.

There were a few exceptions where the concentration index values were positive, indicating that individuals with higher income and self-rated social standing had worse mental health. These included self-rated social standing-related inequality in depression for the rural Manitoba and Newfoundland sub-populations, income-related inequality in self-rated mental health for the rural Saskatchewan sub-population, and self-rated social standing-related inequality in self-rated mental health for the rural Newfoundland and urban Prince Edward Island sub-populations (Table 9). Of these exceptions, the only statistically significant concentration index value was for self-rated social standing-related inequality in depression in the rural Newfoundland population (0.499, $p<0.05$). The other exceptions did not have statistically significant concentration index values, meaning that we could not reject the null hypothesis that the concentration index value was equal to zero, which would indicate no socioeconomic-related inequality.

Although the overall trend of worse-off individuals having worse mental health remained consistent across the majority of provincial urban and rural sub-populations, there were no clear patterns when comparing the sub-populations across the four socioeconomic-related mental health inequalities (i.e., there was no a particular sub-population that had the steepest socioeconomic-related mental health gradient for every mental health inequality). For example, the concentration index value for income-related inequality in depression was -0.464 for rural Manitoba, which was the largest index value of the twenty sub-populations and indicated that rural Manitoba had the steepest income-related gradient in depression. However, rural Manitoba did not have the steepest income and self-rated social standing gradients for the other socioeconomic-related mental health inequalities (Table 9).

We calculated Spearman's rank correlation coefficients to determine the degree of association between mean NDVI and socioeconomic-related mental health inequalities for all sub-populations with statistically significant concentration index values, as well as separately for only urban or only rural sub-populations. There were no significant associations between mean NDVI and socioeconomic-related mental health inequalities measured at the provincial urban/rural sub-population level.

Table 9. Summary of associations between mean NDVI scores and concentration index values by provincial urban and rural sub-populations

		Concentration Index Values			
Sub Population	**Mean NDVI**	*Income-related inequality in depression*	*SRSS-related inequality in depression*	*Income-related inequality in SRMH*	*SRSS-related inequality in SRMH*
Rural AB	0.786	-0.173	-0.278*	-0.421*	-0.558*
Urban AB	0.774	-0.322*	-0.249*	-0.268*	-0.312*
Rural BC	0.815	-0.320*	-0.219*	-0.287*	-0.426*
Urban BC	0.804	-0.291*	-0.262*	-0.328*	-0.396*
Rural MB	0.786	-0.464*	0.010	-0.385	-0.449*
Urban MB	0.759	-0.239*	-0.294*	-0.302*	-0.352*
Rural NB	0.804	-0.240	-0.249*	-0.561*	-0.342*
Urban NB	0.794	-0.246*	-0.356*	-0.606*	-0.626*
Rural NF	0.799	-0.332*	0.499*	-0.362*	0.197
Urban NF	0.818	-0.379*	-0.052	-0.378*	-0.054
Rural NS	0.776	-0.288*	-0.178*	-0.170	-0.327*
Urban NS	0.786	-0.222*	-0.227*	-0.301*	-0.295*
Rural ON	0.823	-0.156*	-0.068	-0.478*	-0.15
Urban ON	0.803	-0.286*	-0.220*	-0.169*	-0.268*
Rural PEI	0.808	-0.147	-0.171	-0.641*	-0.286
Urban PEI	0.774	-0.330*	-0.273*	-0.460*	0.057
Rural QC	0.809	-0.362*	-0.129*	-0.147*	-0.387*
Urban QC	0.789	-0.347*	-0.119*	-0.407*	-0.271*
Rural SK	0.767	-0.277	-0.236	0.161	-0.186
Urban SK	0.766	-0.246*	-0.250*	-0.352*	-0.445*
r (all), *p*		-0.111, *p* = 0.673	0.418, *p* = 0.121	-0.118, *p* = 0.652	-0.160, *p* = 0.570
r (urban only), *p*		-0.445, *p* = 0.197	0.243, *p* =0.499	-0.097, *p* = 0.789	0.143, *p* = 0.736
r (rural only), *p*		0.393, *p* = 0.383	0.200, *p* = 0.747	0.143, *p* = 0.760	-0.450, *p* = 0.310

*$p<0.05$ for the test that the concentration index equals zero (which would indicate perfect equality)

Chapter Six: Discussion

6.1 Overview

The specific objectives of this study were three-fold: 1) to explore the distribution of green space across Canada, as well as the relationships between green space exposure, socioeconomic indicators, and mental health outcomes, 2) to determine if green space exposure is a moderating factor in the relationship between SES and mental health outcomes at an individual level, and 3) to determine if green space exposure is associated with mental health inequalities in provincial-level urban and rural populations. The motivation behind our study was to help further our understanding of how green space affects mental health in individuals with different demographic characteristics and to consider how green space exposure shapes mental health inequalities within a Canadian context. We found statistically significant differences in green space exposure across provinces, as well as by socioeconomic category and mental health status. In our regression analyses, we determined that green space exposure moderated the relationship between self-rated social standing and depression score, and had statistically significant effects on depression score and depression status when controlling for income and other covariates. We did not find any evidence of associations between green space exposure and mental health inequalities measured using the concentration index in provincial-level urban or rural populations.

6.2 Pattern of Green Space Exposure across Canada

Green space exposure, measured by maximum annual NDVI score within 1000m of postal code location, varied between provinces as well as between urban and rural environments. At the provincial level, the Prairie Provinces had the lowest NDVI scores, and coastal provinces had the highest (Table 2). When we compared NDVI scores between urban and rural environments, we found that rural environments had statistically significant higher NDVI scores than urban environments (the mean NDVI score was 0.799 in rural environments compared to 0.791 in urban environments, Table 2), which was expected because urban environments have more built features and generally less natural space than rural environments. However, an NDVI difference of 0.008 is very small, and warrants further investigation into whether it actually represents a meaningful difference in green space between urban and rural environments in Canada.

The patterning of NDVI scores across Canada is reflective of the differences in land cover by ecozone. There are 15 distinct ecozones in Canada, which are defined by their predominant vegetation as well as other characteristics including animals, climate, soil type, landform, and human activity (94). Vegetation in Prairie Provinces is predominantly cultivated cropland, and native vegetation has less tree cover than other ecozones in Canada. In comparison, the predominant vegetation in ecozones on the Pacific and Atlantic coasts is primarily coniferous forest, with some broadleaf forest on the Atlantic coast. Plants with more chlorophyll, such as dark green leaves on trees, absorb more visible light and reflect more near-infrared light than lighter coloured plants such as wheat and other crops. NDVI scores are calculated using the difference between near-infrared light reflection and visible light reflection divided by the sum of near-infrared light reflection and visible light reflection. Therefore, coniferous and broadleaf forests produce higher NDVI scores than cropland (e.g., cereal crops such as wheat), which helps explain the geographic differences in NDVI across Canada.

6.3 Pattern of Green Space Exposure by SES Indicators

There was a statistically significant socioeconomic gradient in green space exposure (measured by NDVI) across income categories, which confirmed our hypothesis that individuals with lower SES (measured using income) would have lower green space exposure. The lowest income category (household income <$20,000 per year) had a mean NDVI score of 0.785, and the highest income category (total household income >$150,000 per year) had a mean NDVI score of 0.795 (Table 1). This finding is consistent with other studies conducted in Canada that have found small, yet statistically significant differences in NDVI score based on income (67–69). Our other measure of SES was self-rated social standing and to our knowledge, our study is the first Canadian study to use self-rated social standing as a socioeconomic indicator when assessing green space exposure. As we expected, green space exposure across self-rated social standing categories mirrors the income gradient in green space exposure, however the differences in mean NDVI between self-rated social standing categories were not statistically significant (Table 1).

Socioeconomic gradients in green space exposure are well documented, especially in urban environments where there may be more pronounced differences in green space between neighbourhoods (67–69,73), and intentional greening initiatives, such as the development of parks, often benefit more affluent communities (73). Additionally, individuals with higher SES have more material and social resources, and therefore better opportunities to choose where they live. These individuals may choose to live in neighbourhoods with desirable environmental features, such as tree-lined streets and neighbourhood parks. Although we did not explore the intentions of individuals' neighbourhood selection in our study, the relationship that we observed between income and green space exposure is consistent with these patterns and behaviours.

When assessing the relationship between self-rated social standing and green space exposure, it is important to consider the direction of the relationship between the variables. Since self-rated social standing is a validated subjective measure of SES (57), we could simply assume that individuals with higher self-rated social standing have more available resources, and therefore the reasons behind the self-rated social standing-NDVI gradient are the same as the income-NDVI gradient (i.e., having higher self-rated social standing results in living in greener environments). The results of our study reflect this gradient, however the difference in NDVI scores between self-rated social standing groups was not statistically significant (the mean NDVI for "low" self-rated social standing was 0.791 compared to 0.792 for "high" self-rated social standing). Another possible explanation for the relationship between self-rated social standing and green space exposure could be explained using neighbourhood effects, which is defined as the effects that neighbourhood characteristics have on individual characteristics (95). Much of the neighbourhood effect literature has assessed the impact of neighbourhood characteristics on objective health outcomes, but a recent study using data from the Canadian Community Health Survey found that individuals living in neighbourhoods with more green space and access to parks had higher life satisfaction (96), which has a strong positive correlation with self-rated social standing (97). It is therefore important to consider the possibility that living in greener environments increases self-rated social standing by improving life satisfaction, or even that individuals who live in greener environments feel they are higher on the social ladder because they live in “better” neighbourhoods.

6.4 Pattern of Green Space Exposure by Mental Health Outcomes

There were differences in green space exposure (measured using mean NDVI) between individuals with and without specific mental health outcomes, and higher green space exposure was associated with better mental health (Table 1). We expected to see this relationship because we know that green space exposure attenuates the stress response and improves psychological restoration, which are both factors affecting mental health outcomes (1,29,37).

Nearly a fifth (18.5%) of study participants had a positive screen for depression (a score ≥10 on the CESD-10 scale) and had a very slight, yet statistically significant, lower mean NDVI compared to participants with a negative screen for depression (0.790 vs. 0.792, Table 1). While it is unclear if a mean NDVI difference of 0.002 is meaningfully different in the real world, the observed association between green space exposure and depression is consistent with findings from other individual studies, as well as systematic reviews, which have identified this relationship in different study populations and countries around the world (2–4,12,98,99).

We also found a statistically significant association between self-rated mental health and green space exposure. Individuals with lower green space exposure had worse self-rated mental health, and as green space exposure increased, so did self-rated mental health (Table 1). The literature on the association between green space and self-rated mental health, specifically, is limited. However, the relationship between green space exposure and other subjective measures of physical and psychological wellbeing (e.g., self-rated general health and self-perceived psychological distress) is well established (100–102), so we expected that higher green space exposure would be associated with better self-rated mental health.

As was the case with urban/rural and socioeconomic categories, the gradients in mean NDVI across mental health outcomes were statistically significant, however the differences in mean NDVI scores were very small (Table 1). As previously discussed, a key limitation of NDVI is that it is an index that captures chlorophyll concentration, and is unable to provide information about the type of vegetation. Therefore, although we are able to measure statistically significant differences in mean NDVI across urban/rural categories, socioeconomic indicators, and mental health outcomes, we have no context on what a difference in magnitude of mean NDVI actually equates to in terms of greenness.

6.5 Green Space Exposure as a Moderator in the Relationship between SES and Mental Health

It is well established that low SES is a risk factor for poor mental health (103–105). SES directly impacts psychosocial, material, and behavioural factors such as stress, the ability to obtain resources (e.g., adequate housing, nutritious food), and health promoting behaviours (e.g., the opportunity to exercise), which all influence an individual's mental health (48). Conversely, green space exposure is thought to modify psychosocial factors associated with SES by decreasing stress, improving social cohesion, and increasing opportunities to exercise (9). There is emerging research that suggests green space may act as an equalizer for mental health outcomes between individuals with low and high SES by reducing psychosocial stress associated with low SES (106,107). For example, Mitchell et al. observed that better access to green space reduced socioeconomic-related inequality in mental well-being by 40% in European cities (107). Other researchers have highlighted the importance of considering green space as an environmental justice issue, and emphasize that improving green space exposure for vulnerable populations will help improve overall health outcomes (73).

We expected to find significant interactions between NDVI and SES in our regression analyses modelling depression and self-rated mental health. We hypothesized that green space exposure would improve mental health outcomes especially for individuals with lower SES who may have fewer mental health promoting factors (e.g., higher stress occupations, less access to material and psychosocial resources that promote mental health), which would result in statistically significant interaction terms between NDVI and SES indicators in our models. However, the only model where NDVI score significantly moderated the relationship between SES and mental health was when we modelled depression score using self-rated social standing and NDVI (Table 5, Figure 5). In this model, increasing NDVI score (by quartile) was associated with more of a decrease in depression score for individuals with low and medium self-rated social standing compared to individuals with high self-rated social standing (Figure 5). As NDVI score increased, inequality in depression score related to self-rated social standing decreased, which indicates that green space exposure, measured using NDVI, moderates the relationship between self-rated social standing and depression score.

Although we hypothesized that we would see significant moderating effects of green space exposure on the other SES/mental health scenarios, including income-mental health relationships, we did not observe this. This may be because the distribution of total household income in the CLSA is uniformly high, with only 28.0% of the study population falling into the “low” income category used in our regression analyses. In comparison, self-rated social standing was more normally distributed, with 13.3%, 65.4%, and 21.3% in the “low”, “medium”, and “high” categories, respectively. We explored the possibility that there was high collinearity between NDVI and income, which could have influenced the significance of regression coefficients. This was an issue in a similar study by Gidlow et al., which found that the relationships between income and stress, and green space and stress, were attenuated beyond significance when income and green space were included in the same model due to high collinearity between the variables (38). When we tested the association between NDVI and income in our data using variance inflation factors (VIF), the VIF was 2.79, which indicates moderate correlation between variables. Because we accepted that there would be some degree of correlation between income and green space exposure based on previous research in Canada (67,68), we continued with our analysis despite the correlation between variables, however this may have influenced the results of our models. In contrast, there was no significant association between self-rated social standing and NDVI variables in our data, which may explain why the only significant effect modification by NDVI on the SES-mental health relationship was when we used self-rated social standing as the socioeconomic indicator.

6.6 Main Effects of Green Space Exposure on Mental Health Outcomes

We expected that green space exposure would be associated with less depression and better self-rated mental health, which we observed in the bivariate associations between depression, self-rated mental health, and NDVI (Table 1), as well as in our baseline regression models adjusted for age and sex. However, it is clear from our adjusted regression models that sociodemographic characteristics (e.g., age, sex, race, income) and lifestyle factors (e.g., physical activity) are better predictors of depression and self-rated mental health than green space measured using NDVI. After adjusting for covariates, the relationship between NDVI and mental health was attenuated, and other variables, including physical activity and social support are better predictors of mental health. Although the relationship between NDVI and mental health is not significant in adjusted models, our analysis highlights potential pathways through which green space exerts a positive influence on mental health (i.e., green space improves mental health by promoting physical activity or social connectedness). Other studies assessing the impact of green space on mental health have determined that physical activity and social cohesion mediate the relationship between green space and mental health (108) and that urban green spaces increase levels of physical activity (109). Further exploration is warranted into how specific greening initiatives that incorporate elements related to exercise or social cohesion may help improve mental health outcomes.

6.7 Association between Green Space Exposure and Socioeconomic-Related Mental Health Inequalities

We were interested in measuring the relationship between green space exposure and socioeconomic-related mental health inequalities in our study population. We wanted to quantify the burden of poor mental health across the socioeconomic distribution, and determine if green space exposure is associated with the magnitude of inequality. Our rationale was that if green space exposure was associated with lower socioeconomic-related mental health inequalities, then our results could help inform green space interventions and policy aimed at reducing inequalities and improving population-level mental health.

The relationship between SES and depression is well established. Meta-analyses have demonstrated a significant relationship between SES and depression, using income, education, and occupation as measures of SES (103,110,111). For example, a meta-analysis by Lorant et al. determined that individuals with low SES have 80% higher odds of having depression than individuals with high SES (when measuring SES using income and education) (103). A Canadian study using data from the National Population Health Survey produced similar results, with individuals with low education and high financial strain experiencing 86% and 65% higher odds of depression compared to individuals with higher education and less financial strain (112). Socioeconomic-related depression inequality is also present when SES is measured using self-rated social status (113).

Similarly, there is also a socioeconomic gradient in self-rated mental health. Interest in self-rated mental health as a measure of mental health has increased over the last two decades because it is a single item question that is easy to use in epidemiologic surveys and is well-correlated with other mental health outcomes, as well as general health (114). Across contexts, individuals with low SES measured using objective indicators (i.e., income, education, and occupation) generally have lower self-rated mental health (80,114), and a study by Statistics Canada using data from the Canadian Community Health Survey determined that more subjective measures of SES, including feelings of social belonging, were also associated with gradients in self-rated mental health (115).

Understanding the distribution and quantifying the impact of socioeconomic-related mental health inequalities is important, however measurable actions must be taken to help address these findings and reduce the burden of poor mental health on individuals with low SES. SES is a major social determinant of health, and governments should aim to reduce socioeconomic inequalities through better education and employment opportunities, reducing income-disparities, addressing systemic racism, improving housing, and other approaches to narrow the gap in SES within populations (116). These are some examples of long-term solutions that would undoubtedly have profound effects on socioeconomic-related mental health inequalities and improve overall population health, but they require coordinated effort across governmental, health, and private sectors.

Increasing green space exposure, particularly for individuals with low SES, has been proposed as a potential strategy to help reduce socioeconomic-related mental health and general health inequalities as an interim measure while addressing other social determinants of health (7,29,47,107). Green space exposure has a proven association with mental health outcomes, including depression, anxiety, stress, and low self-rated mental health (2–4,12,39,98), and increasing green space exposure may reduce socioeconomic-related mental health inequalities because it has a positive effect on mental health regardless of an individual's SES (47,106,107).

To determine the association between green space exposure and socioeconomic-related mental health inequalities we divided our study population into 20 provincial urban and rural sub-populations, calculated mean NDVI scores as well as concentration index scores for each of the four socioeconomic-related mental health inequalities, and used Spearman's rank correlation coefficient to determine the direction and significance of the relationship between NDVI and socioeconomic-related mental health inequalities. We hypothesized that the higher mean NDVI, the less inequality would be, however the only relationship between NDVI and inequality that followed our hypothesized pattern was self-rated social standing-related inequality in depression, and none of the relationships were statistically significant (Table 9).

A potential explanation for these results may stem from our definition of "population". Health inequality measures including the concentration index measure inequality within a defined group. Generally, these groups are geographically defined, such as a national, provincial, or city population. Although members of the population do not always share the same socio demographic characteristics (i.e., individuals in the population have different incomes), we assume that because the groups are geographically defined, aspects of the environment that influence health, such as green space, are shared by everyone in the population. Therefore, any resulting socioeconomic-related inequalities in health outcomes are meaningful because we assume that the socioeconomic indicator is driving the inequality, and not other factors related to the health outcome (i.e., differential green space exposure).

In our study, we created artificial populations by combining individuals from different parts of each province into groups. For example, in Ontario, the "urban" sub-population consists of individuals from multiple cities including Toronto, Hamilton, and Ottawa, which have different environmental conditions. Therefore, we cannot assume that environmental conditions, including green space, are uniform across each sub-population, which may have affected the observed relationships between NDVI and socioeconomic-related mental health inequalities. To accurately measure the relationship between green space exposure and socioeconomic-related mental health inequalities, we recommend further investigation using population groups defined by geographic area, such as specific neighbourhoods or individual towns or cities. This would help ensure the homogeneity of green space exposure across participants in each population group, and would give us a better understanding of how green space exposure affects socioeconomic-related mental health inequalities.

6.8 NDVI as a Measure of Green Space Exposure

NDVI is considered the "gold standard" when measuring green space exposure in epidemiologic and other environmental studies. It is an easily accessible index measure that can be used to compare the amount of vegetation in an environment across contexts, without considering area-level factors such as type of vegetation (14). It provides an overall index score of greenness with a defined spatial and temporal resolution and has a high degree of correlation with experts' subjective ratings of greenness from photographs of the same geographic areas (r=0.69) (85). However, since NDVI is calculated using light reflectance off of vegetation, when used as the sole indicator of green space exposure, it is unable to provide any information about the types of plants, let alone the quality, access, and intended use of green space that may influence the health promoting effects of specific green environments (47,117). Other studies have concluded that the health promoting effects of green space exposure are moderated by factors such as the attractiveness of parks, biodiversity, availability of shade, walking paths, and sporting facilities (106,117), all of which are impossible to measure using only NDVI.

We were limited in our choice of green space measure because NDVI was the only measure available in the CLSA data. We ran analyses using mean annual NDVI score, as well as maximum annual NDVI score at different buffer levels (250m, 500m, and 1000m). Ultimately, we decided to use maximum annual NDVI within 1000m for our study because it reflects participants' highest level of green space exposure and we were concerned that using mean annual NDVI would average out the potential influence of high (or low) green space exposure on mental health outcomes.

We acknowledge the limitations of using NDVI as our only measure of green space. As we observed in our regression analyses, physical activity and social support were both associated with depression and self-rated mental health. Moving forward, it will be important to have a better understanding of how green space facilitates physical activity and social connectedness in our study population in order to better understand and quantify the relationship between green space and mental health. For example, green spaces intended for playing sports and neighbourhood parks that facilitate social connectedness may have more of an influence on mental health outcomes than other types of green space, such as grassy medians or fields. This may be because the former works through all three pathways by which green space affects health (mitigation, restoration, and instoration), while the latter may only work through the mitigation and restoration pathways (i.e., improve environmental conditions, and passively capture attention). Further research using other measures of green space, such as land use databases, experts' subjective ratings of green space, and participant surveys about the quality and access to green space in their environment would clarify the relationship between green space and mental health, and provide more context for public health interventions involving green space.

6.9 Strengths and Limitations

Our study has several key strengths. Our sample size was very large, which increased statistical power and allowed us to draw more meaningful conclusions from our analyses than if we had a smaller study population. We chose to include both objective (income) and subjective (self-rated social status) socioeconomic indicators to capture different aspects of SES. We thought that this was important because while an individual's income may dictate their level of green space exposure (i.e., people with higher income may live in neighbourhoods with more trees and parks), how people rank themselves within their social hierarchy is strongly associated with mental health especially among older adults (56,57). Similarly, we chose to include two mental health outcomes that capture different dimensions of mental health. We chose depression, measured using the CESD-10, as a clinically relevant mental health outcome, and self-rated mental health because it captures a breadth of mental health states. We believed that evaluating how green space exposure affects different types of outcomes would help further our understanding of the relationship between green space and mental health.

Our study also has a few limitations. The most notable is our use of NDVI as the sole measure of green space exposure, which does not account for contextual features of green space that may influence mental health outcomes. We also need to consider the temporal alignment of NDVI with other CLSA data, specifically in the context of measuring a contemporaneous relationship between green space exposure and mental health. When spatially and temporally aligned with other epidemiological data, NDVI is a reliable measure of an individual's green space exposure based on their residential postal code (14). By using maximum annual NDVI scores for the year of baseline data collection, we are assuming that the NDVI score for each participant is representative of their actual green space exposure at the time of data collection. However, if baseline survey data was collected in the winter, the maximum annual NDVI score may be an overestimation of the participant's green space exposure at the time of data collection. Similarly, there may be issues with the seasonality of mental health outcomes, specifically depression since there is a higher risk of experiencing depressive symptoms in the winter months (118). If mental health data was collected in the winter it may underestimate the positive association between green space and mental health because of the higher prevalence of negative mental health outcomes. It is possible that the real relationship between NDVI and mental health outcomes was attenuated due to these temporal issues.

Another limitation is our choice to use income as a measure of SES in older adults, many of whom are retired and therefore not receiving a steady income. We considered using education as an objective measure of SES because it is established earlier in life and is therefore a less variable measure of SES as people leave the work force. However, the CLSA study population is highly educated and the distribution of education does not reflect variability in SES. Although evidence from the literature suggests that income may not be the best measure of SES in older adults, it is still well correlated with health status (119) and therefore we felt comfortable including it in our analysis. We felt that income, in conjunction with self-rated social standing (which is also correlated with health status in older adults), provided an overall view of SES in our study population.

Although the CLSA is a nationally representative survey for age, sex, and provincial population, participants, especially those in the Comprehensive cohort, have higher household income, more education, and better general health than the general Canadian population (81). This is a factor to consider when interpreting the results of our study, particularly when measuring socioeconomic-related mental health inequalities as individuals in the CLSA with "low" SES may not actually be disadvantaged when compared to the general Canadian population. Future studies should attempt to include a more representative sample in terms of socioeconomic indicators.

A final limitation of our study is that participants in the CLSA are predominantly white (>95% of participants in both the Tracking and Comprehensive cohorts). This is not representative of the racial diversity in Canada and limits our ability to draw conclusions about racial inequalities in green space exposure. We know there is a history of environmental racism in Canada (72) which may include inequitable green space exposure. However, due to the limited racial diversity in the CLSA data, we regret that our current study is unable to contribute insight in this area.

6.10 Study Contribution

Our study helps contextualize the association between green space, socioeconomic indicators, and mental health outcomes in Canada. We found that individuals with lower income and self-rated social standing had lower green space exposure measured using NDVI, which is consistent with findings from other studies that have shown an inequitable distribution of green space exposure by SES in Canada (67,68). Acknowledging this inequity, and taking steps to improve green space exposure for individuals and populations with low SES could help improve environmental justice in Canada.

The results of our regression analyses were mixed, and they highlighted potential mediating pathways in the relationship between green space and mental health (e.g., physical activity and social connectedness) that warrant further exploration. There was a significant moderating effect of green space exposure on depression score when using self-rated social standing as a measure of SES, which suggests that greening initiatives may help reduce depressive symptoms for individuals with low SES, and potentially help decrease socioeconomic-related inequalities in depression.

Although we did not measure any significant associations between green space exposure and socioeconomic-related mental health inequalities, the observed associations between green space, SES, and mental health suggest that there could be an association. Further research is warranted using geographically defined populations that share environmental characteristics, as well as using more subjective measures of green space that help contextualize the environment.

References:

1. Markevych I, Schoierer J, Hartig T, Chudnovsky A, Hystad P, Dzhambov AM, et al. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ Res [Internet]. 2017;158(February):301–17. Available from: http://dx.doi.org/10.1016/j.envres.2017.06.028

2. Beyer KMM, Kaltenbach A, Szabo A, Bogar S, Javier Nieto F, Malecki KM. Exposure to neighborhood green space and mental health: Evidence from the survey of the health of wisconsin. Int J Environ Res Public Health. 2014;11(3):3453–72.

3. Klompmaker JO, Hoek G, Bloemsma LD, Wijga AH, van den Brink C, Brunekreef B, et al. Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. Environ Int [Internet]. 2019;129(January):525–37. Available from: https://doi.org/10.1016/j.envint.2019.05.040

4. Wendelboe-Nelson C, Kelly S, Kennedy M, Cherrie JW. A scoping review of mapping research on green space and associated mental health benefits. Int J Environ Res Public Health. 2019;16(12).

5. Moor I, Spallek J, Richter M. Explaining socioeconomic inequalities in self-rated health: A systematic review of the relative contribution of material, psychosocial and behavioural factors. J Epidemiol Community Health. 2017;71(6):565–75.

6. Patten SB, Jian LW, Williams JVA, Currie S, Beck CA, Maxwell CJ, et al. Descriptive epidemiology of major depression in Canada. Can J Psychiatry. 2006;51(2):84–90.

7. Richard M, Frank P. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet [Internet]. 2008;372(9650):1655–60. Available from: http://linkinghub.elsevier.com/retrieve/pii/S014067360861689X

8. Lamb KE, Thornton LE, King TL, Ball K, White SR, Bentley R, et al. Methods for accounting for neighbourhood self-selection in physical activity and dietary behaviour research: A systematic review. Int J Behav Nutr Phys Act. 2020;17(1):1–22.

9. Braubach M, Egorov A, Mudu P, Wolf T, Thompson CW, Martuzzi M. Effects of urban green space on environmental health, equity and resilience. In: Nature-based solutions to climate change adaptation in urban areas. Springer; 2017. p. 187–205.

10. Taylor L, Hochuli DF. Defining greenspace: Multiple uses across multiple disciplines. Landsc Urban Plan [Internet]. 2017;158:25–38. Available from: http://dx.doi.org/10.1016/j.landurbplan.2016.09.024

11. Allen J, Balfour R. Natural solutions for tackling health inequalities. 2014.

12. James P, Banay RF, Hart JE, Laden F. A Review of the Health Benefits of Greenness. Curr Epidemiol Reports. 2015;2(2):131–42.

13. Gandhi GM, Parthiban S, Thummalu N, Christy A. Ndvi: Vegetation Change

Detection Using Remote Sensing and Gis - A Case Study of Vellore District. Procedia Comput Sci [Internet]. 2015;57:1199–210. Available from: http://dx.doi.org/10.1016/j.procs.2015.07.415

14. Helbich M. Spatiotemporal contextual uncertainties in green space exposure measures: Exploring a time series of the normalized difference vegetation indices. Int J Environ Res Public Health. 2019;16(5).

15. Albarakat R, Lakshmi V. Comparison of normalized difference vegetation index derived from landsat, MODIS, and AVHRR for the mesopotamian marshes between 2002 and 2018. Remote Sens. 2019;11(10).

16. Canadian Longitudinal Study on Aging. Linked Data in the Canadian Longitudinal Study on Aging (CLSA) Linked Data in the Canadian Longitudinal Study on Aging (CLSA) the Canadian. 2018;1–2.

17. Hystad P, Payette Y, Noisel N, Boileau C. Green space associations with mental health and cognitive function. Environ Epidemiol. 2019;3(1):e040.

18. Laurent O, Wu J, Li L, Milesi C. Green spaces and pregnancy outcomes in Southern California. Heal Place [Internet]. 2013;24:190–5. Available from: http://dx.doi.org/10.1016/j.healthplace.2013.09.016

19. Kihal-Talantikite W, Padilla CM, Lalloué B, Gelormini M, Zmirou-Navier D, Deguen S. Green space, social inequalities and neonatal mortality in France. BMC Pregnancy Childbirth. 2013;13.

20. Douglas O, Lennon M, Scott M. Green space benefits for health and well-being: A life-course approach for urban planning, design and management. Cities [Internet]. 2017;66:53–62. Available from: http://dx.doi.org/10.1016/j.cities.2017.03.011

21. Dadvand P, Villanueva CM, Font-ribera L, Vrijheid M, Gražulevi R, Kogevinas M. Risks and Benefits of Green Spaces for Children : 2014;122(August):1329–36.

22. Vujcic M, Tomicevic-Dubljevic J, Grbic M, Lecic-Tosevski D, Vukovic O, Toskovic O. Nature based solution for improving mental health and well-being in urban areas. Environ Res [Internet]. 2017;158(September 2016):385–92. Available from: http://dx.doi.org/10.1016/j.envres.2017.06.030

23. Smyth F. Medical geography: Therapeutic places, spaces and networks. Prog Hum Geogr. 2005;29(4):488–95.

24. Clark P. The European city and green space: London, Stockholm, Helsinki and St. Petersburg, 1850-2000. Aldershot, England: Ashgate; 2006.

25. Coseo P, Larsen L. How factors of land use/land cover, building configuration, and adjacent heat sources and sinks explain Urban Heat Islands in Chicago. Landsc Urban Plan [Internet]. 2014;125:117–29. Available from: http://dx.doi.org/10.1016/j.landurbplan.2014.02.019

26. Li D, Sullivan WC. Impact of views to school landscapes on recovery from stress and mental fatigue. Landsc Urban Plan [Internet]. 2016;148:149–58. Available from: http://dx.doi.org/10.1016/j.landurbplan.2015.12.015

27. Ulrich RS. View through a Window May Influence Recovery from Surgery. Science (80-). 1984;224(4647):420–1.

28. Honold J, Lakes T, Beyer R, van der Meer E. Restoration in Urban Spaces: Nature Views From Home, Greenways, and Public Parks. Environ Behav. 2014;48(6):796–825.

29. Roe JJ, Ward Thompson C, Aspinall PA, Brewer MJ, Duff EI, Miller D, et al. Green space and stress: Evidence from cortisol measures in deprived urban communities. Int J Environ Res Public Health. 2013;10(9):4086–103.

30. Jennings V, Browning MH, Rigolon A. Urban Green Spaces: Public Health and Sustainability in the United States. Springer International Publishing; 2019.

31. Maas J, van Dillen SME, Verheij RA, Groenewegen PP. Social contacts as a possible mechanism behind the relation between green space and health. Heal Place. 2009;15(2):586–95.

32. Bratman GN, Daily GC, Levy BJ, Gross JJ. The benefits of nature experience: Improved affect and cognition. Landsc Urban Plan [Internet]. 2015;138:41–50. Available from: http://dx.doi.org/10.1016/j.landurbplan.2015.02.005

33. Pun VC, Manjourides J, Suh HH. Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older U.S adults. Environ Heal A Glob Access Sci Source. 2018;17(1):1–11.

34. Barton J, Rogerson M. The importance of greenspace for mental health. BJPsych Int. 2017;14(4):79–81.

35. Hedblom M, Gunnarsson B, Iravani B, Knez I, Schaefer M, Thorsson P, et al. Reduction of physiological stress by urban green space in a multisensory virtual experiment. Sci Rep. 2019;9(1):1–11.

36. Lee J, Park BJ, Tsunetsugu Y, Ohira T, Kagawa T, Miyazaki Y. Effect of forest bathing on physiological and psychological responses in young Japanese male subjects. Public Health [Internet]. 2011;125(2):93–100. Available from: http://dx.doi.org/10.1016/j.puhe.2010.09.005

37. Kobayashi H, Song C, Ikei H, Park BJ, Lee J, Kagawa T, et al. Population-based study on the effect of a forest environment on salivary cortisol concentration. Int J Environ Res Public Health. 2017;14(8).

38. Gidlow CJ, Randall J, Gillman J, Smith GR, Jones M V. Natural environments and chronic stress measured by hair cortisol. Landsc Urban Plan [Internet]. 2016;148:61–7. Available from: http://dx.doi.org/10.1016/j.landurbplan.2015.12.009

39. Han H, Jongsik Y, Hyun SS. Nature based solutions and customer retention strategy: Eliciting customer well-being experiences and self-rated mental health. Int J Hosp Manag. 2020;86(October 2019).

40. Crouse DL, Pinault L, Christidis T, Lavigne E, Thomson EM, Villeneuve PJ. Residential greenness and indicators of stress and mental well-being in a Canadian national-level survey. Environ Res [Internet]. 2021;192(November 2019):110267. Available from: https://doi.org/10.1016/j.envres.2020.110267

41. Gong Y, Palmer S, Gallacher J, Marsden T, Fone D. A systematic review of the relationship between objective measurements of the urban environment and psychological distress. Environ Int [Internet]. 2016;96:48–57. Available from: http://dx.doi.org/10.1016/j.envint.2016.08.019

42. McCormick R. Does Access to Green Space Impact the Mental Well-being of Children: A Systematic Review. J Pediatr Nurs [Internet]. 2017;37:3–7. Available from: https://doi.org/10.1016/j.pedn.2017.08.027

43. Vanaken GJ, Danckaerts M. Impact of green space exposure on children's and adolescents' mental health: A systematic review. Int J Environ Res Public Health. 2018;15(12).

44. Mygind L, Kjeldsted E, Hartmeyer RD, Mygind E, Bølling M, Bentsen P. Immersive nature-experiences as health promotion interventions for healthy, vulnerable, and sick populations? A systematic review and appraisal of controlled studies. Front Psychol. 2019;10(APR).

45. Felappi JF, Sommer JH, Falkenberg T, Terlau W, Kötter T. Green infrastructure through the lens of "One Health": A systematic review and integrative framework uncovering synergies and trade-offs between mental health and wildlife support in cities. Sci Total Environ [Internet]. 2020;748:141589. Available from: https://doi.org/10.1016/j.scitotenv.2020.141589

46. Zhang Y, Mavoa S, Zhao J, Raphael D, Smith M. The association between green space and adolescents mental well-being: A systematic review. Int J Environ Res Public Health. 2020;17(18):1–26.

47. Hunter RF, Cleland C, Cleary A, Droomers M, Wheeler BW, Sinnett D, et al. Environmental, health, wellbeing, social and equity effects of urban green space interventions: A meta-narrative evidence synthesis. Environ Int [Internet]. 2019;130(December 2018):104923. Available from: https://doi.org/10.1016/j.envint.2019.104923

48. Shavers VL. Measurement of socioeconomic status in health disparities research. J Natl Med Assoc. 2007;99(9):1013–23.

49. Grundy E, Holt G. The socioeconomic status of older adults: How should we measure it in studies of health inequalities? J Epidemiol Community Health. 2001;55(12):895–904.

50. Adler NE, Stewart J. Health disparities across the lifespan: Meaning, methods, and mechanisms. Ann N Y Acad Sci. 2010;1186:5–23.

51. Marmot MG, Stansfeld S, Patel C, North F, Head J, White I, et al. Health inequalities among British civil servants: the Whitehall II study. Lancet. 1991;337(8754):1387–93.

52. Marmot M, Brunner E. Cohort profile: The Whitehall II study. Int J Epidemiol. 2005;34(2):251–6.

53. Gresenz CR, Sturm R, Tang L. Income and Mental Health: Unraveling Community and Individual Level Relationships. J Ment Health Policy Econ. 2001;4(4):197–203.

54. Joy AB, Hudes M. High risk of depression among low-income women raises awareness about treatment options. Calif Agric. 2010;64(1):22–5.

55. Golberstein E. The effects of income on mental health: evidence from the social security notch. J Ment Health Policy Econ. 2015;18(1):27.

56. Demakakos P, Nazroo J, Breeze E, Marmot M. Socioeconomic status and health: The role of subjective social status. Soc Sci Med. 2008;67(2):330–40.

57. Singh-Manoux A, Marmot MG, Adler NE. Does subjective social status predict health and change in health status better than objective status? Psychosom Med. 2005;67(6):855–61.

58. Wagstaff A, Paci P, van Doorslaer E. On the measurement of inequalities in health. Soc Sci Med. 1991;33(5):545–57.

59. Hardardottir H, Gerdtham U-G, Wengström E. What kind of inequality do you prefer? Evaluating measures of income and health inequality using choice experiments. 2019;(April):Lund University WP 2019:7. Available from: https://ideas.repec.org/p/hhs/lunewp/2019_007.html

60. Renard F, Devleesschauwer B, Speybroeck N, Deboosere P. Monitoring health inequalities when the socio-economic composition changes: Are the slope and relative indices of inequality appropriate? Results of a simulation study. BMC Public Health. 2019;19(1):1–9.

61. Hajizadeh M, Bombay A, Asada Y. Socioeconomic inequalities in psychological distress and suicidal behaviours among Indigenous peoples living off-reserve in Canada. Cmaj. 2019;191(12):E325–36.

62. O'donnell O, Van Doorslaer E, Wagstaff A, Lindelow M. The concentration index. In: Analyzing health equity using household survey data: a guide to techniques and their implementation. The World Bank; 2008.

63. Costa-Font J, Hernández-Quevedo C. Measuring inequalities in health: What do we know? What do we need to know? Health Policy (New York) [Internet]. 2012;106(2):195–206. Available from: http://dx.doi.org/10.1016/j.healthpol.2012.04.007

64. Van Doorslaer E, Wagstaff A, Bleichrodt H, Calonge S, Gerdtham UG, Gerfin M, et al. Income-related inequalities in health: Some international comparisons. J Health Econ. 1997;16(1):93–112.

65. Wagstaff A, Doorslaer E V. Measuring and Testing for Inequity in the Delivery of Health Care. J Hum Resour. 2000;35(4):716–33.

66. Mangalore R, Knapp M, Jenkins R. Income-related inequality in mental health in Britain: The concentration index approach. Psychol Med. 2007;37(7):1037–45.

67. Crouse DL, Pinault L, Balram A, Hystad P, Peters PA, Chen H, et al. Urban greenness and mortality in Canada's largest cities: a national cohort study. Lancet Planet Heal. 2017;1(7):e289–97.

68. Pham TTH, Apparicio P, Séguin AM, Landry S, Gagnon M. Spatial distribution of vegetation in Montreal: An uneven distribution or environmental inequity? Landsc Urban Plan. 2012;107(3):214–24.

69. Tooke TR, Klinkenberg B, Coops NC. A geographical approach to identifying vegetation-related environmental equity in Canadian cities. Environ Plan B Plan Des. 2010;37(6):1040–56.

70. Weinstein JN, Geller A, Negussie Y, Baciu A. Communities in action: Pathways to health equity. Communities in Action: Pathways to Health Equity. 2017. 1–558 p.

71. Dutcher GA, Spann M, Gaines C. Addressing health disparities and environmental justice: The National Library of Medicine's Environmental Health Information Outreach Program. J Med Libr Assoc. 2007;95(3):330–6.

72. Waldron I. Re-thinking waste: mapping racial geographies of violence on the colonial landscape. Environ Sociol. 2018;4(1):36–53.

73. Wolch JR, Byrne J, Newell JP. Urban green space, public health, and environmental justice: The challenge of making cities "just green enough." Landsc Urban Plan [Internet]. 2014;125:234–44. Available from: http://dx.doi.org/10.1016/j.landurbplan.2014.01.017

74. Woodward A, Kawachi I. Why reduce health inequalities? J Epidemiol Community Health. 2000;54(12):923–9.

75. Van Oort FVA, Van Lenthe FJ, Mackenbach JP. Material, psychosocial, and behavioural factors in the explanation of educational inequalities in mortality in the Netherlands. J Epidemiol Community Health. 2005;59(3):214–20.

76. Schulz A, Northridge ME. Social determinants of health: Implications for environmental health promotion. Heal Educ Behav. 2004;31(4):455–71.

77. Zimmerman FJ, Katon W. Socioeconomic status, depression disparities, and financial strain: What lies behind the income-depression relationship? Health Econ. 2005;14(12):1197–215.

78. Cundiff JM, Smith TW, Uchino BN, Berg CA. Subjective social status: Construct validity and associations with psychosocial vulnerability and self-rated health. Int J Behav Med. 2013;20(1):148–58.

79. Helbich M, Klein N, Roberts H, Hagedoorn P, Groenewegen PP. More green space is related to less antidepressant prescription rates in the Netherlands: A Bayesian geoadditive quantile regression approach. Environ Res [Internet]. 2018;166(June):290–7. Available from: https://doi.org/10.1016/j.envres.2018.06.010

80. Mawani FN, Gilmour H. Validation of self-rated mental health. Health Rep. 2010;21(3):61–75.

81. Raina P, Wolfson C, Kirkland S, Griffith LE, Balion C, Cossette B, et al. Cohort Profile: The Canadian Longitudinal Study on Aging (CLSA). Int J Epidemiol. 2019;48(6):1752-1753J.

82. Raina PS, Wolfson C, Kirkland SA, Griffith LE, Oremus M, Patterson C, et al. Sampling and computation of response rates and sample weights for the Tracking (telephone interview) participants and Comprehensive participants. 2017;1–32. Available from: https://www.clsa-elcv.ca/doc/3965

83. Raina PS, Wolfson C, Kirkland SA, Griffith LE, Oremus M, Patterson C, et al. The Canadian longitudinal study on aging (CLSA). Can J aging/La Rev Can du Vieil. 2009;28(3):221–9.

84. CANUE. Canadian Urban Environmental Health Research Consortium: CANUE metadata NDVI landsat. 2018;9999:1–4. Available from: https://canue.ca/wp-content/uploads/2018/11/CANUE-Metadata-NDVI-Landsat-Annual.pdf

85. Rhew IC, Vander Stoep A, Kearney A, Smith NL, Dunbar MD. Validation of the Normalized Difference Vegetation Index as a Measure of Neighborhood Greenness. Ann Epidemiol [Internet]. 2011;21(12):946–52. Available from: http://dx.doi.org/10.1016/j.annepidem.2011.09.001

86. Reid CE, Kubzansky LD, Li J, Shmool JL, Clougherty JE. It's not easy assessing greenness: A comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York City. Heal Place [Internet]. 2018;54(February):92–101. Available from: https://doi.org/10.1016/j.healthplace.2018.09.005

87. Foley R, Kistemann T. Blue space geographies: Enabling health in place. Heal Place [Internet]. 2015;35:157–65. Available from: http://dx.doi.org/10.1016/j.healthplace.2015.07.003

88. Su JG, Dadvand P, Nieuwenhuijsen MJ, Bartoll X, Jerrett M. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. Environ Int [Internet]. 2019;126(October 2018):162–70. Available from: https://doi.org/10.1016/j.envint.2019.02.008

89. Chen B, Covinsky KE, Cenzer IS, Adler N, Williams BA. Subjective social status and functional decline in older adults. J Gen Intern Med. 2012;27(6):693–9.

90. Siddaway AP, Wood AM, Taylor PJ. The Center for Epidemiologic Studies-Depression (CES-D) scale measures a continuum from well-being to depression: Testing two key predictions of positive clinical psychology. J Affect Disord [Internet]. 2017;213(February):180–6. Available from: http://dx.doi.org/10.1016/j.jad.2017.02.015

91. Subedi R, Greenberg TL, Roshanafshar S. Does geography matter in mortality? An analysis of potentially avoidable mortality by remoteness index in Canada. Heal Reports. 2019;30(5):3–15.

92. Kim S, Egerter S, Cubbin C, Takahashi ER, Braveman P. Potential implications of missing income data in population-based surveys: An example from a postpartum survey in California. Public Health Rep. 2007;122(6):753–63.

93. Wagstaff A. The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. Health Econ. 2005;14(4):429–32.

94. He Y, Dixon P. NDVI variation and its relation to climate in Canadian ecozones. 2012;(October 2018).

95. Hedman L, Galster G. Neighbourhood Income Sorting and the Effects of Neighbourhood Income Mix on Income : A Holistic Empirical Exploration. 2013;50(January):107–27.

96. Brown M, Fonberg J, Schellenberg G, Yang R. Economic and Social Reports Neighbourhood characteristics and life satisfaction of individuals in lower- , middle- , and higher-income families in Canadian metropolitan areas. 2021;(36).

97. Singh-manoux A, Adler NE, Marmot MG. Subjective social status : its determinants and its association with measures of ill-health in the Whitehall II study. 2003;56:1321–33.

98. Bezold CP, Banay RF, Coull BA, Hart JE, James P, Kubzansky LD, et al. The Association Between Natural Environments and Depressive Symptoms in Adolescents Living in the United States. J Adolesc Heal [Internet]. 2018;62(4):488–95. Available from: https://doi.org/10.1016/j.jadohealth.2017.10.008

99. Sarkar C, Webster C, Gallacher J. Residential greenness and prevalence of major depressive disorders : a cross-sectional , observational , associational study of 94 879 adult UK Biobank participants. Lancet Planet Heal [Internet]. 2010;2(4):e162–73. Available from: http://dx.doi.org/10.1016/S2542-5196(18)30051-2

100. Stigsdotter UK, Ekholm OLA, Schipperijn J, Toftager M, Kamper-jørgensen F, Randrup TB. Health promoting outdoor environments – Associations between green space , and health , health-related quality of life and stress based on a Danish national representative survey. 2010;(February):411–7.

101. Astell-Burt T, Feng X. Association of Urban Green Space with Mental Health and General Health among Adults in Australia. JAMA Netw Open. 2019;2(7).

102. Liu Q, Luo S, Shen Y, Zhu Z, Yao X, Li Q, et al. Urban Forestry & Urban Greening Relationships between students ' demographic characteristics , perceived naturalness and patterns of use associated with campus green space , and self-rated restoration and health. Urban For Urban Green [Internet]. 2022;68(June 2020):127474. Available from: https://doi.org/10.1016/j.ufug.2022.127474

103. Lorant V, Deliège D, Eaton W, Robert A, Philippot P, Ansseau M. META-ANALYSIS Socioeconomic Inequalities in Depression: A Meta-Analysis. Am J Epidemiol [Internet]. 2003 [cited 2020 Jun 10];157(2):98–112. Available from: https://academic.oup.com/aje/article-abstract/157/2/98/90059

104. Zimmerman FJ, Katon W. Socioeconomic status, depression disparities, and financial strain: What lies behind the income-depression relationship? Health Econ [Internet]. 2005 Dec [cited 2020 Jun 10];14(12):1197–215. Available from: http://doi.wiley.com/10.1002/hec.1011

105. Hudson CG. Socioeconomic status and mental illness: Tests of the social causation and selection hypotheses. Am J Orthopsychiatry. 2005;75(1):3–18.

106. Sugiyama T, Villanueva K, Knuiman M, Francis J, Foster S, Wood L, et al. Can neighborhood green space mitigate health inequalities? A study of socio-economic status and mental health. Heal Place [Internet]. 2016;38:16–21. Available from: http://dx.doi.org/10.1016/j.healthplace.2016.01.002

107. Mitchell RJ, Richardson EA, Shortt NK, Pearce JR. Neighborhood Environments and Socioeconomic Inequalities in Mental Well-Being. Am J Prev Med [Internet]. 2015;49(1):80–4. Available from: http://dx.doi.org/10.1016/j.amepre.2015.01.017

108. Van Den Berg MM, Van Poppel M, Van Kamp I, Ruijsbroek A, Triguero-Mas M, Gidlow C, et al. Do Physical Activity, Social Cohesion, and Loneliness Mediate the Association Between Time Spent Visiting Green Space and Mental Health? Environ Behav [Internet]. 2019 Feb 1 [cited 2020 Jun 2];51(2):144–66. Available from: https://doi.org/10.1177/0013916517738563

109. Schipperijn J, Bentsen P, Troelsen J, Toftager M, Stigsdotter UK. Associations between physical activity and characteristics of urban green space. Urban For Urban Green [Internet]. 2013;12(1):109–16. Available from: http://dx.doi.org/10.1016/j.ufug.2012.12.002

110. Barnett A, Zhang CJP, Johnston JM, Cerin E. Relationships between the neighborhood environment and depression in older adults : a systematic review and meta-analysis. Int Psychogeriatrics. 2022;2050(2018):1153–76.

111. Domènech-Abella J, Mundó J, Leonardi M, Chatterji S, Tobiasz-adamczyk B, Koskinen S, et al. The association between socioeconomic status and depression among older adults in Finland , Poland and Spain : A comparative cross-sectional study of distinct measures and pathways. J Affect Disord [Internet]. 2018;241(April):311–8. Available from: https://doi.org/10.1016/j.jad.2018.08.077

112. Wang JL, Schmitz N, Dewa CS. Socioeconomic status and the risk of major depression : the Canadian National Population Health Survey. J Epidemiol Community Health. 2010;64(5):447–52.

113. Hoebel J, Maske UE, Zeeb H, Lampert T. Social Inequalities and Depressive Symptoms in Adults : The Role of Objective and Subjective Socioeconomic Status. PLoS One. 2017;12(1):1–18.

114. Ahmad F, Jhajj AK, Stewart DE, Burghardt M, Bierman AS. Single item measures of self-rated mental health : a scoping review. 2014;1–11.

115. Statistics Canada. Community Belonging and Self-perceived Health: Early CCHS Findings. Heal Stat Div Minsit Ind Cat. 2005;82(621):1–24.

116. NHS Health Scotland. Health Inequalities: What are they? How do we reduce them? 2016.

117. Francis J, Wood LJ, Knuiman M, Giles-Corti B. Quality or quantity? Exploring the relationship between Public Open Space attributes and mental health in Perth, Western Australia. Soc Sci Med [Internet]. 2012;74(10):1570–7. Available from: http://dx.doi.org/10.1016/j.socscimed.2012.01.032

118. Øverland S, Woicik W, Sikora L, Whittaker K, Heli H, Skjelkvåle FS, et al. Seasonality and symptoms of depression: A systematic review of the literature. Epidemiol Psychiatr Sci. 2019;

119. Darin-Mattsson A, Fors S, Kåreholt I. Different indicators of socioeconomic status and their relative importance as determinants of health in old age. Int J Equity Health. 2017;16(1):1–11.

Appendix A.

Table 1. ANOVA results for differences in green space exposure (measured using max annual NDVI score within 1000m of postal code location) for whole study population vs. urban only population

	WHOLE CLSA POPULATION (n= 35,176)		***URBAN ONLY POPULATION (n= 29,453)***	
Measure	**NDVI Score (Mean, SD)**	***p***	**NDVI Score (Mean, SD)**	***p***
Income				
Less than $20,000	0.785 (0.057)	<0.001*	0.785 (0.046)	<0.001*
$20,000 or more, less than $50,000	0.791 (0.041)		0.788 (0.040)	
$50,000 or more, less than $100,000	0.792 (0.041)		0.790 (0.039)	
$100,000 or more, less than $150,000	0.794 (0.035)		0.792 (0.034)	
$150,000 or more	0.795 (0.031)		0.794 (0.030)	
Self-Rated Social Status				
Low (1-3)	0.791 (0.041)	0.119	0.789 (0.039)	0.169
Medium (4-7)	0.792 (0.038)		0.791 (0.036)	
High (8-10)	0.792 (0.039)		0.791 (0.037)	
Depression Status				
Positive Screen for Depression (CESD-10 score ≥10)	0.790 (0.040)	<0.001*	0.788 (0.039)	<0.001*
Negative Screen for Depression (CESD-10 score <10)	0.792 (0.040)		0.791 (0.037)	
Self-Rated Mental Health				
Poor	0.789 (0.035)	<0.001*	0.788 (0.035)	<0.001*
Fair	0.787 (0.058)		0.786 (0.049)	
Good	0.791 (0.039)		0.790 (0.037)	
Very Good	0.792 (0.039)		0.791 (0.037)	
Excellent	0.793 (0.037)		0.792 (0.0036)	