Associations between green space and depressive symptoms in young adults: a longitudinal study

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Abstract

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As the number of people living in urban areas rises, it is becoming increasingly important to quantify the relationship between exposure to green space and physical and mental health. Young adulthood in particular is a critical period with profound impacts on health, and often has implications for health outcomes later in life. Our study population consists of 779 Seattle area young adults (aged 18-23), followed for 30 months. Generalized linear mixed models were used to quantify the longitudinal associations between green space, measured by Normalized Difference Vegetation Index (NDVI), and self-reported depressive symptoms, measured by Patient Health Questionnaire 9 (PHQ-9), adjusting for covariates. Data from 3 time points were included in the models, with PHQ-9 collected at later times than NDVI to account for lag time: baseline NDVI with month 12 PHQ-9, month 12 NDVI with month 24 PHQ-9, and month 24 NDVI with month 30 PHQ-9. We found no significant associations between depressive symptoms and green space in our main models. In a sensitivity analysis, we did find that looking only at one time interval (baseline NDVI and month 12 PHQ-9), green space was inversely associated with depressive symptoms when comparing the lowest two quartiles of green space values (RR: 0.76, 95% CI: 0.61, 0.96). No other study has examined this age group making it difficult to draw firm conclusions. More research to further investigate the association between green space and depressive

symptoms in the young adult population will further shed light on the role of green space in mental health.

Introduction

As the number of people living in urban areas rises, it is becoming increasingly important to quantify the relationship that exposure to environmental features, such as green space, has with both physical and mental health. Beneficial associations between green space and birth outcomes,[1,2] diabetes,[3] cardiovascular disease,[4] prostate cancer,[5] and mortality[6,7] (among others) have been observed. Markevych et al. propose that the pathways by which green space affects health can be put into one of three categories: reducing harm (reducing exposures like noise and pollution), restoring capabilities (attention restoration and stress recovery), and building capacities (increased physical activity and social cohesion).[8]

With regards to mental health, although the exact underlying mechanisms are unclear, it is thought that restoring capabilities and building capacities may be important pathways in the green space-mental health relationship.[9–12] Specifically looking at depression, Van Den Bosch and Meyer-Lindenberg[13] summarize that physical environments (e.g., air pollution, noise), proximate contextual environments (e.g., neighborhood, work, social relations), and distant contextual environments (e.g., ecosystem, political system, urbanicity) can all impact brain function via allostatic load, specifically via dopamine and epinephrine,[14] and can be linked to depression.

Depression is becoming an increasing public health concern. An estimated 3.8% of the global population is afflicted with depressive symptoms,[15] with an estimated 7.8% of US young adults aged 18-34 years experiencing a major depressive episode in 2017.[16] These numbers are likely a conservative estimate, as many people experiencing depression do not receive a diagnosis. Further, there is research suggesting that the past year prevalence of major depressive disorder in young adults (aged 18 to 25) increased from 8.8% in 2005 to 9.6% in 2014.[17] Increasing our understanding of how daily environmental factors, such as exposure to green space, might protect against depression may provide key insights on possible future interventions.

Many studies have reported associations of exposure to green space and related indicators with depressive symptoms, utilizing a variety of study designs and measures, although there are limited studies focusing on young adult populations. Looking at short term effects, Brooks et al.[18] found that among Canadian university students (mean age: 21 years), both looking at pictures of nature and actual contact with nature (via a short walk) were associated with a decrease in depressive symptoms. In a similar study, Song et al. (2015)[19] found that among a small sample (n=20) of male university students (mean age: 22) in Japan, self-reported depression was marginally lower for those who walked in an urban park compared to those walking in a non-green city area in the fall.

Some studies that looked at a wider age group also found associations. A cross-sectional study among adults in Spain (mean age: 43 years) found that self-reported views of nature through a home window were associated with lower self-reported depressive symptoms.[20] Other cross-sectional studies that used residential greenspace exposures found that more greenspace was associated with lower self-reported depressive symptoms in adults living in Wisconsin[21] and Washington State.[22] Some longitudinal studies have supported these findings as well. Gonzales-Inca et al.[23] found that among Finnish adults (20-54 years), higher levels of residential greenspace (measured cumulatively over 5 and 14-year follow-up periods) was associated with lower levels of doctor-diagnosed depression. Bezold et al.[24] also found that higher childhood and adolescent residential exposure to vegetation density was associated with lower self-reported high depressive symptoms in an adult US population.

However, other studies found mixed results. Gubbels et al.[25] found that improvements in neighborhood green space (via intervention), did not consistently improve depressive symptoms across the full sample, but that among adults in deprived (defined as very low SES) neighborhoods in the Netherlands, more positive perceptions of green space were associated with a decrease in depressive symptoms. In contrast to the results of the fall nature walking experiment, Song et al. (2014) found no associations between walking in nature (vs. walking in a non-green urban space) in the spring and self-reported depressive symptoms that among 17 male university students in Japan (mean age: 21). [26]

Although there are many studies on green space and depression, much of the current literature is cross-sectional and therefore cannot rule out reverse causation. [7,27] For example, a cross-sectional association between green space and depressive symptoms may indicate that those with depressive symptoms are selecting into less green neighborhoods, and not that a lack of green space is causing depressive symptoms. Additionally, there is not much literature on green space and depression among young adults specifically. Young adulthood (generally defined as 18-26 years old) is a critical period in health, and often has implications for health outcomes later in life.[28] This study adds to the existing literature in a unique way by focusing on this critical period and utilizing longitudinal data to assess both between and within person associations.

We hypothesize that participants will have lower depression scores when they live in more green areas compared to when they live in less green areas (within-person associations), and that compared to those living in less green spaces, participants living in census tracts with higher green space values will have lower depression scores (between-person associations).

Methods

The data used for this study was originally collected for Project Transitions, a longitudinal study designed to examine social role transitions and their associations with alcohol use among young adults in the Greater Seattle, WA, area. Participants were enrolled between February of 2015 and January 2016. Recruitment of study subjects was done via online avenues including email, Facebook, University of Washington registrar lists, and craigslist, in addition to newspaper adds, flyers, tabling at community colleges, and word of mouth. Eligible participants who completed both the screener and baseline survey were asked to complete monthly surveys for a duration of 24 consecutive months. An additional follow-up survey at 30 months was also completed. Monthly survey completion ranged from 75.96% to 96.92%. The current study used data from baseline surveys and surveys from months 12, 24, and 30.

There were 779 participants at recruitment who completed baseline surveys. To be eligible for the study, participants must have been between the ages of 18 and 23 years old at the time of screening. Additionally, participants needed to be willing to come into the lab for baseline survey and other consent forms, report drinking alcohol at least once in the past month or past year (depending on when they enrolled) and chosen either “male” or “female” for biological sex. Participants must also have not already been enrolled in other studies conducted at the research center at the time of the screening survey. At the time of study enrollment, participants lived within 60 miles of Seattle, Washington based on reported zip code. During the study period, participants who moved away from the Seattle area continued to be followed as part of the study. However, only green space data for those who remained in the Seattle area was available. Other than the baseline survey (which was completed in-person on University of Washington, Seattle campus), all surveys were completed online.

The procedures of the parent study were approved by an Institutional Review Board (IRB) at the University of Washington. The current study was exempt from IRB approval.

Measures

The exposure of interest is residential green space, measured by the average Normalized Difference Vegetation Index (NDVI) of the census tract of the participant. Both median and summertime (the median NDVI between April 1st and September 30th) NDVI were used. NDVI values were first measured for the 200-meter buffer around the census block centroid and then all block centroids were averaged to the tract-level using a population weight. That is, blocks with larger populations received a larger weight in the final tract level NDVI measure. A 200-meter buffer was chosen to ensure that the buffers did not include areas from other census tracts, although the measure is imperfect because tracts vary in shape and size.

NDVI values are based on satellite imagery from the Multi-Resolution Land Characteristics Consortium from the year 2006. NDVI values traditionally range from -1 to 1 but were converted to a 0-255 scale where values close to 50 are areas of water, while areas with lush vegetation have values around 200.[29] In a validation study conducted in the Seattle area, NDVI values were shown to strongly correlate with independent expert ratings of greenness.[30] In the current study, NDVI was linked to participant data via census tract at each time point and scaled (divided by 10).

The outcome of interest is depressive symptoms, as determined through the Patient Health Questionnaire 9 (PHQ-9), a tested and validated, reliable tool to determine depression severity.[31] A validity study found that when compared to psychiatric diagnostic interviews for major depressive disorder, a score cut off of 10 or higher on the PHQ-9 survey showed 88% sensitivity and 88% specificity.[31] Cronbach alpha scores for the PHQ-9 in this study sample ranged from 0.878 to 0.901, showing good internal consistency.[32] The PHQ-9 is a nine item scale asking about feelings, thoughts, and behaviors such as interest and pleasure, tiredness, appetite, feeling bad about oneself, concentration, and thinking of self-harm (in addition to others), and was administered at baseline and months 12, 24, and 30. Each of the questions asked participants to indicate how often they experience each in the past two weeks (0=not at all, 1=several days, 2=more than half the days, 3=nearly every day), and a composite score ranging from 0-27 was calculated, with higher scores indicating more depressive symptoms.[33]

Covariates

Covariates of interest were identified via existing studies exploring green space and depressive symptoms. A directed acyclic graph was then created to depict causal relationships.[32] Non time-varying variables collected at baseline include age (in years) at baseline, and mother and father's highest level of education (collapsed into two categories: neither parent has a bachelor's degree or higher, or one or more parents has a bachelor's degree or higher).

Although gender and sexually minoritized identity and race are potentially time-varying, because our sample population showed relatively stable responses across surveys, baseline responses were treated as non-time-varying. A binary LGBTQ identity variable was created from the gender and sexual orientation variables. Those identifying as cisgender *and* heterosexual were in one category, and those who identified as transgender *or* bisexual, gay, lesbian, queer, two-spirit, questioning, or other were in another category. Due to small numbers of study participants reporting certain racial identities, race was also collapsed into two categories (person of color and white). Persons of color include Asian/South Asian, Native Hawaiian/other Pacific Islander, Black/African American, American Indian/Alaskan Native, Arab/Middle Eastern/North African, more than one race, or other (specified). We are using race as a proxy for unmeasured effects of systematic racism.

Time-varying covariates of interest include financial difficulties experienced by participant, participant education status, participant work situation, health insurance, and the season in which survey was taken (fall, spring, summer, winter). Financial difficulties were defined by combining survey responses to the following items: cash-flow difficulties, difficulty saving money, difficulties with ability to do the things financially, difficulties with ability to pay bills, difficulties trying to secure loans, or other. Responses were coded as yes or no and collapsed into two categories: those with no reported financial difficulties, and those with 1 or more reported financial difficulties. Education status was also collapsed into two categories: student (refers to any participant who identified that they were in any of the following categories: high school student, working toward a general education development (GED), trade or vocational school student, 2-year/community college student, 4-year college or university student, graduate or professional school student) and non-students (anyone who did not select one of the above categories). Work situation was grouped into two categories: those who reported having a full-time job (paid), multiple jobs (paid), or in the military and those who did not report any of those positions. The second group includes those who reported working part-time (paid), volunteer work (unpaid), internship/apprenticeship (paid or unpaid), homemaker/caring for household/stay at home parent, unemployed and actively looking for work, unemployed and not looking for work, on leave, receiving disability/SSI income, receiving unemployment benefits, or other. Since participants were able to select more than one option, in order to be grouped into the second category, participants must not have reported having a full-time job (paid), multiple jobs (paid), or being in the military. Health insurance status was also collapsed into a binary variable: no health insurance/pay out of pocket and insured. Those in the "insured" category included anyone who reported having health insurance through their parents' plan, covered at work or school, Medicaid, or other. The address of residence for each respondent was recorded at baseline and months 12 and 24, which was geocoded and linked to census tract level median household income (in dollars) and census-level NDVI data (our exposure of interest).

Statistical Analysis

Longitudinal Models

Due to the correlated nature of these data (repeated measures for each participant) a random intercept generalized linear mixed model (GLMM) was used to analyze the association between census tract level NDVI and depressive symptoms across 3 time points. Random intercepts for both individuals and census tracts were included to account for clustering at those levels. Because depressive symptoms as measured by the PHQ-9 are positive count outcomes (ranging from 0-27) and showed positive skewness with overdispersion, we used a negative binomial form of the GLMM. This type of model allows for inclusion of both fixed and random effects and does not assume a normal outcome distribution. NDVI exposure accounts for lag time between exposure and outcome because we assume that a change in greenspace does not instantly influence depressive symptoms. Thus, PHQ-9 score reports were regressed on NDVI and all covariates at the previous time point. Specifically, survey month 12 PHQ-9 scores were regressed on NDVI measured at baseline, month 24 PHQ-9 scores were regressed on NDVI measured at month 12, and month 30 PHQ-9 scores were regressed on NDVI measured at month 24. All covariates adjusted for in all models were measured at the same time as NDVI to ensure that potential confounders occurred before the outcome. In these longitudinal models, NDVI was modeled continuously (scaled by dividing by 10).

Making distinctions between within-person and between-person associations in longitudinal data is important not only for policy implications, but also to understand what level associations are stemming from. Without separating the between and within person results, it is difficult to determine if the relationship is the same for both, and if there are differences in magnitude and direction. All time-varying covariates were person-mean centered and all time-invariant variables were grand-mean centered in order to distinguish within and between person associations. A grand mean centered person-mean variable for NDVI was also included.

Person-mean centering was done by first calculating the mean of a given variable across all time points for each individual (person mean). Then, to center the variable, the person mean was subtracted from the raw value at each time point. Grand mean centered variables for the time-invariant variables were calculated simply by subtracting the mean of a given variable (across all individuals) from a given individuals value. Grand mean centering variables does not have any effect on point estimates, but rather helps with the interpretation of the intercept term.

The grand mean centered person mean NDVI variable was created by first calculating the person mean of NDVI for each individual across time points. The average of the person mean NDVI variable was then calculated, and subtracted from each person's mean NDVI, resulting in a grand mean centered person mean NDVI variable. Using these person-mean centered variables in the model allows us to make inference on the within-person associations for time-varying variables, and between-person inference can be made from the grand-mean centered person mean NDVI variable.[34,35]

The continuous GLMM model takes the following form:

$$\begin{aligned}\log(Y_{ijt}) = {} & \beta_0 + \beta_1\, pmc\ NDVI_{ij(t-1)} + \beta_2\, gmc\_pm\ NDVI_i + + \beta_3 survey_{it} + \beta_4 gmc\ lgbt_i \\ & + \beta_5 gmc\ age_i + \beta_6 gmc\ race_i + \beta_7\ gmc\ parental\ education_i \\ & + \beta_8\ pmc\ Fall_{i(t-1)} + \beta_9\ pmc\ Summer_{i(t-1)} + \beta_{10} pmc\ Spring_{i(t-1)} \\ & + \beta_{11}\ pmc\ median\ income_{ij(t-1)} + \beta_{12} pmc\ financial\ difficulty_{i(t-1)} \\ & + \beta_{13} pmc\ participant\ education_{i(t-1)} + \beta_{14} pmc\ work\ status_{i(t-1)} \\ & + \beta_{15} pmc\ health\ insurance_{i(t-1)} + (\varepsilon_i) + (\varepsilon_j)\end{aligned}$$

Where log Y is the estimated log PHQ-9 score nested within individual i in census tract j at time t. ε_i refers to the error term for the random intercept for the individual, and ε_j refers to the error term for the random intercept for census tract. Including random intercepts allows us to account for clustering by individuals and by census tract. However, we are still assuming that all individuals are equally influenced by neighborhood effects (no random slope). All time varying variables in the model were person-mean centered (except for survey number) (indicated by *pmc)*, and all time-invariant variables were grand-mean centered (indicated by *gmc)*. Including the grand mean center person mean NDVI variable does not change the person mean centered NDVI coefficient, but it does allow us to make between-person inference.

Sensitivity Analyses

We conducted a few sensitivity analyses. First we looked at each of the 3 time points separately to examine whether all time points estimated similar associations and second we used summer NDVI values to see if the "best case scenario" greenness had different associations with depressive symptoms. Specifically, for individual time point models, we regressed survey 12 PHQ-9 scores on baseline NDVI, survey 24 PHQ-9 on survey 12 NDVI, and survey 30 PHQ-9 scores on survey 24 NDVI in 3 separate models. Since there is no clustering at the individual level (each participant only has one observation per variable), only a random intercept for census tract was included in the individual time point GLMM models. In these individual time point models, NDVI was modeled both as a continuous variable and as quartiles, resulting in a total of

6 individual time point models. To examine the summertime NDVI, we simply replaced median NDVI with the summertime measurements in the original longitudinal GLMM model.

Binary covariates adjusted for in all models include minoritized gender or sexual identity, parental education level, financial difficulty, participant education situation, work status, health insurance, and race. Season in which the survey was taken (time-varying,) was also included as a factor variable. Age at baseline was modeled continuously in years (fixed), as was median household income for the tract in which the participant resided (time-varying). Median income was scaled by dividing each value by 1,000.

Individual Time Point Models

The individual time point GLMM models take the following form. All time-varying covariates in the models are associated with the time point in which median NDVI is being represented.

$$\log(Y_j) = \beta_0 + \beta_1\, NDVI_j + \beta_2 lgbt + \beta_3 age + \beta_4 race + \beta_5 parental\ education + \beta_6\, Fall + \beta_7\, Summer + \beta_8\, Spring + \beta_9\, pmc\ median\ income_j + \beta_{10}\, financial\ difficulty + \beta_{11} participant\ education + \beta_{12} work\ status + \beta_{13} health\ insurance + (\varepsilon_j)$$

Where $log\ Y$ is the estimated average log PHQ-9 score nested within census tract j. ε_j refers to the error term for the random intercept for census tract.

NDVI was also modeled in quartiles for each individual time point model. The quartile models take a similar form, but with 3 indicator terms for the median NDVI quartiles, with the lowest quartile as the reference group.

Summer NDVI

Models using summer NDVI are identical to the longitudinal models described above, with the median NDVI replaced with the summer NDVI values.

Rate ratios (RR) and 95% confidence intervals (CI) were estimated from all models by exponentiating estimated coefficients. A rate ratio of 1.15, for example, would indicate a 15% higher PHQ- score for each 1 unit increase in the predictor. All models were fit using the “glmmTMB” package in R, version 4.1.3.

Results

Descriptive results

On average, of the 4 surveys used in the analysis (baseline, month 12, month 24, and month 30), participants either partially or fully completed 3.68 (SD: 0.74) surveys. Of the total variance in PHQ-9 scores, 2.6% comes from between census tracts and an average of 97.1% of tracts had 5 participants or fewer across timepoints, indicating very little clustering at the tract level. More than half (59.6%) of the variance in PHQ-9 is between subject, and 39.7% is within subject. However, 68% of the variability of NDVI values is between-person, and only 32% is within-person variability. The mean scaled NDVI value across all participants and time points was 15.12 (standard deviation: 2.55), and ranged from 7.28 to 21.03.

Of the 754 participants who had complete NDVI data at baseline, the mean age was 20.6 years (SD 1.72), was majority non-LGBTQ identifying (75.5%), and white (58.6%) (Table 1). Looking across quartiles, we see similar characteristics with regards to participant education (74.1%

students), work status (26.4% have either a full-time job, multiple jobs, or were in the military), health insurance status (93.5% insured), and season of survey completion (participants split evenly across the 4 seasons). Differences between NDVI groups are observed with regards to parental education level (21.1% of participants in the lowest NDVI quartile have less educated parents, compared to 37.4% of those in the third quartile NDVI group) and financial difficulties (32.1% of participants in the lowest NDVI quartile report having no financial difficulties, compared to 22.6% of those in the highest quartile of NDVI) (Table 1).

The largest differences across quartiles are among median household income, with higher quartiles of NDVI showing the highest average median income (lowest quartile of NDVI shows an average median household income of $41,000, while the average median household income for the highest quartile NDVI is $89,200) (Table 1).

Baseline depressive symptoms among those with baseline NDVI data as measured by the PHQ-9 had a mean of 7.48 with a variance of 29.49, indicating overdispersion. Similar means and variances are seen in months 12, 24, and 30. Looking at the trend of average PHQ-9 of all participants by survey number, it appears that the baseline average PHQ-9 score is slightly higher than at other time points, but no clear trend is detected (Figure 1a). We see similar trends when looking at differences in average PHQ-9 score across survey number by sexual orientation/gender identity at baseline. Average PHQ-9 scores are highest for both groups (those who identify as LGBTQ vs. those who do not), but that across all time points, those with LGBTQ identities have higher average PHQ-9 scores (Figure 1b). Differences in average PHQ-9 trajectories across survey number also appear when looking at different racial categories. Although there are slightly higher average PHQ-9 scores for white participants in baseline surveys, on average, those who identify as a person of color have higher PHQ-9 scores at months 12 and 24, with similar average PHQ-9 scores for each group at month 30 (Figure 1c).

The distribution of participant NDVI across all time points is displayed and show a roughly normal distribution (Figure 2). The distributions at each time point look similar, and thus were not shown.

Multivariable Regression Results

We saw no evidence of an association between continuous median NDVI and PHQ-9 scores in our model adjusting for covariates (Table 2). Unadjusted models (results not shown) also showed no evidence of association. Comparing the within-person and between-person RRs, we see very similar estimates (small differences appear when additional significant digits are included) (within and between RR: 0.99, 95% CI: 0.96, 1.02).

Individual Time Point Model Results

Sensitivity analyses using individual time point models with continuous median NDVI also show no evidence of association with PHQ-9, and all have similar point estimates (Month 12: 0.98 (0.94, 1.02), Month 24: 1.02 (0.99, 1.06), Month 30: 0.99 (0.95, 1.04)). However, when NDVI is modeled as quartiles, we do see one statistically significant association. From our month 12 model, we see that on average, comparing participants in the second quartile of NDVI to those in the lowest quartile (at baseline), there is a 24% lower PHQ-9 score (measured at month 12) (RR: 0.76, 95% CI: 0.61, 0.96) (Table 3). However, comparisons between the third and fourth quartiles to the lowest quartile in the month 12 model did not show statistically significant associations, and neither did any of the point estimates in the Month 24 or Month 30 models (Table 3).

Summer NDVI Model Results

Replacing median NDVI with summer NDVI did not substantively change results, and we did not see any statistically significant associations between summer NDVI and depressive symptoms when modeled continuously. Point estimates and confidence intervals were almost identical to the median NDVI results (both within and between RR: 0.99, 95% CI: 0.96, 1.02) (Table 2).

Discussion

Based on our main model and subsequent sensitivity analyses, our study showed no evidence of an association between green space as measured by NDVI on depressive symptoms as measured by PHQ-9 among our sample of Seattle area young adults with one exception. We did find there to be a statistically significant association between PHQ-9 and NDVI when comparing those in the second lowest quartile to those in the lowest in the month 12 individual time point model.

The overall null findings may be a result of several different factors. First, just over two thirds of the variability in NDVI is between person, while less than a third of the variability is within-person. Because so much of the sample has no within-person variability in NDVI, the model we chose *a priori* might not be the best fit for this data. However, in the unadjusted model using data subset to only those that have some within-person variability we still see no association, which may be indicative that there is truly no association in our data. In future work, either recruiting a sample that has more variability in their exposure or choosing a model that answers a different question would be appropriate.

Second, when using NDVI as a measurement for exposure to green space, we do not know how green space is being utilized (we only have general greenness in the area). One study looking specifically at visits to green space concluded that decreasing visits to green space was associated with an increase in odds of depressive symptoms.[36] Another study looking specifically at the ability to view green space from windows at home found that on average, adults (aged 18-64) who have a view of nature from one of their home windows have lower risks of depression compared to those who have no view of green space.[20] Because we were not able to determine how participants were interacting with green space in the current study (either through visits or views), we may not be capturing a measure of green space that is important in predicting depressive symptoms, which may partially explain our null findings. Additionally, participant geographic information was only available at the census tract level, while NDVI data was available at the block level. This required us to average the block level NDVI up to the census tract level. If large variations of NDVI exist within census tracts, participant exposure may be misclassified (since we do not have exact residential addresses).

Third, there was a large proportion of missing NDVI at survey 24 (39.4%). Although there is no evidence to support that these values are missing differentially, the month 12 individual time point GLMM model using only baseline NDVI (which only had 3.2% missingness), did show some association between NDVI and PHQ-9 scores comparing the second quartile to the first quartile. This may indicate that had we had more power for all time points, more significant associations would have been detected. One way to address this issue of missing data would be to conduct an imputation with multiple chained equations, which was outside the scope of this study.

Fourth, our sample population may not be representative of all Seattle area young adults. People eligible for this survey but with more severe depressive symptoms may have declined to participate (a form of selection bias). If those with the most severe depressive symptoms are also in the least green spaces and are excluded from the sample, we would see a bias towards the null.

Finally, it is possible that there truly is no lagged association between green space and depressive symptoms in this age and location specific combination. However, more longitudinal studies would need to be conducted on this specific population to confirm this result.

Although there are no studies to our knowledge looking specifically at American young adults and associations between green space and depressive symptoms longitudinally, our findings are consistent with some similar studies. Gubbels et al.[25] looked longitudinally at both adolescents (age 12-15 years) and adults living in low SES neighborhoods in the Netherlands and surveyed participants on their perceptions of greenery (numbers of trees and nature) at 2 time points 1 year apart. Although there were no significant associations between changes in the perception of number of trees in the adolescent subgroup, adult participants who had an increase in their perception of the number of trees had significant lower depressive symptoms (whether or not the number of trees increased). Because this study relied on self-reported perceptions of greenery (and not an objective measure like NDVI), they may have better captured how participants interact with green spaces. However, there may also be issues with reverse causality where those with elevated depressive symptoms may perceive their areas to be less green.

Neither Pun et al., [37]Astell-Burt and Feng,[38] nor Gonzalez-Inca et al. [23] found associations between green space (NDVI, total green space (measured by tree canopy cover, grass cover, and low-lying vegetation), and cumulative green space respectively) and self-reported depressive symptoms in large longitudinal studies. However, Pun et al. found that for some subcategories (white participants, those with higher SES, and physically active participants), there were small statistically significant inverse associations, [37] and Gonzalez-Inca et al. did find some significant associations with physician diagnosed depression. Like our study, the exact address of participants was not available in the Astell-Burt and Feng paper, and an area roughly equivalent to a U.S census block was used to estimate the green space around residences, which likely led to some degree of exposure measurement error.

Some studies using longitudinal designs did report associations between green space and depressive symptoms. Bezold et al.[24] found an inverse association between childhood greenness (measured with NDVI) and subsequent depressive symptoms. However, they also found that the association was stronger in adolescence than early adulthood. Similarly, a large longitudinal study on participants living in China found associations among green space (measured both by per capita public recreational green space and urban green coverage area) and self-reported depressive symptoms among the elderly subpopulation (aged 60+ years) but not in the middle-aged population (45-59 years). [39] The results from both studies may indicate that depressive symptoms are not affected by green space in the same way across age groups. Additionally, both of these studies utilized data from longer time frames (1996-2013 and 2011-2015 respectively) which may explain the differences in results from the current study. Further longitudinal studies looking specifically at a young adult population would be helpful in determining if the null findings we found are a result of methodological/data quality issues, or if there truly is no association in this age group.

Because no other study looks specifically at young adults living in the U.S, it is hard to directly compare our findings to those of a similar study. To determine if the null results of the current study are reflective of a true null association, more studies focused on the critical time period of young adulthood should be conducted.

Strengths and Limitations

This study utilized rich longitudinal data, with very little missing outcome and covariate data. Techniques to disentangle the between and within-person associations were used (person-mean centering), which allowed us to interpret our results in a meaningful way. This is a major strength of our study and is often overlooked in multi-level longitudinal studies. Additionally, two different measures of NDVI were utilized (median NDVI and summer NDVI), which allowed us to see if the season in which NDVI was collected mattered in the observed associations.

This study also has some limitations. A limitation that all studies dealing with mental health is that questions about mental health can be sensitive, and the self-report nature of the survey may cause issues of social desirability, resulting in measurement error. However, the data were collected via online survey, which is thought to reduce social desirability bias in comparison to a face-to-face interview. In addition, this was not a random sample, so results may not be generalizable to a broader young adult population.

Finally, we were not able to test if other lag times would have resulted in significant associations, as PHQ-9 data was only collected once a year and at the 6 month follow up (survey 30). Future studies should investigate how associations between greenness exposure and depressive symptoms are modified by different lag times.

Although no consistent significant associations were found in this study population between depressive symptoms and greenspace as measured by NDVI, there is a need for future studies to verify results. Specifically, studies with larger sample sizes, more variability in the exposure, and different lag times would make valuable contributions in this area of research. Additionally, the considerations made in the current study surrounding the disentanglement of between and within person associations should be applied in future longitudinal studies to ensure that interpretations are reflective of the associations of interest.

Tables and Figures

Table 1. Baseline characteristics of survey participants in Project Transitions study by Normalized Difference Vegetation Index (NDVI), 2006. Only participants with complete NDVI data at baseline are included. All covariates are baseline measures and are represented as n (%) unless otherwise indicated.

	Lowest Quartile [a] (N=190)	**Second Quartile** (N=187)	**Third Quartile** (N=187)	**Highest Quartile** (N=190)	**Overall** (N=754)
Age at Baseline (Years)					
Mean (SD)	20.6 (1.75)	20.8 (1.56)	20.8 (1.85)	20.3 (1.67)	20.6 (1.72)
Median [Min, Max]	21.0 [18.0, 24.0]	21.0 [18.0, 24.0]	21.0 [18.0, 24.0]	20.0 [18.0, 24.0]	21.0 [18.0, 24.0]
Race					
Person of Color [b]	72 (37.9%)	66 (35.3%)	94 (50.3%)	73 (38.4%)	305 (40.5%)
White	116 (61.1%)	121 (64.7%)	88 (47.1%)	117 (61.6%)	442 (58.6%)
Missing	2 (1.1%)	0 (0%)	5 (2.7%)	0 (0%)	7 (0.9%)
Sexual Orientation and Gender Identity					
Non-LGBTQ Identity	142 (74.7%)	152 (81.3%)	142 (75.9%)	133 (70.0%)	569 (75.5%)
LGBTQ Identity [c]	47 (24.7%)	35 (18.7%)	44 (23.5%)	56 (29.5%)	182 (24.1%)
Missing	1 (0.5%)	0 (0%)	1 (0.5%)	1 (0.5%)	3 (0.4%)
Participant Education Status					
Student [d]	141 (74.2%)	142 (75.9%)	139 (74.3%)	137 (72.1%)	559 (74.1%)
Non-Student	49 (25.8%)	44 (23.5%)	47 (25.1%)	52 (27.4%)	192 (25.5%)
Missing	0 (0%)	1 (0.5%)	1 (0.5%)	1 (0.5%)	3 (0.4%)
Participant Work Status					
Full Time Job, Multiple Jobs, or in Military	53 (27.9%)	44 (23.5%)	53 (28.3%)	49 (25.8%)	199 (26.4%)
None of the above [e]	137 (72.1%)	143 (76.5%)	132 (70.6%)	141 (74.2%)	553 (73.3%)
Missing	0 (0%)	0 (0%)	2 (1.1%)	0 (0%)	2 (0.3%)
Parental Education Level					
Both Parents < Bachelor's Degree	40 (21.1%)	54 (28.9%)	70 (37.4%)	62 (32.6%)	226 (30.0%)
≥1 Parent ≥ Bachelor's Degree	141 (74.2%)	126 (67.4%)	104 (55.6%)	120 (63.2%)	491 (65.1%)
Missing	9 (4.7%)	7 (3.7%)	13 (7.0%)	8 (4.2%)	37 (4.9%)
Financial Difficulties					
No financial Difficulties [f]	61 (32.1%)	55 (29.4%)	44 (23.5%)	43 (22.6%)	203 (26.9%)
One or More Financial Difficulties	128 (67.4%)	131 (70.1%)	141 (75.4%)	146 (76.8%)	546 (72.4%)
Missing	1 (0.5%)	1 (0.5%)	2 (1.1%)	1 (0.5%)	5 (0.7%)
Median Household Income ($) [g]					
Mean (SD)	41,000 (24,400)	56,900 (25,900)	70,500 (24,100)	89,200 (25300)	65200 (30500)
Median [Min : Max]	40,500 [59,40 : 10,4000]	53,200 [17,500 : 114,000]	64,800 [18,100 : 151,000]	84,800 [41,400, 185,000]	63600 [5940, 185000]
Missing	25 (13.2%)	0 (0%)	0 (0%)	0 (0%)	25 (3.3%)
Health Insurance Status					
No Insurance/Pay out of Pocket	8 (4.2%)	9 (4.8%)	14 (7.5%)	11 (5.8%)	42 (5.6%)
Insured [h]	180 (94.7%)	178 (95.2%)	168 (89.8%)	179 (94.2%)	705 (93.5%)
Missing	2 (1.1%)	0 (0%)	5 (2.7%)	0 (0%)	7 (0.9%)
Season [i]					

Fall	49 (25.8%)	40 (21.4%)	51 (27.3%)	40 (21.1%)	180 (23.9%)
Spring	63 (33.2%)	59 (31.6%)	29 (15.5%)	46 (24.2%)	197 (26.1%)
Summer	44 (23.2%)	44 (23.5%)	53 (28.3%)	54 (28.4%)	195 (25.9%)
Winter	34 (17.9%)	44 (23.5%)	54 (28.9%)	50 (26.3%)	182 (24.1%)

a Lowest Quartile represents the lowest 25% of NDVI values (≤135.37), Second quartile NDVI is between 25% and 50% (between 135.37 and 146.86), Third Quartile NDVI is between 50% and 75% of NDVI values (between 146.86 and 171.37), and the Highest Quartile represents the top 25% NDVI(≥171.37) .Quartiles are based off of baseline median NDVI values and higher values indicate more greenness. NDVI values are missing at baseline for 25 participants.

b Persons of color include Asian/ south Asian; Black/ African American; American Indian or Alaskan Native; Native Hawaiian or other Pacific Islander; Arab, middle eastern, or north African; more than 1 race; other.

c LGBTQ is defined as those who self-identify as one or more of the following: transgender, bisexual, gay, lesbian, queer, two-spirit, questioning, or other. Non-LGBT identities were defined as those who identified as both cisgender and heterosexual.

d Student refers to any participant who identified that they were in any of the following categories: High school student, working toward a General Education Development (GED), Trade or Vocational school student, 2-year or Community College student, 4-year College or University student, Graduate or Professional school student.

e Participants in this category did not report having a full time job (paid), multiple jobs (paid), or being in the military, and selected one of the following categories from the survey options: Working part-time (paid), Volunteer work (unpaid), Internship/apprenticeship (paid or unpaid), Homemaker/caring for household/stay at home parent, Unemployed and actively looking for work, Unemployed and not looking for work , On leave, Receiving disability/SSI income, Receiving unemployment benefits, Other.

f Financial difficulties defined as difficulties with any of the following: Cash-flow difficulties; saving money; Ability to do the things financially; Ability to pay bills; Trying to secure loans; Other.

g Median household income for census tracts.

h Insured indicates receiving health insurance from any of the following categories: Parents' plan, Covered at work or school, Medicaid, Other.

i Season in which the participant took the baseline survey.

Figure 1a. Average PHQ-9 scores by survey number. PHQ-9 scores range from 0-27, with higher scores indicating more/severe depressive symptoms.

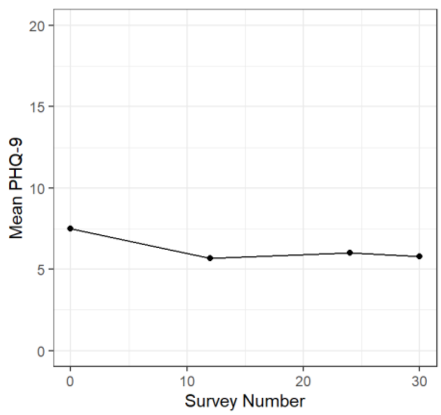

Figure 1b. Average PHQ-9 scores across survey numbers by LGBTQ identity.

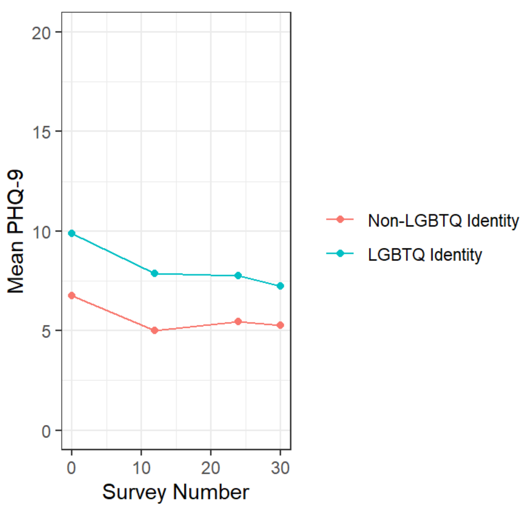

Figure 1c. Average PHQ-9 scores across survey numbers by race.

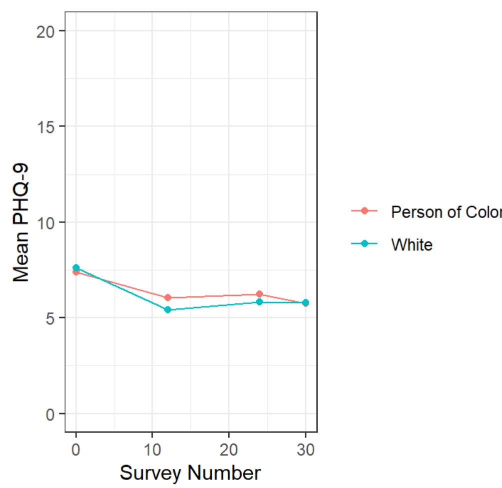

Figure 2. NDVI distribution across all time points. NDVI ranges from 0-250, with higher numbers indicating more greenness. The y-axis represents proportion of the study population within each NDVI bin.

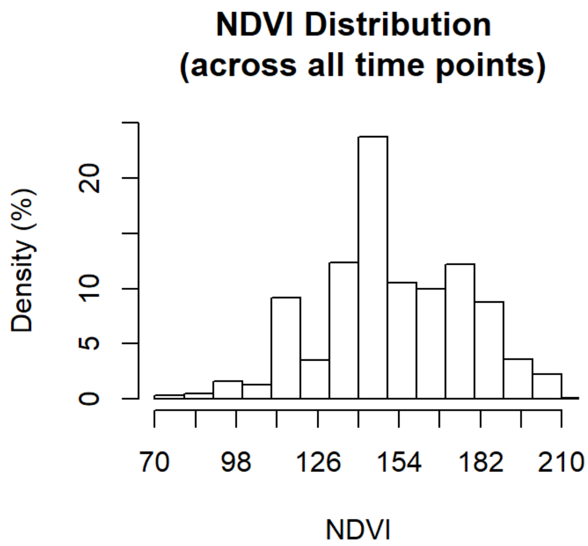

Table 2. Rate ratios (RR) and 95% confidence intervals (CI) from the negative binomial GLMM models (Median NDVI and Summer NDVI models) individual time point GLMM models (Month 12, Month 24, and Month 30 models) with continuous NDVI. The within-person RR reflects the person mean centered coefficient, while the between person RR reflects the grand-mean-centered person-mean coefficient. The RRs in the individual time point models represent between-person associations, as each variable was only collected at one time point.

	RR	95% CI	
Median NDVI [a] *(n=630)*			
Within-person	0.99	0.96	1.02
Between Person	0.99	0.96	1.02
Summer NDVI [a] *(n=630)*			
within-person	0.99	0.96	1.02
between-person	0.99	0.96	1.02
Month 12 [b] *(n=573)*	0.98	0.94	1.02
Month 24 [c] *(n=507)*	1.02	0.99	1.06
Month 30 [d] *(n=375)*	0.99	0.95	1.04

a NDVI values were scaled by dividing by 10
b Baseline NDVI values and covariates regressed on survey 12 PHQ-9-socres
c Survey 12 NDVI values and covariates regressed on survey 24 PHQ-9-socres
d Survey 24 NDVI values and covariates regressed on Survey 30 PHQ-9-socres It should be noted that only 375 observations were included in this model due to missingness and results should be interpreted with caution.

Table 3. Rate ratios (RR) and 95% confidence intervals (CI) for individual time point GLMM models (Month 12, Month 24, and Month 30 models) with NDVI modeled in quartiles. The lowest quartile is the reference group in all models, and RRs represent within-person associations. Significant associations are bolded.

		RR	95% CI	
Month 12[a, b] *(n=573)*				
	Q2	**0.76**	**0.61**	**0.96**
	Q3	0.89	0.69	1.14
	Q4	0.88	0.67	1.16
Month 24[c, d] *(n=507)*				
	Q2	1.03	0.80	1.31
	Q3	1.21	0.95	1.54
	Q4	1.22	0.93	1.60
Month 30[e, f] *(n=375)*				
	Q2	1.03	0.77	1.37
	Q3	1.18	0.88	1.60
	Q4	0.98	0.70	1.36

a Survey 12 PHQ-9 scores regressed on Baseline NDVI values and all covariates.
b Quartiles were defined as follows: Q1: ≤ 134.48. Q2: >134.40, <146.36; Q3: ≥ 146.36, <169.81; Q4: ≥169.81
c Survey 24 PHQ-9 scores regressed on Survey 12 NDVI values and all covariates
d Quartiles were defined as follows: Q1: ≤ 137.56; Q2: >137.56, <149.59; Q3: ≥149.59, <172.48; Q4: ≥ 172.48
e Survey 30 PHQ-9 scores regressed on Survey 24 NDVI values and all covariates. It should be noted that only 375 observations were included in this model due to missingness and results should be interpreted with caution.
f Quartiles were defined as follows: Q1: ≤ 136.17; Q2: >136.17, <149.59; Q3: ≥149.59, <172.48; Q4: ≥ 172.48

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