Street-View Greenspace Exposure and Objective Sleep Characteristics among Children

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ABSTRACT

Greenspace may benefit sleep by enhancing physical activity, reducing stress or air pollution exposure. Studies on greenspace and children's sleep are limited, and most use satellite-derived measures that do not capture ground-level exposures that may be important for sleep. We examined associations of street view imagery (SVI)-based greenspace with sleep in Project Viva, a Massachusetts pre-birth cohort.

We used deep learning algorithms to derive novel metrics of greenspace (e.g., %trees, %grass) from SVI within 250m of participant residential addresses during 2007-2010 (mid-childhood, mean age 7.9 years) and 2012-2016 (early adolescence, 13.2y) (N=533). In early adolescence, participants completed >5 days of wrist actigraphy. Sleep duration, efficiency, and time awake after sleep onset (WASO) were derived from actigraph data. We used linear regression to examine cross-sectional and prospective associations of mid-childhood and early adolescence greenspace exposure with early adolescence sleep, adjusting for confounders. We compared associations with satellite-based greenspace (Normalized Difference Vegetation Index, NDVI).

In unadjusted models, mid-childhood SVI-based total greenspace and %trees (per interquartile range) were associated with longer sleep duration at early adolescence (9.4 min/day; 95%CI:3.2,15.7; 8.1; 95%CI:1.7,14.6 respectively). However, in fully adjusted models, only the association between %grass at mid-childhood and WASO was observed (4.1; 95%CI:0.2,7.9). No associations were observed between greenspace and sleep efficiency, nor in cross-sectional early adolescence models. The association between greenspace and sleep differed by racial and socioeconomic subgroups. For example, among Black participants, higher NDVI was associated with better sleep, in neighborhoods with low socio-economic status (SES), higher %grass was associated with worse sleep, and in neighborhoods with high SES, higher total greenspace and %grass were associated with better sleep time.

SVI metrics may have the potential to identify specific features of greenspace that affect sleep.

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INTRODUCTION

Healthy sleep is vital for optimal health in children and adolescents, and it entails adequate duration, good quality, regularity, and the absence of sleep disorders.[1] Greater sleep quality and quantity have been found to be positively associated with cognition,[2] academic performance,[3] and mental health and behavioral outcomes in children and youth.[4] Nevertheless, insufficient sleep is prevalent among children. A recent study showed that only 5% of United States (U.S.) high school students (3% of girls; 7% of boys) spend the optimal time sleeping.[5]

Greenspace may positively influence sleep through improved health behaviors, such as physical activity and social engagement,[6–8] or through mental health benefits, such as stress reduction, possibly via attention restoration.[6,9] Greenspace can also benefit sleep through reducing exposure to air pollution, noise, and extreme temperatures.[6] The literature is fairly consistent about the beneficial contribution of greenspace to sleep quality and quantity among adults.[10] However, the association of greenspace and sleep in children and adolescents is less clear. The few studies that have assessed greenspace and sleep in children were cross-sectional, used subjective metrics of access to greenspace,[11] and were inconclusive.[12]

Most studies examining the association between greenspace and health have quantified exposure to greenspace using a satellite-based measure, i.e., the normalized difference vegetation index (NDVI), in the area around a residential address.[13] NDVI ranges from −1 to 1, with more positive values representing higher quantities of vegetation. While NDVI is well-established and standardized across studies, it cannot distinguish between trees, grass, crops, or other types of vegetation. The latter is fundamental for causal inference and policy relevance. In addition, the most direct connection between individuals and their environment is best represented by ground-based measures that capture what a person can actually view from the ground, but few studies have been able to incorporate exposure information from this perspective. This is especially important for sleep-related pathways, which may be related to visual greenspace. Novel methods, such as deep learning algorithms combined with street view imagery (SVI), may provide rapid advances in exposure assessment and new insights into the health impacts of greenspace on sleep.[14]

To overcome limitations of greenspace exposure assessment, we used deep learning algorithms applied to SVI to classify detailed types of vegetation from a ground-based view as participants experience them, in association with objective actigraphy-estimated sleep characteristics in adolescents. The aim of this study was to analyze cross-sectional and prospective associations between SVI greenspace exposure and sleep among children and adolescents, and to evaluate whether differently operationalized greenspace metrics (i.e., street view vs. satellite-based) led to diverging results.

METHODS

Data

We used data from Project Viva, a pre-birth cohort based in Eastern Massachusetts participating in the Environmental influences on Child Health Outcomes consortium. Project Viva recruited pregnant women from Atrius Harvard Medical Associates between 1999–2002 and has been following mother-child pairs since pregnancy. Of 2,128 children, 1,038 participated in the adolescent in-person visit (mean [SD] age was 13.2 [0.9] years; range: 11.9–16.6 years) and were eligible for the sleep examination. Of these participants, 829 provided valid actigraphy measurements and 533 had complete data on SVI-based metrics. All mothers provided written informed consent at each visit, and children began providing verbal consent at mid-childhood. The Institutional Review Board of Harvard Pilgrim Health Care approved this study.

Exposure

Georeferenced SVI captured from 2007-2018 by Google were used to develop novel measures of the natural environment representing an on-the-ground perspective. We created a 250 m grid for the entire Commonwealth of Massachusetts. For each grid point in each year, we used the Google application programming interface (API) to obtain the location of the nearest images. For each location nearest a grid point, we then used four images representing North, South, East, and West orientations within view. We then applied the pyramid scene parsing network (PSPNet)[15] deep learning model, pre-trained on the ADE20K dataset[16,17], to derive computer vision-based measures of greenspace from SVI. The ADE20K dataset has densely annotated images covering a diverse set of scenes, object, and object part categories.[17] Driven by powerful deep neural networks,[18–20] PSPNet incorporates local and global contextual cues together to derive pixel-level segmentation of each image with an overall accuracy higher than 93% on pixel-level prediction tasks.[21] Each pixel within each image (640 x 640 resolution) was classified into one of 150 pre-defined classes from ADE20K,[22] including natural features, such as trees, shrubs, grass, plants, and flowers. For each image, the algorithm estimates the percentages of each output class (e.g., 50% trees in an image). We then averaged across the four orientations to estimate the percentages of each class within a 360° view for a given location. Using the percentages at each location, we created a raster file for each SVI year with a 250 m spatial resolution, which was linked to geocoded participant addresses (latitude and longitude were assigned) for the corresponding year. For example, mid-childhood visits took place from

2007-2010; therefore, we linked SVI-based exposure from 2007-2010. If no SVI data were available for a particular year, we carried forward SVI data from the year prior and up to 2 years before if needed. The key exposure metrics that we examined included: % total greenspace (% trees, % grass, % flowers, and % plants combined), % trees, and % grass; all exposure metrics were treated as continuous variables. We used interquartile ranges (IQR) for the main analyses.

We also estimated satellite NDVI for study participants to compare the results with our new SVI measures. NDVI is a satellite-derived indicator of the quantity of vegetation on the ground that has been used as a marker for exposure to greenspace in numerous previous epidemiological studies[13,23,24] and in this cohort.[25] Briefly, we used Landsat satellite data at 30 m resolution for each participant's geocoded address. We used the estimate for July of the specific year of follow-up (mid-childhood and early adolescence) averaged across a 90 m buffer around each address to evaluate the immediate area around residences.

Outcome

Nighttime sleep at early adolescence was assessed from actigraphy data analyzed using ActiLife-6 software (ActiGraph, Inc, Pensacola, FL). Participants were asked to wear an actigraph, which collected activity data in 60-second epochs, on their nondominant wrist for 7-10 consecutive days and nights and complete daily sleep logs. The primary sleep period was based on logs and observation of a sharp decrease in activity with a subsequent increase.[26] Data from participants with ≥5 days of recordings with ≥10 hours of wear-time were included. More details in the algorithm on the classification of sleep and wake periods has been published elsewhere.[27] The following sleep metrics were averaged over all nights of valid recording: (1) duration (sleep time in minutes), (2) maintenance efficiency (percentage of time between sleep onset and final awakening spent asleep), and (3) wake after sleep onset (WASO) (time awake after sleep onset in minutes). All sleep metrics were treated as continuous variables.

Covariates

At baseline, mothers reported their education level (% ≥ college graduate), spouse's education level (% ≥ college graduate), and household income (% > $70,000/year). Information on child's sex (female or male) was obtained from the delivery interview, and mothers reported their child's race/ethnicity (White, African American, Asian American, Hispanic, or Other) at the early childhood (3-year) visit. Child's age was based on the early adolescent visit (continuous age in years). Neighborhood socioeconomic status (NSES) was assessed by census tract median annual household income at the mid-childhood visit based on 2000 U.S. Census data [census tract median household income at enrollment (continuous)] and urbanicity [based on population density at the census tract level].

Statistical Analyses

We used linear regression to quantify the association between greenspace metrics and sleep among adolescents in Project Viva. To evaluate whether differently operationalized greenspace metrics (i.e., street view vs. satellite-based) led to diverging results, we estimated models separately for SVI metrics and NDVI. As previously noted, actigraphy-based sleep metrics were assessed only at early adolescence, and green space exposure was measured at mid-childhood and early adolescence. We examined prospective associations of greenspace at mid-childhood with sleep at early adolescence and cross-sectional associations of greenspace at early adolescence with sleep at early adolescence (Figure S1). To assess the shape of exposure-outcome associations, we fit generalized additive models for continuous exposures. Penalized splines did not suggest deviations from linearity (p value > 0.1) for associations with all sleep metrics; therefore, we present the results from linear models. Additionally, we performed a sensitivity analysis using a log transformation to account for non-normality of the distribution of the sleep metrics. Results using log-transformed sleep metrics yielded similar results, thus we kept the un-modified metrics to facilitate interpretation. We present unadjusted models and models adjusted for potential confounders based on prior evidence[28] and directed acyclic graphs.[29] Model 0 is unadjusted; Model 1 is adjusted for child's age, sex, and race/ethnicity; and Model 2 is further adjusted for maternal and paternal education, marital status, household income, census tract level household income, and urbanicity. In addition, we assessed the effect measure modification of associations of greenspace with sleep by child's sex, race/ethnicity (White/Black/Other), NSES (tertiles), and neighborhood population density (tertiles) using stratified analyses. Race/ethnicity was included in the models to capture the effects of perceived race, along with other aspects, such as quality of schools, which are correlated with parental skin color, cultural context, and racism.[30] We used likelihood ratio tests to evaluate statistically significant effect modification. Lastly, we used multiple imputation to impute missing covariate values. We used SAS 9.4 with 50 imputations and 2,128 participants. Following guidelines,[31] the imputation model included all model variables, plus main predictors of missingness (parity, maternal pre-pregnancy BMI, maternal age at enrollment, birthweight [z-value], gestational age, parental smoking, pregnancy smoking status, child's asthma, cognitive function, executive function and behavior, BMI, among others). Regression analyses were run across 50 imputed datasets, and the pooled estimates were reported. Imputed results were broadly similar to those obtained using observed values; the former are presented. Statistical analyses were performed in R version 3.4.0 (R Core Team, Vienna, Austria)[32].

RESULTS

From the 829 participants with valid actigraphy measurements, 533 participants had complete data on SVI-based metrics of greenspace at early adolescence and 328 had complete data for SVI-based metrics of greenspace at both the early adolescence and mid-childhood in-person visits. On average, participants' age at the early adolescence visit was 12.9 (0.7) years, and 59% of the sample were White; this percentage increased among the higher quartiles of greenspace (Table 1). About half of mothers and fathers in the lowest quartile of greenspace reported having a college education (54.9% and 52.1% respectively) compared with 87.7% and 70.0% in the highest quartile of greenspace, respectively. Household income also varied across greenspace quartiles from 57.9% reporting a household income larger than $70,000 in the lowest quartile to 88.3% in the highest quartile. We observed similar gradients by greenspace for census tract median household income (Table 1). All sleep metrics were slightly better in the top quartile of greenspace compared with the lowest quartile, e.g., sleep duration was 452 (39) minutes in the top quartile compared with 434 (41) minutes in the lowest quartile.

The median percentage of total greenspace within view based on SVI metrics was 28% (IQR 25%) for mid-childhood and 34% (24%) for early adolescence. The median percentage of trees within view was 22% (23%) for mid-childhood and 25% (19%) for early adolescence while the median percentage of grass was 1% (5%) and 4% (7%), respectively. The median NDVI was 0.5 (0.2) for mid-childhood and 0.6 (0.2) for early adolescence. The correlation between SVI-based metrics of greenspace and NDVI varied by type of vegetation. For example, the correlation between NDVI and the percentage of total greenspace was 0.6, whereas it was 0.53 for the percentage of trees and only 0.01 for the percentage of plants (Figure S2). The correlations between the percentage of total greenspace and sleep were similar to the correlations between NDVI and sleep (e.g., 0.15 vs 0.13 for average sleep time).

Table 2 shows the estimates for SVI-based exposure measured at mid-childhood in association with sleep duration (sleep time in minutes), efficiency (percentage), and time awake after sleep onset (WASO; in minutes) measured prospectively in early adolescence. Unadjusted analyses showed a consistent, but small, positive relationship between SVI-based and satellite-based greenspace and average daily sleep duration. For example, in unadjusted models, we saw that a one IQR increase in SVI-based greenspace was associated with 9.4 (95% CI: 3.2, 15.6) more minutes of sleep per night. This association seemed to be driven by the percentage of trees (8.1; 95% CI: 1.7,14.6). We also observed a positive, albeit slightly smaller, unadjusted association between NDVI and sleep duration (5.1; 95% CI: -0.4,10.6). However, these associations were attenuated and no longer statistically significant after adjusting for age, sex, and race/ethnicity, with the latter having a bigger impact on the estimate for greenspace. In the fully adjusted model for daily sleep duration, all the CIs included the null (e.g., % total greenspace 3.5, 95% CI: -3.8, 10.7; NDVI -0.1, 95% CI: -6.5, 6.5; Table 2). We observed a positive association between the percentage of grass and WASO, where one IQR increase in SVI-based grass was associated with 4.1 (95% CI: 0.3, 7.9) more minutes of WASO in fully adjusted models. High levels of WASO indicate sleep fragmentation and may result in non-restorative sleep.[33] This association was observed only after adjusting for confounders. We did not observe evidence of associations between SVI-based or satellite-based greenspace metrics and sleep efficiency (Table 2). In sensitivity analyses we further adjusted for clustering by Census tract and our results remained consistent.

Table 3 shows the estimates for the cross-sectional association between SVI-based exposure and sleep metrics in early adolescence. In unadjusted models, analyses showed a consistent beneficial relationship between SVI-based and satellite-based greenspace and all sleep metrics. We also saw evidence that the positive associations were driven by the presence of trees. However, in adjusted models, associations were generally attenuated and all CIs included the null.

Stratified Analyses

We observed no differences in the association between greenspace and sleep metrics in Project Viva when we stratified the analyses by child's sex and urbanicity level, as CIs included the null for all strata (Figures S3-S4). In models stratified by NSES, we observed that in neighborhoods with a high SES, one IQR increase in total percentage of greenspace (17.8, 95% CI: 5.0, 30.7) and percentage of grass (8.3, 95% CI: 1.4, 15.3) were associated with more minutes of sleep per night (Figure 1). We also observed that in neighborhoods with a low SES, one IQR increase in the percentage of grass was associated with less sleep efficiency (-1.6, 95% CI: -3.0, -0.2) and more sleep fragmentation, as measured by WASO (10.5, 95% CI: 2.0, 19.0) (Figure 1). All other findings were null. In models stratified by race/ethnicity, we observed that among Black participants, one IQR increase in NDVI was associated with more sleep efficiency (2.6, 95% CI: 0.6, 4.6) and less sleep fragmentation (fewer minutes of WASO; -14.8, 95% CI: -25.9, -3.6) (Figure 2). Estimates for other race/ethnicity categories were null across greenspace metrics (Figure 2).

DISCUSSION

In a prospective cohort in Massachusetts, novel metrics of greenspace exposure based on SVI at mid-childhood were not associated with objectively measured sleep duration or efficiency in early adolescence, but we did observe an association between percentage of grass at mid-childhood and more sleep fragmentation in early adolescence, as measured by WASO. We also examined cross-sectional associations of greenspace at early adolescence with sleep at early adolescence, and all CIs consistently crossed the null. The association between greenspace and sleep did not differ by sex or urbanicity level, but we did observe differences by race/ethnicity and NSES. Specifically, we observed that among Black participants, higher NDVI was associated with better sleep, and in neighborhoods with a high SES, a higher total percentage of greenspace and grass were associated with better sleep time. In contrast, in neighborhoods with a low SES, a higher percentage of grass was associated with worse sleep.

SVI combined with deep learning provided a unique approach to estimate specific natural features from a ground-level perspective. Our results on sleep duration and efficiency were consistent with nationally representative studies of Australian (N=2,814) and German (N=4,172) adolescents, which found no significant associations between residential greenspace and insufficient sleep or poor sleep quality.[28] The observed unadjusted association between percentage of trees and sleep duration is in accordance with a study that found that an increased percentage of tree canopy in a census block group was associated with lower odds of short weekday sleep (<6 hours) (OR 0.76 [0.58-0.98]; N=2,712).[6] Another study of adolescents found that 1-SD increase in neighborhood tree canopy was associated with more favorable sleep timing (e.g., an 18-minute earlier sleep onset ($\beta = -0.31$, 95% CI: -0.49, -0.13).[34] Further, the analysis by type of vegetation also suggested that the association between greenspace and increased WASO, or more non-restorative sleep, was driven by percentage of grass. The pathways through which specific natural features may influence sleep are complex. Particularly, percentage of grass could positively influence sleep through higher opportunities for physical activity, but it could also negatively influence sleep through limited attenuation of urban heat island effects[35] or crime in cities,[36] as compared to the attenuation provided by trees. A recent systematic review of neighborhood environments and sleep among children reported that living in a neighborhood with high crime was associated with poorer sleep outcomes.[37] This result is in contrast to a study that evaluated adults older than 45 years of age and reported no statistically significant associations between insufficient sleep and open grass or other low-lying vegetation or total greenspace (N=38,982).[38] That study and those by Feng et al. (2020) and Johnson et al. (2018) did not adjust for NSES.

Stratified analysis by sex and urbanicity level did not support the hypothesis that the association between greenspace and sleep differed by these factors. These results are similar to those found in a study of neighborhood determinants of sleep problems in U.S. children and adolescents, where the authors examined interaction models of built-environment characteristics (e.g., parks/playgrounds), household SES, and sex, but none were statistically significant.[11] However, we found evidence that the association between greenspace and sleep differed by race/ethnicity and NSES. Consistent with the findings of Grigsby-Toussaint et al. (2015),[39] we found that the satellite-based measures of greenspace (NDVI) were associated with better sleep among Black participants. Research has shown that racial minorities experience a greater burden of environmental features, such as higher exposure to air pollution, neighborhood disorder, lower social cohesion, more crime, and less proximity to green space.[40] Racial/ethnic minorities also have a high prevalence of insufficient sleep, poorer sleep quality and unrecognized sleep disorders.[41] Evidence indicates that the neighborhood environment is an important determinant of insufficient sleep for racial/ethnic minorities.[42,43] Our results are in accordance to a study on the neighborhood social environment and objective measures of sleep that found an association among African Americans, but not among other racial/ethnic groups.[43] If the hypothesis that unhealthy sleep patterns among minorities contribute to racial/ethnic health disparities holds,[44] then ameliorating environmental features, particularly green space exposure, across racial/ethnic groups can potentially improve overall population health.

We observed an association between percentage of grass and less efficient sleep (higher WASO and lower sleep efficiency) among participants living in neighborhoods of low SES. In addition, among participants living in neighborhoods with a high SES, we observed that the total percentage of greenspace and grass was associated with better sleep (more minutes of sleep per night). These findings are in contrast to the "equigenesis" hypothesis of greenspace, which states that greenspaces may mitigate health inequalities by providing health benefits for socioeconomically disadvantaged groups who usually have lower access to health-promoting resources.[8] The observed association between percentage of grass and insufficient sleep in neighborhoods of low SES may also be related to the differing health effects depending on vegetation types discussed previously. A recent systematic review on green space quality and health found that health benefits were more consistently observed in areas with greater tree canopy, but not grassland.[45] A reason may be that due to their foliage, trees have the capacity to intercept airborne pollutants and buffer against traffic noise, whereas grass might not convey the same range and levels of benefit.[45] In a longitudinal cohort study of adolescents, results showed that higher neighborhood noise was associated with lower odds of sufficient sleep, measured using actigraphy.[34] On the other hand, a systematic review on green space and healthy equity reported that parks in low-SES neighborhoods tend to be of lower quality (e.g., lower maintenance) and have higher crime rates than parks in more privileged communities.[46] The authors discuss that research has shown associations between low park quality and low health status in North American contexts perhaps due to the fact that when parks are of low quality or unsafe, people may choose to engage in less physical activity in them. Other studies have shown that large areas of open grass may reduce walkability if it is fenced-off, as can be the case for private green spaces or golf courses;[47] and that large areas of open grass where strangers may be less easily identified by members of the community may create opportunities for crime.[48] A study of sleep efficiency using actigraphy data found that living in economically and socially disadvantaged neighborhoods predicts risk for shorter and lower quality sleep in children.[49]

The strengths of this study include longitudinal data, use of objective detailed greenspace metrics representing the ground level and objective individual-level sleep measures, and the inclusion of many covariates to control for confounding. Self-reports of sleep duration, sleepiness, or trouble sleeping, while convenient and less time consuming to collect, may not be particularly accurate.[50] In this study, we used wrist activity monitoring (actigraphy) to measure three sleep parameters: sleep duration, efficiency and WASO. Unlike the gold standard of polysomnography, the advantage of actigraphy is that it is unlikely to actually affect bedtime, sleep latency, and duration.[50] This study represents an advancement in greenspace assessment compared with previous studies, which were often restricted to satellite-based data. Our approach, based on individualized addresses as opposed to administrative units in which participants live, expanded on advances in computer vision and deep learning and resulted in more accurate exposure metrics that correspond well to participants' ground-level perspective.

To our knowledge, this is the first study to examine specific types of greenspace in association with objective metrics of sleep among children and adolescents. To date, only a handful of studies have examined greenspace and sleep, and to our knowledge, even fewer have explored this association in children. Health behaviors during childhood are a strong predictor of health in adulthood and thus more work in this area is needed.

The limitations of this study should be noted. First, the limited sample size could be a potential reason for relatively wide CIs. However, we were still able to observe some associations between SVI and NDVI metrics with sleep, which suggests that future research should explore these relationships in other datasets. Second, the strong association between SVI-based greenspace and SES measures suggested potential confounding, and although we adjusted for individual- and neighborhood-level measures of SES, residual confounding is likely. Third, we examined features of greenspace in isolation, but research has shown that there is likely a combination of multiple environmental exposures that may exert a positive/negative impact on health.[14,51] Fourth, while use of SVI and deep learning algorithms to create novel metrics of greenspace features is an advancement in this area of research, images themselves have limitations as they exclude behavioral aspects of exposure, including time spent indoors or actual use of the greenspace.[14] Images are also a snapshot of a location at a given time and may not provide an accurate representation of seasonal variability. We also used images within 250 m of a participant's address, but these images may not be representative of where a participant spends time, which would contribute to exposure measurement error. Furthermore, studies have suggested that infancy is a sensitive period of exposure to greenspace that may have repercussions on health later in life.[52] Thus, it may be possible that exposure to greenspace earlier in life, before mid-childhood, has a stronger association with sleep in early adolescence.

Since Google SVI started in 2007, and the Project Viva children were born from 1999-2002, we were not able to test exposure to SVI-based greenspace at earlier periods of life. In addition, we do not have information on school exposure to greenspace in childhood or adolescence, a possible source of measurement error. Finally, a recent analysis of sleep characteristics in Project Viva participants reported that only 2.2% of adolescents met the lower bound of the National Sleep Foundation's recommended sleep duration and a majority (58.4%) were classified as having low sleep efficiency.[27] Because insufficient sleep is prevalent among participants in Project Viva, the beneficial impact of greenspace on sleep may have been harder to detect.

CONCLUSION

Our study was among the first to integrate deep learning methods into greenspace exposure assessment in association with objectively measured sleep among children and adolescents. The results suggested that greenspace overall and specific features of greenspace (e.g., trees, grass) were not associated with sleep among adolescents in Project Viva. When stratified by NSES and race/ethnicity, we observed beneficial associations for Black participants and neighborhoods with a high SES but unfavorable associations for neighborhoods with a low SES. Future studies should examine whether these results can be replicated in other populations and whether investment in trees in urban areas is cost-effective.

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Disclaimer

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The authors declare that there are no financial arrangements or connections that are pertinent to the submitted manuscript and that there are no financial interests that could be relevant to the submitted manuscript.

Data Availability Statement

The datasets for this manuscript are not publicly available because, per the NIH-approved ECHO Data Sharing Policy, ECHO-wide data have not yet been made available to the public for review/analysis. Requests to access the datasets should be directed to the ECHO Data Analysis Center, ECHO-DAC@rti.org.

REFERENCES

1. Paruthi S, Brooks LJ, D'Ambrosio C, et al. Recommended Amount of Sleep for Pediatric Populations: A Consensus Statement of the American Academy of Sleep Medicine. *J Clin Sleep Med*. 2016;12(6):785-786. doi:10.5664/jcsm.5866

2. Short MA, Blunden S, Rigney G, et al. Cognition and objectively measured sleep duration in children: a systematic review and meta-analysis. *Sleep Health*. 2018;4(3):292-300. doi:10.1016/j.sleh.2018.02.004

3. Faught EL, Ekwaru JP, Gleddie D, Storey KE, Asbridge M, Veugelers PJ. The combined impact of diet, physical activity, sleep and screen time on academic achievement: a prospective study of elementary school students in Nova Scotia, Canada. *Int J Behav Nutr Phys Act*. 2017;14(1):29. doi:10.1186/s12966-017-0476-0

4. Hirshkowitz M, Whiton K, Albert SM, et al. National Sleep Foundation's sleep time duration recommendations: methodology and results summary. *Sleep Health*. 2015;1(1):40-43. doi:10.1016/j.sleh.2014.12.010

5. Knell G, Durand CP, Kohl HW, Wu IHC, Pettee Gabriel K. Prevalence and Likelihood of Meeting Sleep, Physical Activity, and Screen-Time Guidelines Among US Youth. *JAMA Pediatr*. 2019;173(4):387-389. doi:10.1001/jamapediatrics.2018.4847

6. Johnson BS, Malecki KM, Peppard PE, Beyer KMM. Exposure to neighborhood green space and sleep: evidence from the Survey of the Health of Wisconsin. *Sleep Health*. 2018;4(5):413-419. doi:10.1016/j.sleh.2018.08.001

7. Astell-Burt T, Feng X, Kolt GS. Does access to neighbourhood green space promote a healthy duration of sleep? Novel findings from a cross-sectional study of 259 319 Australians. *BMJ Open*. 2013;3(8). doi:10.1136/bmjopen-2013-003094

8. Mitchell R, Popham F. Effect of exposure to natural environment on health inequalities: an observational population study. *The Lancet*. Published online 2008. doi:10.1016/S0140-6736(08)61689-X

9. Faber Taylor A, Kuo FE. Children With Attention Deficits Concentrate Better After Walk in the Park. *J Atten Disord*. 2009;12(5):402-409. doi:10.1177/1087054708323000

10. Shin JC, Parab KV, An R, Grigsby-Toussaint DS. Greenspace exposure and sleep: A systematic review. *Environ Res*. 2020;182:109081. doi:10.1016/j.envres.2019.109081

11. Singh GK, Kenney MK. Rising Prevalence and Neighborhood, Social, and Behavioral Determinants of Sleep Problems in US Children and Adolescents, 2003–2012. *Sleep Disorders*. 2013;2013:1-15. doi:10.1155/2013/394320

12. Reuben A, Rutherford GW, James J, Razani N. Association of neighborhood parks with child health in the United States. *Prev Med*. 2020;141:106265. doi:10.1016/j.ypmed.2020.106265

13. Fong K, Hart JE, James P. A Review of Epidemiologic Studies on Greenness and Health: Updated Literature Through 2017. *Curr Environ Health Rep*. 2018;5:77-87. doi:10.1007/s40572-018-0179-y.A

14. Weichenthal S, Hatzopoulou M, Brauer M. A picture tells a thousand...exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology. *Environ Int*. Published online November 22, 2018. doi:10.1016/j.envint.2018.11.042

15. Zhao H, Shi J, Qi X, Wang X, Jia J. *Pyramid Scene Parsing Network*.; 2017. doi:10.1109/CVPR.2017.660

16. ADE20K. Accessed September 24, 2021. https://groups.csail.mit.edu/vision/datasets/ADE20K/

17. Zhou B, Zhao H, Puig X, Fidler S, Barriuso A, Torralba A. *Scene Parsing through ADE20K Dataset*. Massachusetts Institute of Technology; University of Toronto Accessed September 24, 2021. https://people.csail.mit.edu/bzhou/publication/scene-parse-camera-ready.pdf

18. Krizhevsky A, Sutskever I, Hinton GE. ImageNet Classification with Deep Convolutional Neural Networks. *Advances In Neural Information Processing Systems*. 2012;39:1320-1334. doi:10.1016/j.protcy.2014.09.007

19. Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *International Conference on Learning Representations (ICRL)*. Published online 2015. doi:10.1016/j.infsof.2008.09.005

20. He K, Zhang X, Ren S, Sun J. Deep Residual Learning for Image Recognition. *ArxivOrg*. Published online 2015. doi:10.3389/fpsyg.2013.00124

21. Lu Y. The Association of Urban Greenness and Walking Behavior: Using Google Street View and Deep Learning Techniques to Estimate Residents' Exposure to Urban Greenness. *Int J Environ Res Public Health*. 2018;15(8). doi:10.3390/ijerph15081576

22. Zhao H, Puig X, Zhou B. Scene Parsing list of 150 objects. Accessed September 16, 2021. https://github.com/CSAILVision/sceneparsing/blob/master/objectInfo150.csv

23. James P, Hart JE, Banay RF, Laden F. Exposure to greenness and mortality in a nationwide prospective cohort study of women. *Environmental Health Perspectives*. 2016;124:1344-1352. doi:10.1289/ehp.1510363

24. Crouse DL, Pinault L, Balram A, et al. Urban greenness and mortality in Canada’s largest cities: a national cohort study. *The Lancet Planetary Health*. 2017;1:e289-e297. doi:10.1016/S2542-5196(17)30118-3

25. Jimenez MP, Oken E, Gold DR, et al. Early life exposure to green space and insulin resistance: An assessment from infancy to early adolescence. *Environment International*. 2020;142:105849. doi:10.1016/j.envint.2020.105849

26. Cole RJ, Kripke DF, Gruen W, Mullaney DJ, Gillin JC. Automatic sleep/wake identification from wrist activity. *Sleep*. 1992;15(5):461-469. doi:10.1093/sleep/15.5.461

27. Cespedes Feliciano EM, Quante M, Rifas-Shiman SL, Redline S, Oken E, Taveras EM. Objective Sleep Characteristics and Cardiometabolic Health in Young Adolescents. *Pediatrics*. 2018;142(1):e20174085. doi:10.1542/peds.2017-4085

28. Feng X, Flexeder C, Markevych I, et al. Impact of Residential Green Space on Sleep Quality and Sufficiency in Children and Adolescents Residing in Australia and Germany. *Int J Environ Res Public Health*. 2020;17(13):E4894. doi:10.3390/ijerph17134894

29. Hernan MA. Causal Knowledge as a Prerequisite for Confounding Evaluation: An Application to Birth Defects Epidemiology. *American Journal of Epidemiology*. 2002;155(2):176-184. doi:10.1093/aje/155.2.176

30. VanderWeele TJ, Robinson WR. On the causal interpretation of race in regressions adjusting for confounding and mediating variables. *Epidemiology*. 2014;25(4):473-484. doi:10.1097/EDE.0000000000000105

31. Sterne JA, White IR, Carlin JB, et al. Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. *BMJ*. 2009;338:b2393. doi:10.1136/bmj.b2393

32. R Core Team. *R: A Language and Environment for Statistical Computing*.; 2020. https://www.R-project.org/.

33. Shrivastava D, Jung S, Saadat M, Sirohi R, Crewson K. How to interpret the results of a sleep study. *J Community Hosp Intern Med Perspect*. 2014;4(5):24983. doi:10.3402/jchimp.v4.24983

34. Mayne SL, Morales KH, Williamson AA, et al. Associations of the residential built environment with adolescent sleep outcomes. *Sleep*. 2021;44(6):zsaa276. doi:10.1093/sleep/zsaa276

35. Ng E, Chen L, Wang Y, Yuan C. A study on the cooling effects of greening in a high-density city: An experience from Hong Kong. *Building and Environment*. 2012;47:256-271. doi:10.1016/j.buildenv.2011.07.014

36. Corrieri U. [Trees and woods are true medicines for people]. *Epidemiol Prev*. 2021;45(3):214-217. doi:10.19191/EP21.3.P214.067

37. Mayne SL, Mitchell JA, Virudachalam S, Fiks AG, Williamson AA. Neighborhood environments and sleep among children and adolescents: A systematic review. *Sleep Med Rev*. 2021;57:101465. doi:10.1016/j.smrv.2021.101465

38. Astell-Burt T, Feng X. Does sleep grow on trees? A longitudinal study to investigate potential prevention of insufficient sleep with different types of urban green space. *SSM Popul Health*. 2020;10:100497. doi:10.1016/j.ssmph.2019.100497

39. Grigsby-Toussaint DS, Turi KN, Krupa M, Williams NJ, Pandi-Perumal SR, Jean-Louis G. Sleep insufficiency and the natural environment: Results from the US Behavioral Risk Factor Surveillance System survey. *Prev Med*. 2015;78:78-84. doi:10.1016/j.ypmed.2015.07.011

40. Johnson DA, Billings ME, Hale L. Environmental Determinants of Insufficient Sleep and Sleep Disorders: Implications for Population Health. *Curr Epidemiol Rep*. 2018;5(2):61-69. doi:10.1007/s40471-018-0139-y

41. Chen X, Wang R, Zee P, et al. Racial/Ethnic Differences in Sleep Disturbances: The Multi-Ethnic Study of Atherosclerosis (MESA). *Sleep*. 2015;38(6):877-888. doi:10.5665/sleep.4732

42. Johnson DA, Brown DL, Morgenstern LB, Meurer WJ, Lisabeth LD. The association of neighborhood characteristics with sleep duration and daytime sleepiness. *Sleep Health*. 2015;1(3):148-155. doi:10.1016/j.sleh.2015.06.002

43. Johnson DA, Simonelli G, Moore K, et al. The Neighborhood Social Environment and Objective Measures of Sleep in the Multi-Ethnic Study of Atherosclerosis. *Sleep*. 2017;40(1). doi:10.1093/sleep/zsw016

44. Hale L, Do DP. Racial differences in self-reports of sleep duration in a population-based study. *Sleep*. 2007;30(9):1096-1103. doi:10.1093/sleep/30.9.1096

45. Nguyen PY, Astell-Burt T, Rahimi-Ardabili H, Feng X. Green Space Quality and Health: A Systematic Review. *Int J Environ Res Public Health*. 2021;18(21):11028. doi:10.3390/ijerph182111028

46. Rigolon A, Browning MHEM, McAnirlin O, Yoon HV. Green Space and Health Equity: A Systematic Review on the Potential of Green Space to Reduce Health Disparities. *Int J Environ Res Public Health*. 2021;18(5):2563. doi:10.3390/ijerph18052563

47. Reid CE, Clougherty JE, Shmool JLC, Kubzansky LD. Is All Urban Green Space the Same? A Comparison of the Health Benefits of Trees and Grass in New York City. *Int J Environ Res Public Health*. 2017;14(11):E1411. doi:10.3390/ijerph14111411

48. Shepley M, Sachs N, Sadatsafavi H, Fournier C, Peditto K. The Impact of Green Space on Violent Crime in Urban Environments: An Evidence Synthesis. *Int J Environ Res Public Health*. 2019;16(24):E5119. doi:10.3390/ijerph16245119

49. Bagley EJ, Fuller-Rowell TE, Saini EK, Philbrook LE, El-Sheikh M. Neighborhood Economic Deprivation and Social Fragmentation: Associations With Children's Sleep. *Behav Sleep Med*. 2018;16(6):542-552. doi:10.1080/15402002.2016.1253011

50. Lauderdale DS, Knutson KL, Yan LL, et al. Objectively measured sleep characteristics among early-middle-aged adults: the CARDIA study. *Am J Epidemiol*. 2006;164(1):5-16. doi:10.1093/aje/kwj199

51. Yitshak-Sade M, Fabian MP, Lane KJ, et al. Estimating the Combined Effects of Natural and Built Environmental Exposures on Birthweight among Urban Residents in Massachusetts. *Int J Environ Res Public Health*. 2020;17(23):E8805. doi:10.3390/ijerph17238805

52. Jimenez MP, Wellenius GA, James P, et al. Associations of types of green space across the life-course with blood pressure and body mass index. *Environmental Research*. 2020;185:109411. doi:10.1016/j.envres.2020.109411

FIGURE CAPTIONS

Figure 1. Effect modification by neighborhood socioeconomic status (NSES) of the association between SVI-based metrics of greenspace and sleep in Project Viva (N=328)

Figure 2. Effect modification by race/ethnicity of the association between SVI-based metrics of greenspace and sleep in Project Viva (N=328)

SUPPLEMENTARY MATERIAL

Figure S1. Cross-sectional and prospective associations examined in this study

Figure S2. Pearson correlation coefficients between SVI-based metrics of greenspace (measured in early adolescence), NDVI (90 m buffer, measured in early adolescence) and sleep outcomes (also in early adolescence) (N=530)

Figure S3. Effect modification by sex of the association between SVI-based metrics of greenspace in mid-childhood and sleep in early adolescence in Project Viva (N=328)

Figure S4. Effect modification by urbanicity level of the association between SVI-based metrics of greenspace in mid-childhood and sleep in early adolescence in Project Viva (N=328)

Table 1. Project Viva study participant characteristics by quartiles of Google street view imagery-based total greenspace in mid-childhood[a]

	Quartile 1 0.0-0.15 N=82	Quartile 2 0.16-0.28 N=82	Quartile 3 0.28-0.41 N=83	Quartile 4 0.41-0.77 N=81	Overall N=328
Child's age at early adolescence, mean (SD)	13.0 (0.8)	12.9 (0.7)	13.0 (0.6)	12.8 (0.6)	12.9 (0.7)
Child's race/ethnicity %					
White	45.1	48.8	61.4	80.2	58.8
Black	34.1	26.8	14.5	6.2	20.4
Other	20.7	24.4	24.1	13.6	20.7
Child's sex % female	48.8	45.1	49.4	59.3	50.6
Mother's education % college	54.9	64.2	63.9	87.7	67.6
Father's education % college	52.1	55.1	71.6	70.0	62.6
Mother's marital status % married	84.1	86.4	89.2	100.0	89.9
Household income % >$70K	57.9	60.8	76.5	88.3	70.9
Census tract median household income in mid-childhood ($), mean (SD)	44864.9 (15662.2)	47984.2 (16316.9)	63374.6 (21302.4)	72009.4 (21530.4)	56966.5 (21832.1)
Urbanicity in mid-childhood (population density), mean (SD)	974.5 (171.9)	921.1 (206.5)	859.3 (208.7)	671.7 (308.4)	857.8 (254.9)
Sleep time in minutes per night in early adolescence, mean (SD)	433.7 (40.9)	436.5 (37.6)	437.8 (39.6)	452.2 (38.5)	440.0 (39.7)
Time awake in minutes after sleep onset (WASO) in	74.2 (24.9)	73.6 (25.7)	78.1 (28.8)	79.6 (35.7)	76.4 (29.0)

early adolescence, mean (SD)					
% Sleep efficiency in early adolescence, mean (SD)	84.0 (4.2)	84.2 (4.4)	83.6 (5.3)	83.8 (5.6)	83.9 (4.9)
SVI-based metrics of greenspace in mid-childhood					
% Greenspace, median (IQR)	10.6 (6.2)	22.2 (7.1)	34.9 (5.2)	48.9 (11.3)	28.3 (25.1)
% Trees	8.8 (6.2)	17.9 (7.4)	29.5 (9)	44.2 (12.9)	22.2 (23)
% Grass	0.5 (1)	0.9 (3.1)	2.8 (5.2)	2.7 (9.2)	1.3 (4.6)
% Plants	0.5 (1.5)	0.9 (1.4)	0.8 (1.7)	0.6 (1.7)	0.8 (1.6)
Satellite-based metric of greenspace in mid-childhood, median (IQR)					
NDVI	0.4 (0.1)	0.5 (0.1)	0.5 (0.1)	0.6 (0.1)	0.5 (0.2)

[a]Table based on participants with complete data for exposure in mid-childhood and outcome in early adolescence (N=328).
IQR, interquartile range; NDVI, normalized difference vegetation index; SD, standard deviation; SVI, street view imagery.

Table 2. Associations of greenspace exposure in mid-childhood with sleep in early adolescence (N=328)[a]

	Average daily sleep duration, min			Average daily sleep efficiency, %			Average time awake after sleep onset, min		
Early adolescence	**Model 0 estimate (95% CI)**	**Model 1 estimate (95% CI)**	**Model 2 estimate (95% CI)**	**Model 0 estimate (95% CI)**	**Model 1 estimate (95% CI)**	**Model 2 estimate (95% CI)**	**Model 0 estimate (95% CI)**	**Model 1 estimate (95% CI)**	**Model 2 estimate (95% CI)**
SVI-based exposure (per IQR)									
% Total greenspace	**9.4 (3.2, 15.6)**	3.3 (-2.7, 9.3)	3.5 (-3.8, 10.7)	0.2 (-0.5, 1.0)	0.0 (-0.8, 0.8)	-0.2 (-1.1, 0.8)	0.5 (-4.1, 5.2)	0.7 (-4.1, 5.4)	1.8 (-3.9, 7.5)
% Trees	**8.1 (1.7, 14.6)**	1.9 (-4.3, 8.1)	1.4 (-5.7, 8.4)	0.3 (-0.5, 1.0)	0.0 (-0.8, 0.9)	0.0 (-1.0, 0.9)	0.2 (-4.5, 4.9)	0.2 (-4.7, 5.1)	0.6 (-5.0, 6.1)
% Grass	**5.3 (0.6, 10.0)**	3.6 (-0.7, 7.9)	3.8 (-1.1, 8.7)	-0.2 (-0.8, 0.4)	-0.2 (-0.8, 0.3)	-0.5 (-1.2, 0.1)	2.1 (-1.3, 5.6)	2.1 (-1.3, 5.5)	**4.1 (0.3, 7.9)**
Satellite-based exposure (per IQR)									
NDVI	5.1 (-0.4, 10.6)	0.9 (-4.2, 6.1)	-0.1 (-6.5, 6.5)	0.3 (-0.3, 1.0)	0.3 (-0.4, 0.9)	0.3 (-0.6, 1.1)	-1.0 (-5.0, 3.1)	-1.2 (-5.3, 2.9)	-1.2 (-6.4, 3.9)

[a]Table 2 includes N=328 participants with non-missing mid-childhood exposure and early adolescent outcome data. We used imputed data for missing covariates.
Model 0: Unadjusted
Model 1: Adjusted by child's age, sex, and race/ethnicity
Model 2: Model 1 + maternal and paternal education, marital status, household income, census tract level household income and urbanicity.
NDVI, normalized difference vegetation index; IQR, interquartile range; SVI, street view imagery.

Table 3. Cross-sectional associations of greenspace exposure in early adolescence and sleep in early adolescence (N=533)[a]

	Average daily sleep duration, min			Average daily sleep efficiency, %			Average time awake after sleep onset, min		
Early adolescence	**Model 0 Estimate (95% CI)**	**Model 1 Estimate (95% CI)**	**Model 2 Estimate (95% CI)**	**Model 1 Estimate (95% CI)**	**Model 1 Estimate (95% CI)**	**Model 2 Estimate (95% CI)**	**Model 0 Estimate (95% CI)**	**Model 1 Estimate (95% CI)**	**Model 2 Estimate (95% CI)**
SVI-based exposure									
% Total greenspace	**8.7 (3.7, 13.7)**	2.9 (-2.1, 7.9)	0.7 (-5.0, 6.5)	0.3 (-0.3, 0.9)	0.2 (-0.4, 0.9)	0.4 (-0.3, 1.1)	-0.2 (-3.7, 3.3)	-1.2 (-5.0, 2.5)	-2.7 (-7.1, 1.6)
% Trees	**7.5 (2.6, 12.3)**	2.3 (-2.5, 7.1)	0.5 (-4.9, 5.8)	0.2 (-0.4, 0.8)	0.1 (-0.5, 0.7)	0.3 (-0.4, 1.0)	0.1 (-3.3, 3.5)	-0.8 (-4.4, 2.7)	-2.0 (-6.0, 2.0)
% Grass	**4.9 (-0.3, 10.1)**	0.8 (-4.1, 5.8)	-1.1 (-6.4, 4.1)	0.4 (-0.2, 1.0)	0.3 (-0.3, 1.0)	0.4 (-0.2, 1.1)	-1.6 (-5.2, 2.1)	-2.2 (-5.9, 1.5)	-3.0 (-7.0, 0.9)
Satellite-based exposure (IQR)									
NDVI	**7.1 (2.6, 11.7)**	1.3 (-3.3, 5.9)	-2.7 (-8.5, 3.2)	0.1 (-0.4, 0.7)	0.0 (-0.5, 0.6)	0.2 (-0.5, 1.0)	0.6 (-2.6, 3.8)	-0.2 (-3.6, 3.2)	-2.0 (-6.4, 2.4)

[a]Table 3 includes N=533 participants with non-missing early adolescent exposure and outcome data. We used imputed data for missing covariates.

Model 0: Unadjusted

Model 1: Adjusted for child's age, sex, and race/ethnicity

Model 2: Model 1 + maternal and paternal education, marital status, household income, census tract level household income, and urbanicity

IQR, interquartile range; NDVI, normalized difference vegetation index; SVI, street view imagery.