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Green Space Exposure Assessment and Association with Maternal Mental Health

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Green Space Exposure Assessment and Association with Maternal Mental Health

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Public Health

by

Yi Sun

Dissertation Committee:
Professor Jun Wu, Chair
Professor Scott Bartell
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2022

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Sun Y, Molitor J, Benmarhnia T, Getahun D, Wu J, et al. Associations between green space and postpartum depression, and role of physical activity. (In preparation)

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ABSTRACT OF THE DISSERTATION

Green Space Exposure Assessment and Association with Maternal Mental Health

by

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Existing studies regarding green space and mental health were mainly with general population and relied on satellite-based imagery, without considering eye-level green space and vegetation types, which is important to elucidate the underlying mechanisms linking green space and health. To improve green space exposure assessment, a machine learning model was evaluated and applied to investigate the associations between street green space and socioeconomic factors. Microsoft Bing Maps images in conjunction with deep learning was used to measure street green space, which were compared to normalized difference vegetation index (NDVI) as commonly-used satellite-based green space measure. The results show that street view imagery coupled with deep learning can accurately and efficiently measure eye-level street green space and distinguish vegetation types (i.e., tree, low-lying vegetation, grass); street view data reflect different aspects of natural environments compared to satellite imagery. In Los Angeles County, lower socioeconomic status and racial/ethnic minority communities had substantively less street green space.

Relationships between green space and postpartum depression (PPD) has not been studied. I investigated the relationships between PPD and green space and examined the mediation

effect of physical activity during pregnancy. Clinical data were obtained for 415,020 pregnancies in southern California (2008-2018) from Kaiser Permanente Southern California. PPD was based on both diagnostic codes and prescription medications. Multiple indicators were used to characterized green space exposure, including street view-based green space and vegetation types, satellite-based measures (i.e., NDVI, land-cover green space, and tree canopy cover), and proximity to the nearest park. The results indicate that street green space and tree coverage were associated with a decreased risk of PPD. Protection and restoration of trees may translate into a more pronounced reduction of PPD in southern California. Physical activity could be considered as one of the plausible pathways linking green space to depression (mediation effect: 9.6% -15.6%).

To further explore the underlying mechanism, an experimental study was conducted to examine physiological and affective responses to green space on stress recovery among pregnant women, using simulated green space exposure through virtual reality (VR). Participants (n=63) were randomly assigned to view one of three, 5-min, VR videos with different green space levels (i.e., low, moderate, and high) after a laboratory stressor, the Trier Social Stress Test. Physiological stress responses and self-reported affect were measured during the experiment. This study demonstrated that even a short immersion in VR green space environments, especially park-like setting, could effectively ease both physiological and affective stress and improve mental health during pregnancy.

This study contributes to the improvement of green space exposure assessment methodology for health studies, and provide evidence of the relationship between green space and maternal mental health during postpartum period, and potential pathways.

Chapter 1. INTRODUCTION

About 55% of the global population lives in urban areas as of 2018 and this percentage is predicted to reach 68% by 2050 (United Nations, 2018). Due to rapid urbanization, an increasing number of people live in complex environments with many high-rise buildings, high population density and low-level green space (H. Li et al., 2015; Skyscrapercity, 2015; Urban Audit, 2007). Concerns are mounting about the association between lack of green space and various adverse health outcomes in urban-dwelling populations (Bettencourt LM, 2007; Fong et al., 2018; James et al., 2015; Nieuwenhuijsen et al., 2017; World Health Organization, 2016). Green space may have a positive effect on health outcomes through several pathways, including reducing stress, increasing social cohesion, promoting physical activity, improving immune status, and lowering levels of environmental nuisances such as air pollution, ambient noise, and outdoor temperature (Bowler et al., 2010a; Hartig et al., 2014; Lee & Maheswaran, 2011; Markevych et al., 2017; Twohig-Bennett & Jones, 2018; Vienneau et al., 2017; World Health Organization, 2016).

Green Space Exposure Assessment

There are various sources, scales and types of green space indicator used in epidemiological studies (Cusack et al., 2017; Klompmaker et al., 2018; Larkin & Hystad, 2019; Mitchell et al., 2011; Reid et al., 2018; Villeneuve et al., 2018). The most commonly used method to objectively assess exposure to green space is based on remote sensing data (Markevych et al., 2017; Mitchell et al., 2011), such as normalized difference vegetation index (NDVI) (Tucker, 1979) and land use or land cover databases (Helbich et al., 2018; James et al., 2015; Zock et al., 2018). However, green space from downward-facing remotely sensing imagery including NDVI and traditional land-use measures, may significantly differ from surrounding green space at the eye level. Green space from satellite data cannot fully reflect the vertical dimension of green space, especially in locations with dense greenness (Jiang et al., 2017; Li, 2018), but can better represent the horizontal dimension of green space. For example, both seen and unseen trees may improve air quality by filtering air pollutants or reducing emission sources due to the competitive land use between green space and sources of air pollution, or provide cooling benefits for their surroundings. Green space from street view images may represent how environments are perceived and experienced by people on the ground (Dong et al., 2018; Lu et al., 2018), which is critical to better understand the underlying mechanisms linking green space with human behaviors and various health outcomes. For example, eye-level street green space may be more related to mental health and physical activity (Helbich et al., 2019; Lu, 2018; Lu et al., 2018) than the overhead-view satellite assessments. According to the Stress Recovery Theory (Ulrich, 1983; Ulrich et al., 1991), natural elements (e.g. scenes, odors and sounds) activate the parasympathetic system that could decrease blood pressure, heart rate, skin conductance, and salivary cortisol level. Only eye-level, perceived and experienced green space can cause these physiological responses that could induce relaxation and help to reduce stress (Ulrich et al., 1991). Further, eye-level street green space may promote both transportation walking and recreational walking behaviors. The evidence suggests that street green spaces improve the perceived aesthetics and quality of a neighborhood's built environment, which are key predictors of route choice and walkability (Nagata et al., 2020; Saelens & Handy, 2008; Sallis et al., 2012).

Moreover, types of green space could be efficiently recognized from high resolution street view imagery. The differences in the composition of vegetation, such as the proportion of trees and grass, might have distinctive impacts on human behavior and health through different pathways. So far, only a few epidemiological studies have investigated the effects of different types of green space (Astell-Burt & Feng, 2019; Astell-Burt & Feng, 2020; Reid et al., 2017; Zhang & Tan, 2019). For example, higher tree density within 1000 m was associated with better self-reported health in New York City, but not grass density (Reid et al., 2017). A study in Singapore measured urban green space in different buffer sizes between 400 m to 1600 m using three metrics: vegetation cover, canopy cover and park area. Although all three metrics were positively related to mental health, overall, canopy cover showed the strongest associations with mental health at most spatial scales (Zhang & Tan, 2019). Another study in Australia reported urban tree canopy may be a better option for promoting community mental health and preventing insufficient sleep than other urban greening (Astell-Burt & Feng, 2019; Astell-Burt & Feng, 2020). Therefore, measuring types of green space may help to better capture different aspects of green space and improve our understanding of the mechanisms that underlie green space exposure and health.

To overcome the constraints of remote sensing assessments of green space, people can use street view imagery, such as Google Street View (GSV) images to effectively characterize visual greenery along roads (Gong et al., 2018; Li, 2018; Middel et al., 2019). Street view data in combination with machine learning approach has been shown to be effective to characterize overall green space (Dong et al., 2018; Seiferling et al., 2017; Weichenthal et al., 2019). However, no prior study has applied deep learning techniques to characterize different types of green space based on high resolution street view image data. Only a few studies have applied computer vision (Larkin & Hystad, 2019; X. Li et al., 2015) to detect green color features or semantic segmentation techniques (Helbich et al., 2019; Lu, 2018) to measure overall green space from street view images. The types of green space were only measured using satellite imagery rather than eye-level street view data (Astell-Burt & Feng, 2020; Brandt et al., 2020). More advanced and robust deep learning architectures are needed to reliably classify types of green space based on high-resolution street view image data and thus refine the methodology and underlying pathway of health impact studies of green space.

Green Space, Physical Activity and Postpartum Depression

The biophilia hypothesis and psycho-evolutionary theory suggest that humans have an inherent need of affiliation with nature which may affect our mental health by bringing emotional stability, and helping with stress recovery (Ulrich et al., 1991; Wilson, 2017). Green space exposure has been associated with mental health benefits in several studies, including general mental health, depression and stress (Fong et al., 2018; James et al., 2015; Pun et al., 2018; Song et al., 2019; van den Bosch & Ode Sang, 2017). However, the existing body of knowledge is mainly with general population (Gascon et al., 2018; Kardan et al., 2015; Nutsford et al., 2013; Reklaitiene et al., 2014), youth (Dzhambov et al., 2018; Kabisch et al., 2017) or elderly people (Garrett et al., 2019; Helbich et al., 2019; Kabisch et al., 2017; Pun et al., 2018). Only a few studies addressed mental health outcomes among pregnant women (Feng & Astell-Burt, 2018; McEachan et al., 2016; Nichani et al., 2017; Runkle et al., 2022), and reported inconsistent results. In a cross-sectional study in England, McEachan et al. assessed depressive symptoms through self-reported General Health Questionnaire and found that pregnant women living in areas with higher quintiles of residential NDVI within 100 m buffer zone were 18-23% less likely to have depressive symptoms than those in the least green quintile (McEachan et al., 2016). In addition to residential individual-level green space, neighborhood-level green space may also facilitate beneficial effects on mental health and well-being (Helbich et al., 2019; Kardan et al., 2015; Nutsford et al., 2013), although limited studies showed no association of neighborhood green space with mental health outcomes during pregnancy. For example, a longitudinal study in Australia reported that no association was found between land-use green space quantity within the "Statistical Area 2" (with populations of 10,000 on average, ranging from 3000 to 25,000) and symptoms of psychological distress among pregnant women (Feng & Astell-Burt, 2018). Another study in New Zealand found exposure to higher proportion of land-cover green space within the "census area unit" (median area: 1.6 km^2 for the Auckland and Counties Manukau District Health Board regions, 6.6 km^2 for the Waikato District Health Board region) were not associated with decreased antenatal depression (Nichani et al., 2017). To our knowledge, no study has investigated the association between green space exposure and postpartum depression (PPD), as well as the underlying mechanisms that links green space exposure with postpartum mental health.

Approximately 10% to 20% of new mothers experience PPD (Gavin et al., 2005; Gelaye et al., 2016). Women are especially vulnerable to depression during postpartum period, likely because of hormonal fluctuations, stress and other biological and psychosocial factors (Yim et al., 2015). PPD has been linked to both short- and long-term negative health-related behaviors and adverse outcomes, such as psychological and developmental disturbances for infants and children, and increasing emotional and behavioral problems among family members (Field, 2010; Gelaye et al., 2016). In addition, physical activity (PA) is an important pathway linking green space and mental well-being (Nieuwenhuijsen et al., 2017). There was limited evidence regarding the role of PA on the relationship of green space exposure and mental health in pregnant women; the literature reports conflicting findings (McEachan et al., 2016; Nichani et al., 2016). Whether PA could be the mechanism by which green space impacted on PPD is unclear. Therefore, it is necessary to examine the relationship between green space, physical activity and maternal mental health with richer exposure and outcome information rather than single or neighborhood-scale exposure assessment and cross-sectional design (Banay et al., 2017).

Green space measurements from remote sensing data were most commonly used in previous environmental health studies (Klompmaker et al., 2018; Markevych et al., 2017), such as NDVI (Tucker, 1979) and land-use or land-cover databases (Helbich et al., 2018; James et al., 2015; Zock et al., 2018). However, the downward-facing remotely sensing imagery may not fully reflect the eye-level green space that are perceived by people in their daily life (Lu et al., 2018). Therefore, eye-level green space is critical to explore underlying mechanisms linking green space to human behaviors and health. For example, it is expected that eye-level green space can be perceived and experienced to cause physiological responses (e.g., blood pressure, heart rate, and skin conductance) that could induce relaxation and reduced stress. Previous studies also suggest that eye-level street green space may promote physical activity (Helbich et al., 2019) and walking behaviors (Nagata et al., 2020) than the bird's eye view satellite assessments.

While types of green space might be differentially associated with health outcomes through different pathways (e.g., encouragement of health-enhancing behaviors and mitigation of harmful environmental nuisances), only a few epidemiological studies have investigated the effects of different types of green space (Astell-Burt & Feng, 2019; Reid et al., 2017; Zhang & Tan, 2019). For example, higher tree density within 1000 m was associated with better self-rated health in New York City, but not grass density (Reid et al., 2017). Another study in Australia reported urban tree canopy may be a better option for promoting mental health than other urban greening such as low-lying vegetation or grass (Astell-Burt & Feng, 2019). Better understanding of the effects of different types of green space on health can not only expand knowledge on mechanisms that underlie green space and health, but also provide evidences to support specific public health and urban planning practices. Recently, street view imagery has been coupled with machine learning approach to accurately and efficiently measure (Helbich et al., 2019; Larkin & Hystad, 2019; Villeneuve et al., 2018) and distinguish green space types (Sun et al., 2021). The previous work of our team (Sun et al., 2021) has laid foundation to examine the effects of different types of green space on health.

Physiological and Cognitive Responses to Green Space Virtual Reality (VR)

The biophilia hypothesis and psycho-evolutionary theory claim that human beings have an innate biological connection to nature and that natural environments bring emotional stability, attention restoration and stress recovery (Ulrich et al., 1991; Wilson, 2017). According to the Stress Recovery Theory (Ulrich, 1983; Ulrich et al., 1991), natural elements such as scenes, odors and sounds can activate the parasympathetic system, thereby leading to decreases in blood pressure, heart rate, skin conductance, and salivary cortisol level. These physiological responses could induce relaxation and help to reduce stress and autonomic arousal (Ulrich et al., 1991).

Epidemiological and experimental studies consistently suggest that green space is associated with better health outcomes. For example, epidemiological studies suggest that green space is positively associated with a wide range of health benefits, including reduced risk of all-cause mortality, cardiovascular disease, type 2 diabetes, improved pregnancy outcomes such as decreased risk of low birth weight and preterm birth, as well as improved mental health (Fong et al., 2018; Gascon et al., 2015; Grinde & Patil, 2009; Hartig et al., 2014; James et al., 2015; Laurent et al., 2019; Laurent et al., 2016; Sun et al., 2020; Twohig-Bennett & Jones, 2018; World Health Organization, 2016). Moreover, experimental studies found that exposure to natural environment is positively associated with recovery from surgery (Ulrich, 1984), productivity (Lohr et al., 1996), cognitive and affective improvement (Berman et al., 2012), and stress reduction (Berto, 2014).

A subset of experimental studies has used virtual stimuli to examine and manipulate the impacts of the natural environment on health and well-being. Virtual stimuli representing green space exposure include photographs (Berto, 2005), images in slideshows (Brown et al., 2013) and plasma display "windows" (Kahn et al., 2008). With the rapid advances in technology, researchers are seeking new ways for a more immersive experience of exposure to the natural environment, such as the use of virtual reality (VR). These studies explore the potential beneficial effects of immersing individuals into green space VR after stressor tasks (Hedblom et al., 2019; Jiang et al., 2014; Jiang et al., 2016; Valtchano & Ellard, 2010; Yin et al., 2019; Yin et al., 2018). Previous research found that immersion in virtual nature environments has similar physiological and cognitive responses compared to immersion in real or actual nature environments (Browning et al., 2019; Higuera-Trujillo et al., 2017; Kjellgren & Buhrkall, 2010; Kuliga et al., 2015; Nukarinen et al., 2020; Yin et al., 2018). Several studies show that virtual nature immersion results in restorative effects such as increased positive affect, decreased negative affect, decreased stress, as well as decreases in physiological markers of stress such as blood pressure, skin conductance and salivary cortisol (Hedblom et al., 2019; Jiang et al., 2014; Valtchano & Ellard, 2010; Yin et al., 2018).

Most existing studies to date have focused on the general population in work or study settings. There is a lack of understanding of the link between physiological mechanisms and green space among special populations (Li et al., 2021), such as pregnant women. Green space can enhance restoration and relaxation by affecting the brain and body via psycho-endocrine mechanisms, including the function of the hypothalamic pituitary adrenal (HPA) axis (Aspinall et al., 2015; Egorov et al., 2017; Haluza et al., 2014; Roe et al., 2013). During pregnancy, the regulation of the maternal HPA axis undergoes dramatic changes. These changes may be further modified by maternal stress, and dysregulation of the maternal HPA axis has been linked to adverse outcomes in both the mother and her offspring, including perinatal mood disturbances, low birth weight and preterm birth (Duthie & Reynolds, 2013; Latendresse, 2009; Yim et al., 2015). Similarly, positive effects on the HPA axis system, such as those documented through green space exposure, may have beneficial effects for maternal-fetal health, making this a particularly interesting time of life to study.

It should be noted that accessing nature green space can in some circumstances be difficult, especially for housebound or mobility-constrained individuals including some pregnant women, or under unusual circumstances (e.g., extreme weather, pandemic). Under such conditions, the VR technology may be an alternative (White et al., 2018).

Chapter 2. Green Space Exposure Assessment

2.1 Objective of Present Study

In Chapter 1, I aimed to: 1) test and evaluate machine learning models that can reliably and efficiently classify three types of green space, i.e., tree, low-lying vegetation, and grass based on street view imagery; and 2) apply this model to examine street-level green space types and investigate their associations with socioeconomic factors in Los Angeles County, California, U.S.

2.2 METHODS

2.2.1 Study population

This study was set in Los Angeles County, excluding the island areas. The primary unit of analysis was census tract (n=2343). Los Angeles County is an ideal site to investigate the environmental justice or disparity issue related to urban greenness because it is one of the most populous (>10 million people) and racially/ethnically diverse counties in the U.S. (U.S., 2015a). Minority and low-income communities in the city of Los Angeles have a high prevalence of chronic diseases and poor mental health (Brown et al.; Jennings et al., 2017; LA County, 2017; Robles et al., 2019). In terms of plant biodiversity, Los Angeles County has a particularly mild climate with high-plant species richness due to the large range of vegetation species that can thrive there (Hondagneu‐Sotelo, 2014).

2.2.2 Socioeconomic Factors

The CalEnviroScreen3.0 dataset (2018 update) was obtained from the California Communities Environmental Health Screening Tool (OEHHA, 2018). CalEnviroScreen (CES) was created and designed by the California Environmental Protection Agency (CalEPA) to address the issue of environmental justice and screening disadvantaged communities, which is suitable for community-level estimates. This tool integrates 20 indicators representing pollution and population vulnerability for all 58 counties in California. There are two main categories of indicators: pollution burden (7 exposure indicators and 5 environmental effects indicators) and population characteristics (3 sensitive population indicators and 5 socioeconomic factors). The CES Score was calculated by combining all these components (Faust et al., 2017). To comprehensively capture the population characteristics and SES for Los Angeles County at census tract-level, I included all five socioeconomic indicators (i.e., educational attainment, housing burden, linguistic isolation, poverty and unemployment), and two SES-related summary indicators (Population Characteristics Score and CalEnviroScreen3.0 score) (Figure 2.1) in this analysis.

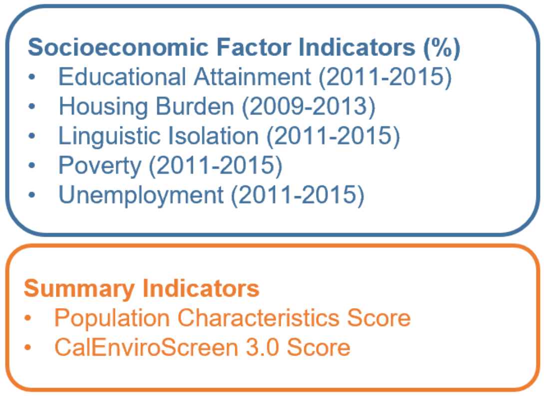

Figure 2.1 Selected indicators and year of data source from CalEnviroScreen3.0
Educational Attainment: Percent of population over 25 with less than a high school education; Housing Burden: Percent housing burdened low-income households; Linguistic Isolation: Percent limited English speaking households; Poverty: Percent of population living below two times the federal poverty level; Unemployment: Percent of the population over the age of 16 that is unemployed and eligible for the labor force.
Note: Full version and further information on the construction of the individual metrics is given in CalEnviroScreen3.0 Report (Faust et al., 2017).

Another notable use of CES was that Senate Bill 535 requires CalEPA to identify disadvantaged communities based on geographic, socioeconomic and environmental hazard criteria. Disadvantaged community (DAC) pursuant to SB 535 (CalEPA, 2017), defined as the top 25% scoring census tracts from CalEnviroScreen3.0, was included in this analysis as a binary variable (1,038 DAC, and 1,305 non-DAC in Los Angeles County). Total population and race/ethnicity data from the 2010 Census were also constructed from the CalEnviroScreen3.0 dataset.

2.2.3 Outcome Variable: Green Space

2.2.3.1 Street view green space

Street view images were requested using Microsoft Bing Maps API. Bing StreetSide provides 360-degree panoramic imagery of street-level scenes across large regions of the United

States. The street network data for Los Angeles County were obtained from the U.S. Census Bureau (U.S., 2015b) and include all features within the "Road/Path Features" (e.g., primary, secondary, local neighborhood, and rural roads, city streets, alleys, bike paths or trails, etc.). Sampling points for street view images were constructed along the road network with a 200 m space interval between each point and geocoded with ArcMap 10.5 (Esri, Redlands, CA, USA)(X. Li et al., 2015; Li, 2018). To include the entire streetscape, four main cardinal directions at each point were retrieved (e.g., 0, 90, 180, and 270 degrees; vertical angle: 0 degrees) (Helbich et al., 2019; Li, 2018; Lu, 2018). The amount of eye-level street green space for each point was determined by the average proportion of greenery pixels in the images of four directions. The proportion of different vegetation types in the image was predicted by the deep learning model described below. Total green space was defined as the sum of area proportion of all types of green space in each image. The size of each image was 480×320 pixels. To create census tract variables, all sampling points were assigned one of Los Angeles County's census tract in ArcMap. The proportion of green space for all points in a census tract were averaged to assess the census tract-level street green space, and then linked to the CalEnviroScreen3.0 data. The summary statistics of green space level and socioeconomic factors are shown in Appendix 2.1. In the U.S., census tracts generally have a population size about 4,000 inhabitants with similar population characteristics, economic status, and living conditions. In Los Angeles County, the areas of census tracts range from 0.1 to 74.5 km2 in urban area. The largest census tract in rural area has an area of 1460.5 km2. The spatial size of census tracts (5.1±45.3 km2) varies widely depending on the population density. The number of sampling points (103±231) per census tract varies depending on the area and street density. The distribution of street network and summary statistics of sampling points are shown in Appendix 2.2.

Deep learning model and image segmentation

A machine learning model using semantic segmentation was applied to identify three different types of vegetation including tree (e.g., canopy), low-lying vegetation (e.g., shrub, bush), and grass based on high resolution street view image data.

- *Model Structure*

Deep convolutional neural networks have achieved state-of-the-art results in semantic segmentation (Li et al., 2018). Two recent studies used classical semantic segmentation models, namely fully convolutional neural network (FCN-8s) and Pyramid scene parsing network (PSPNet), to identify total green space from streetscape images, achieving 81.4% and 93.4 % accuracy, respectively (Helbich et al., 2019; Lu, 2018). I compared top ranked semantic segmentation models on Cityscapes test in 2020 (PapersWithCode, 2020); the FCN and PSPNet models ranked 71 and 32 on the list respectively. Summary of the comparison for the top nine ranked models plus the FCN and PSPNet models are described in Appendix 2.3. After thorough model comparison, I chose to apply a deep high-resolution representation learning model named High-Resolution Net (HRNet) coupled with the object-contextual representations (OCR) method for the classification of green space types (Wang et al., 2020; Yuan et al., 2019). The HRNet has the advantage of maintaining high-resolution representations throughout the network, making the model not only semantically strong but also spatially precise. This model can leverage multi-scale fusion mechanism, e.g., repeatedly exchange the information between high- and low-resolution subnetwork, to improve its capacity to capture both high- and low-resolution features. The OCR technique can characterize a pixel by exploiting the representation of the corresponding object class. This HRNetV2+OCR+ model, with a high accuracy of 84.5% on Cityscapes test dataset, ranked among the top semantic segmentation models (PapersWithCode, 2020).

- Model Training

Annotated images from three data sources were combined to create the training and validation datasets. First, two hundred annotated images including three green space categories were obtained from ADE20K dataset, which is a densely annotated dataset covering a diverse set of scenes and object categories (Zhou et al., 2017). The existing public datasets of annotated green space images are not big enough to train and test the model. Therefore, 1000 additional Google/Tencent Street View images randomly located in southern California (N=500)/ Beijing, China (N=500) were manually annotated using the open annotation tool "LabelMe" (Russell et al., 2007) by three researchers, and verified by a senior researcher from April, 2020 to June, 2020. I further increased the sample size of the training and validation data by annotating 300 street images from Cityscapes, which focuses on semantic understanding of complex urban street scenes (Cordts et al., 2016). In total, 1500 annotated images were obtained as the training and validation data for the model.

Ninety percent of the annotated images were randomly selected as the training dataset and the remaining 10% as the validation dataset.

Since the proportion of images with low-lying vegetation (14.3% of images) or grass (19.1% images) was much smaller compared to that with trees (66.6 % of images), the focal loss was used to address sample imbalance (Lin et al., 2017). For the training process, I combined the focal loss function with the Adam optimizer (Kingma & Ba, 2015), which improved the model performance by 4% compared with the use of cross entropy and stochastic gradient descent (SGD) optimizer in the original model (Robbins & Monro, 1951).

The image segmentations were obtained by feeding the street view images into the trained model. Then, the total number of pixels of each green space type (i.e., tree, low-lying vegetation, grass) were identified and the proportion of each type was determined (in % of pixels) for each image.

- *Model Validation*

Intersection over union (IoU) was used to evaluate the performance of the models. Briefly, IoU is the number of overlap pixel between predicting and ground-truth divide by the union of the predicting and ground-truth, which is a common method in image segmentation field to judge the quality of predicting images (Garcia-Garcia et al., 2017). The 10-fold cross-validation was used to further evaluate the accuracy of the model (Bengio & Grandvalet, 2004). The original dataset was randomly partitioned into 10 equal-sized subsets. Of the ten subsets, one subset was retained as the validation data for testing the model, and the remaining nine subsets were used the training data. The cross-validation process was then repeated 10 times, with each of the 10 subsamples used exactly once as the validation data. Additionally, one hundred Google Street View images of Los Angeles County were randomly selected as an independent test set to assessed the performance of the model.

2.2.3.2 Normalized Difference Vegetation Index (NDVI)

To compare the street view green space with satellite imagery-based green space, I also used the NDVI (Tucker, 1979) to characterize green space. Briefly, NDVI ranges from -1 to 1 and describes the different reflectance between visible and near-infrared wavelength of vegetation cover from satellite data, where higher values indicate more greenness. Negative values, representing water bodies, were recorded to zero before further analyses were conducted (Markevych et al., 2017), so that the effects of blue space do not negate the presence of green space. The NDVI estimates were based on the Moderate Resolution Imaging Spectroradiometer (MODIS) products from NASA. I combined measurements from both the Terra (MOD13Q1) and the Aqua (MYD13Q1) satellite instruments. The data had a spatial resolution of 250 m x 250 m and a temporal resolution of every 8-days (46 time-points annually). Because of the year-round mild-to-hot climate in Los Angeles County, green spaces do not change substantially across seasons. Previous study showed the NDVI values are highly correlated during the entire year in California (Sun et al., 2020). Therefore, the distinction between seasons and thus the recognition of species (evergreen or deciduous species) was not taken into account. Annual average NDVI in 2015 was calculated and assigned to each census tract based on the NDVI values in all 250 m grids within the census tract. In addition to the census tract-level assessment, I extracted the NDVI grid's value at the location of each sampling point along the street (N= 361,213) to examine the correlation between NDVI and street view-based green space at point level.

2.2.4 Statistical analyses

A GIS map was generated to show the spatial pattern of street green space across census tracts. The street green space level was calculated based on all sampling points along the road network within each census tract, and the percentage of green space for all points were averaged to assess the census tract-level street green space. The outcome variables in this analysis are four percentage of street green space (greenery pixels/total pixels) variables at a continuous scale: total and three types of green space, tree, low-lying vegetation, and grass. Percentage of green space were visualized according to their quintiles. Pearson's correlation was used to examine the correlation between green space types; t-test was applied to determine the difference between disadvantaged and other communities.

The generalized linear mixed models (GLMMs) with an identify link function and normal distribution were applied to examine the association between SES factors and street green space levels (Proc GLIMMIX in SAS). Ordinary least squares (OLS) regression was not employed because significant spatial autocorrelation was found among the residuals of OLS. Thus, I used GLMMs with spherical spatial covariance structure to account for the spatial autocorrelation in the green space outcome variables. All models included one of SES factors as the main fixed effect and adjusted for population density and rural/urban status.

The distribution of street network and spatial size vary across different census tracts (Appendix 2.2). The sampling points in larger rural areas with sparse street network may not represent the true green space level at census tract-level due to a small number of sampling points. Therefore, I conducted sensitivity analyses restricting to only urban areas. Urban areas were defined as those with a rural-urban commuting area (RUCA) code of 1.0, which indicates the metropolitan area core with primary flow of the population within an urbanized area (U.S., 2020) (Appendix 2.2). All analyses were conducted with SAS 9.4 (SAS Institute, Inc., Cary, NC).

2.3 RESULTS

The accuracy of our model was high with 92.5% mean IoU. The IoU values for tree, low-lying vegetation and grass were 96.2%, 86.5% and 94.4%, respectively (Appendix 2.4). Figure 2.2 shows examples of training and predicting process through the HRNetV2+OCR+ model. The results of cross-validation were shown in Appendix 2.5. The mean IoU in 10-fold cross-validation was 90.6% with a range of 89.4% and 91.9%, demonstrating the reliability and stability of the deep learning model. The average IoU in 10-fold cross-validation for tree, low-lying vegetation and grass were 95.4%, 84.9%, and 92.0%, respectively. Moreover, the mean IoU in the independent test set was 83.8%, and the IoU for tree, low-lying vegetation and grass were 93.7%, 71.3%, and 86.6%, respectively.

Los Angeles County population characteristics with definitions and street green space levels are presented in Table 2.1. Total green space and the three specific types were lower in disadvantage communities than in other communities ($p<0.001$). The spatial distribution of street view green space and neighborhood SES in Los Angeles County at census tract-level are depicted in Figure 2.3. The map shows that total street green space had a similar spatial pattern with street tree coverage and NDVI; whereas the total green space, street tree coverage and NDVI value showed an opposite distribution pattern of CES scores.

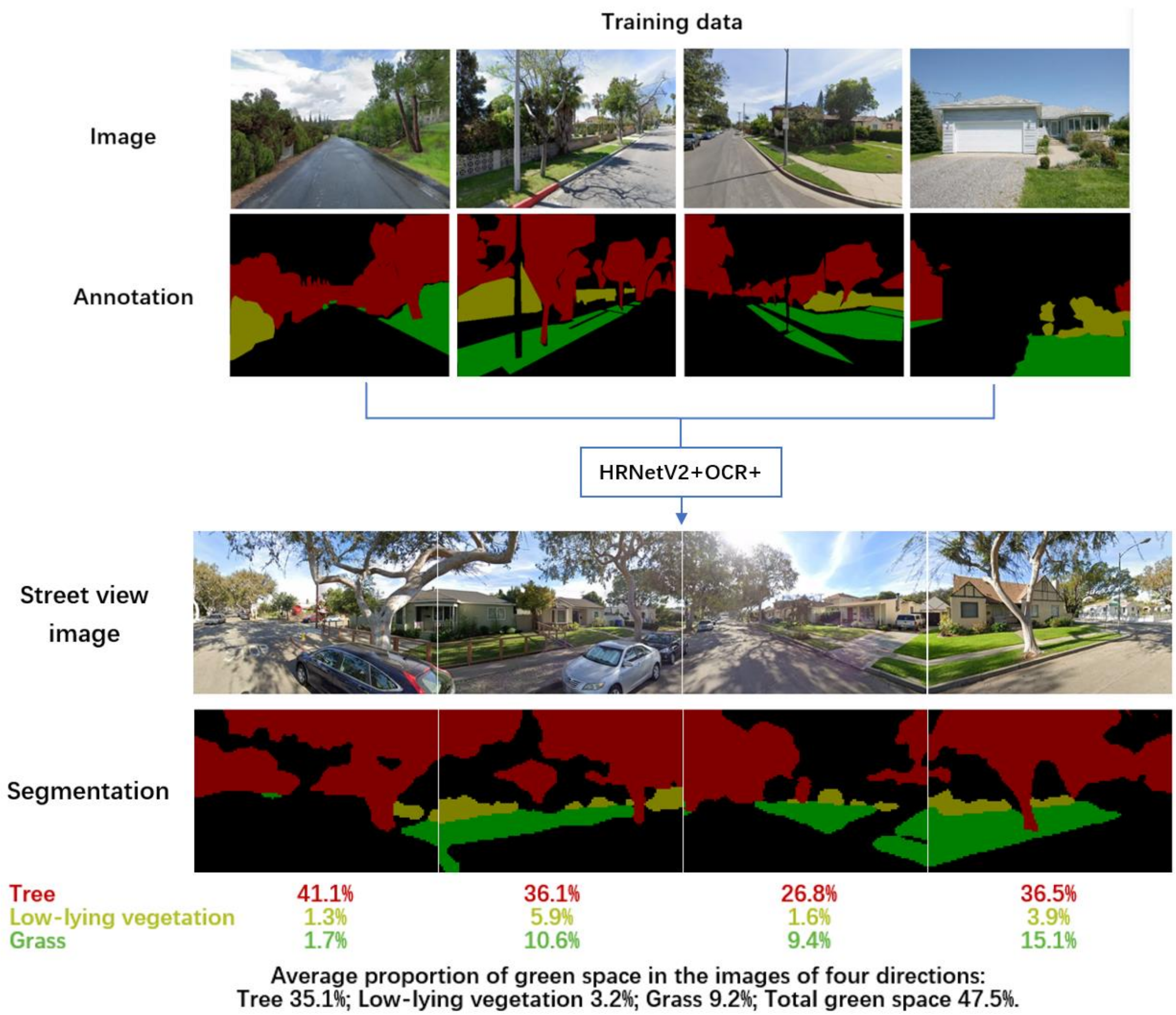

Figure 2.2 Examples of green space type segmentation through HRNetV2+OCR+.

Table 2.1 Description of the population characteristics and street green space levels.

Characteristics	Disadvantaged Communities n = 1,038	Other Communities n = 1,305	Total n = 2,343
CalEnviroScreen3.0 Indicators, mean (SD)			
Educational Attainment, %	38.0 (15.4)	13.3 (11.7)	24.3 (17.9)
Linguistic Isolation, %	21.4 (11.2)	9.8 (9.2)	15.0 (11.6)
Poverty, %	56.3 (15.4)	28.6 (16.3)	40.8 (21.0)
Unemployment, %	12.2 (5.0)	8.7 (3.8)	10.3 (4.7)
Housing Burden, %	29.1 (8.3)	18.6 (7.8)	23.3 (9.6)
Population Characteristics Score, 0-10	7.5 (1.0)	4.4 (1.7)	5.8 (2.1)
CalEnviroScreen3.0 score, 0-100	51.7 (8.2)	24.3 (9.3)	36.5 (16.3)
Racial/ethnic minority groups, n (%)			
High (4th quartile)	524 (50.5)	70 (5.4)	594 (25.3)
Moderate/low (1st – 3rd quartile)	514 (49.5)	1235 (94.6)	1749 (74.7)
Green space, mean (SD)			
Tree, %	14.9 (2.9)	18.4 (4.8)	16.8 (4.4)
Low-lying, %	4.2 (0.9)	4.9 (1.6)	4.6 (1.4)
Grass, %	4.6 (1.2)	5.2 (1.5)	4.9 (1.4)
Total green space, %	23.7 (2.9)	28.5 (5.1)	26.3 (4.9)
NDVI, 0-1	0.11 (0.03)	0.15 (0.04)	0.13 (0.04)

SD, standard deviation. NDVI, normalized difference vegetation index.

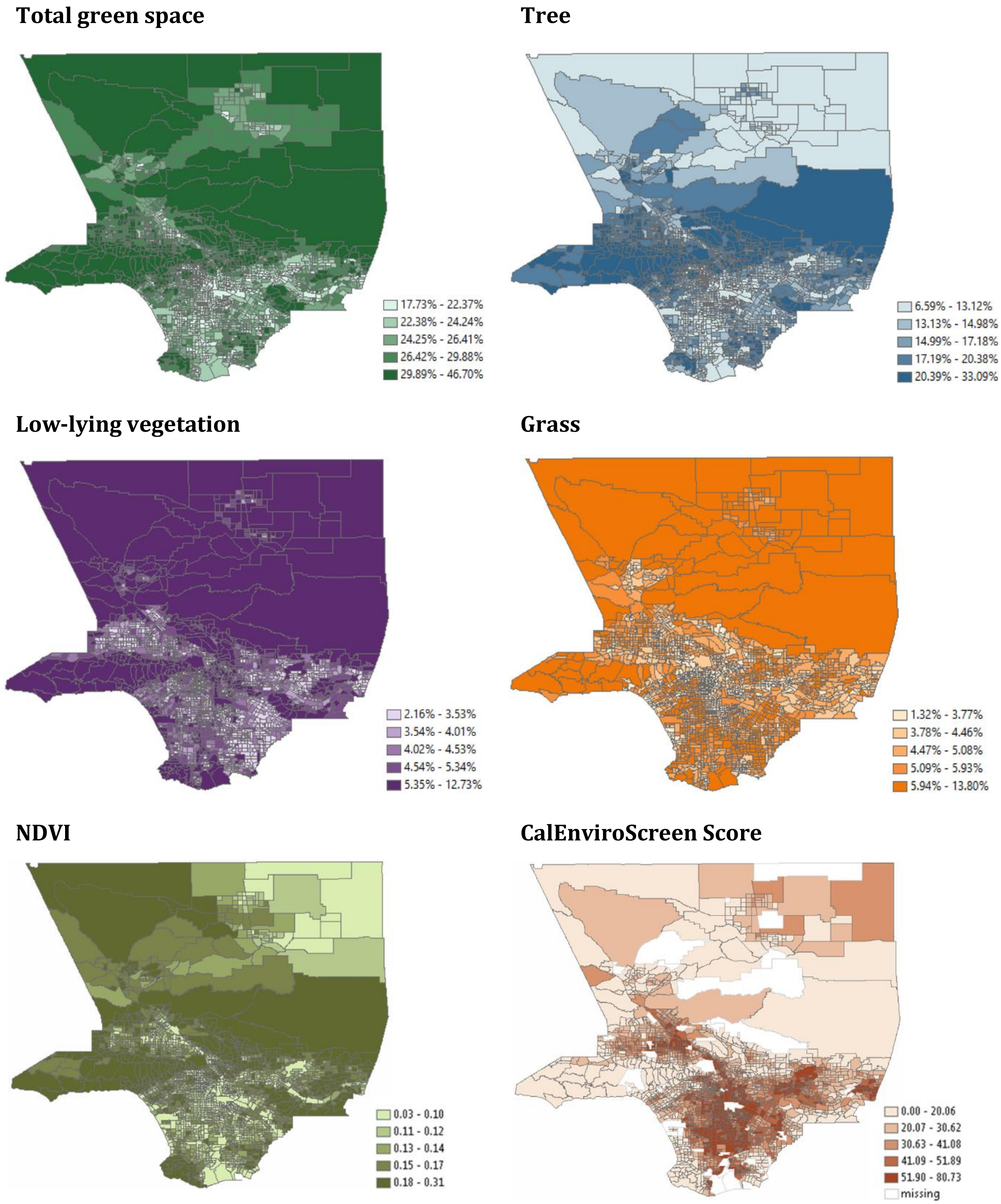

Figure 2.3 Spatial pattern of street green space and neighborhood socioeconomic status in Los Angeles County, census tracts.

Table 2.2 shows the correlations between each type of green space from street view images and NDVI. Total tract-level green space was positively correlated with all green space types, and the correlations were most pronounced with tree (r = 0.90), followed by low-lying vegetation (r = 0.36) and grass (r = 0.29). The correlations between street tree, low-lying vegetation and grass were weak. For NDVI, it was moderately highly correlated with total tract-level green space from street view imagery (r=0.73). Point-level correlation between NDVI and street view green space was lower than the tract-level (r=0.57). NDVI was moderately correlated with street tree for both point- and tract-level. However, the correlations between NDVI and low-lying vegetation and grass were weak. Moreover, green space indicators were negatively correlated with all CES socioeconomic factors. Summary statistics of green space indicators and socioeconomic factors are shown in Appendix 2.1.

Table 2.3 shows the results of the GLMMs to assess the association of street green space with neighborhood SES, controlling for population density and urban/rural status. Overall, I found statistically significant inverse associations between SES factors and street green space. For example, for each interquartile range (IQR) increase in CES score (26 unit), the percentage of total green space decreased by 2.62 (95% CI: -3.02 to -2.21, $p < 0.001$). The percentage of total green space in disadvantaged communities was 1.26 less than in other communities, accounting for approximately 5% of average street green space in Los Angeles County.

Table 2.2 Correlations between tract-based types of street green space, point- and census tract-based NDVI, and census tract socioeconomic factors. (Number of sampling points: 361,213; number of census tracts: 2,343).

Type	Tree	Low-lying vegetation	Grass	Total green space	Tract-NDVI	Point-NDVI	Education	Linguistic Isolation	Poverty	Unemployment	Housing Burden	Population Score	CES 3.0
Tree	1.00	0.03	0.05	0.90	0.63	0.49	-0.46	-0.31	-0.44	-0.26	-0.28	-0.49	-0.45
Low-lying vegetation		1.00	0.19	0.36	0.31	0.23	-0.29	-0.26	-0.30	-0.10	-0.28	-0.34	-0.36
Grass			1.00	0.29	0.23	0.16	-0.23	-0.38	-0.28	-0.03	-0.27	-0.11	-0.21
Total green space				1.00	0.73	0.57	-0.56	-0.46	-0.56	-0.27	-0.41	-0.57	-0.57
Tract-NDVI					1.00	1.00	-0.55	-0.53	-0.63	-0.29	-0.52	-0.59	-0.59

Table 2.3 Associations between neighborhood socioeconomic status and green space in Los Angeles County, census tracts.

	IQR[a]	Tree		Low-lying vegetation		Grass		Total green space		NDVI[c]	
Socioeconomic status		regression coefficient	95% CI[b]	regression coefficient	95% CI	regression coefficient	95% CI	regression coefficient	95% CI	regression coefficient	95% CI
CalEnviroScreen 3.0 score, 0-100	26.0	-2.26	(-2.64, -1.88)	0.07	(-0.05, 0.19)	-0.42	(-0.55, -0.30)	-2.62	(-3.02, -2.21)	-0.022	(-0.026, -0.019)
Population Characteristics Score, 0-10	3.3	-1.89	(-2.27, -1.52)	-0.18	(-0.30, -0.07)	-0.46	(-0.59, -0.34)	-2.54	(-2.94, -2.15)	-0.019	(-0.022, -0.015)
Educational Attainment, %	30.2	-1.81	(-2.20, -1.42)	-0.08	(-0.20, 0.04)	-0.44	(-0.57, -0.31)	-2.33	(-2.74, -1.92)	-0.014	(-0.018, -0.011)
Linguistic Isolation, %	15.7	-0.78	(-1.02, -0.54)	-0.03	(-0.10, 0.04)	-0.25	(-0.33, -0.17)	-1.06	(-1.32, -0.80)	-0.010	(-0.012, -0.007)
Poverty, %	35.9	-1.87	(-2.20, -1.54)	-0.03	(-0.14, 0.07)	-0.51	(-0.62, -0.40)	-2.41	(-2.76, -2.07)	-0.018	(-0.020, -0.015)
Unemployment, %	5.6	-0.29	(-0.30, -0.01)	0	(-0.04, 0.05)	-0.01	(-0.06, 0.04)	-0.16	(-0.32, -0.01)	-0.001	(-0.002, 0.000)
Housing Burden, %	13.6	-0.60	(-0.81, -0.39)	-0.01	(-0.08, 0.05)	-0.21	(-0.28, -0.14)	-0.82	(-1.04, -0.60)	-0.006	(-0.008, -0.004)
Disadvantaged community, yes	-	-0.97	(-1.29, -0.66)	-0.01	(-0.11, 0.08)	-0.27	(-0.38, -0.17)	-1.26	(-1.59, -0.93)	-0.010	(-0.013, -0.007)
Racial/ethnic minority groups, high	-	-0.92	(-1.32, -0.51)	-0.11	(-0.23, 0.02)	-0.23	(-0.36, -0.10)	-1.25	(-1.68, -0.82)	-0.006	(-0.010, -0.003)

a IQR, interquartile range; b CI, confidence interval; c NDVI, normalized difference vegetation index.

All models were adjusted for population density and urban/rural status.

A similar trend was observed in sensitivity analyses by restricting to urban areas. In addition, associations between socioeconomic factors and street green space were slightly stronger after restricting to urban areas (Appendix 2.6).

2.4 DISCUSSION

To the best of our knowledge, this is the first study to examine different types of green space using street view images in combination with deep learning techniques. The results from this study suggest that Bing StreetSide images are valuable sources and machine learning techniques are powerful tools to measure overall and types of street green space. In this analysis, street view-based green spaces were inequitably distributed in populations with different neighborhood SES in Los Angeles County, the most populous county in the U.S. I found that communities with a higher percentage of low SES and higher percentage of residents from racial/ethnic minority groups had substantively less street green space availability.

The fact that low-income neighborhoods have less green space is well established (Astell-Burt et al., 2014; Dai, 2011; Wen et al., 2013; Wolch et al., 2014). Several studies have revealed that the distribution of urban green space often disproportionately benefits predominantly non-Hispanic White and more affluent communities. However, most previous studies used geographic information system-based methods to measure green space from an overhead view (e.g., satellite data). The results support the previous findings by measuring eye-level street view-based green space, suggesting that populations who have higher prevalence of poor health outcomes (Shaw, 2016) live in environments that contain the least green space for supporting positive lifestyle modification. Furthermore, the results showed that the magnitude of association between green space and neighborhood SES varied between vegetation types. The greatest reduction was observed among the tree, followed by grass. However, I observed inconsistent associations of low-lying vegetation and neighborhood SES, which warrants further research. In addition, the relative associations of lower SES with NDVI are greater than total street green space, suggesting that deprived communities may contain additionally reduced "unseen" green space, such as private green spaces or large areas of park, forest away from the road.

Street view data and deep learning techniques are increasingly used for environmental exposure assessments for health-related studies. Previous studies have suggested that walking behavior and physical activity is affected by eye-level street green space (Lu, 2018; Villeneuve et al., 2018). For example, a study in Canada compared the NDVI with the google street view measure of green space, and found that only street green space was positively associated with participation in recreational physical activities (Villeneuve et al., 2018). In addition, contact with surrounding green space might be more important if green space has the greater influence on health via restorative properties and stress reduction (Mitchell et al., 2011). For instance, street view green spaces were protective against depression for the elderly in China, whereas no significant associations were found with satellite-based green space estimates (Helbich et al., 2019). Two previous studies used the FCN-8s and PSPNet models to identify total green space from street view images with moderate to excellent performance (81.4% and 93.4 % accuracy, respectively) (Helbich et al., 2019; Lu, 2018).

However, no prior study has applied street view data in conjunction with deep learning approach to classify vegetation types. Measuring types of green space is important to better understand the mechanisms linking green space to health and design urban planning interventions. Different vegetation types shown different capacity to provide the ecosystems services of air purification and microclimate regulation (Vieira et al., 2018). In addition, green space types can affect human behaviors. For example, more proportions of walking and running people were observed on the lawn and in the shade of trees than in other settings (H. Wang et al., 2019). Investigating their different roles may contribute to better understanding of etiological mechanisms and the ability to design targeted interventions. Existing studies regarding different types of green space and health are sparse and mainly focused on tree canopy. Two recent studies measured green space using machine learning and image classification processes across satellite imagery (Astell-Burt & Feng, 2020; Brandt et al., 2020). However, grass and low-lying vegetation were likely under-estimated in areas where they were beneath tree canopy. Our model overcomes the limitations of existing green space metrics and contributes to the improvement of green space exposure assessment methodology for health studies. Future studies are warranted to investigate the relationships between types of green space and other environmental factors and health outcomes using this deep learning technique.

Previous studies observed poor correlation between street view-based green space and satellite-derived NDVI (Helbich et al., 2019; Larkin & Hystad, 2019; Villeneuve et al., 2018). In the correlation analyses, I observed that both community-level and point-level street view-based total green space were moderately correlated with NDVI. The differences in the climate and vegetation density in the study area may partially explain the variation in results compare to the literature. First, green spaces did not change substantially across seasons due to the year-round mild-to-hot climate in Los Angeles County. The NDVI values are highly correlated during the entire year in California (Sun et al., 2020). However, the variation of NDVI and street view green space in Los Angeles County might not represent green space levels in other geographical settings, such as Beijing, China (Helbich et al., 2019), and Ottawa, Canada (Villeneuve et al., 2018) with four distinct seasons. Second, the overhead-view assessments cannot fully capture the vertical dimension of green space, especially in locations with high-density vegetation (Jiang et al., 2017; Li et al., 2018). The substantially lower NDVI in Los Angeles County suggested it has thinner greenness than other study regions, such as Portland and Ottawa (Larkin & Hystad, 2019; Villeneuve et al., 2018). Thus, the NDVI may be more highly correlated with overall street green space in Los Angeles County than those in previous research. Moreover, the NDVI captures both public and private (e.g., residential backyard or gated community) green spaces, while the street view imagery mainly captures publicly-accessible street-based green spaces that may be most relevant to people's daily activity patterns, such as walking, jogging/running, and driving. Los Angeles metropolitan area has the nation's densest road network (road length $\approx$ 55,785 km) (Sorensen, 2009). Therefore, we may expect the denser street network, the higher correlations between NDVI and street view green space. Indeed, I found the correlation coefficient for urban census tracts (r=0.77) with denser streets was higher than rural census tracts (r=0.54) in this study. Furthermore, the method of extracting green space and the density of street networks might be potential explanations of the differences between point-level and tract-level correlations.

The point-level variations can be caused by the different perspective and spatial resolution between NDVI and street view green space. The street view-based estimate represents the horizontal panoramic 360 degrees view of each sampling point along the road thus localized green space at the particular point; while the NDVI-based estimate reflects the bird's eye view green space within a grid with cell size 250 m × 250 m. The street view sampling points are likely not in the center of satellite-based NDVI grids. The tract-level green space that contains multiple points or grids may smooth out the local variations and spatial mismatch in point vs. grid measurements, thus I observed higher correlation (r=0.73) between tract-level street view green space and NDVI, both of which reflect overall community green space level, especially for urban areas with high-density roads. It is also noteworthy that tree canopy is what people see the most for the total green space (64%) at the horizontal level. The correlation is only 0.49 for point-based NDVI and tree, indicating that vertical NDVI may not be a good indicator of horizontal tree canopy at a local level. In addition, correlations between NDVI and low-lying vegetation or grass were weak, indicating that the street view-based metrics capture additional information of visible street green space. Street view and satellite data reflect different aspects of natural environments. Green space assessments combining remote-sensing imagery and street view imagery may therefore represent more comprehensive characteristics of green space than assessments based on a single green space indicator (Larkin & Hystad, 2019), and provide a potential new approach to examine green space in epidemiological research.

The main strengths of this study include the diversity of the types of street view-based green space as well as the diversity of race/ethnic composition and SES of the population in Los

Angeles County; the comparison with the predominant, satellite-based green space indicator - NDVI; the use of Bing Maps data that are publicly available and provides high-resolution images with mostly full coverage in the U.S.; the robust performance and application of an advanced deep learning model; and the generalizability of this deep learning approach in other regions in the future.

However, this study has limitations, which suggest avenues for further research. First, street view images from Bing Maps were captured in different years and dates thus this database is most suitable for long-term estimation rather than seasonal or higher temporal resolution measurement. Nevertheless, given the year-round mild and dry climate in LA, the temporal variation of green space in urban areas tends to be small. Moreover, the training data directly impact the quality of the prediction. This model was trained mainly based on the street view images from southern California. Further evaluation of the model is warranted when the model applies to other regions with different streetscapes or landforms. Additionally, a single-round annotation was used in this study. Future studies may perform double annotation (i.e., a second round of annotation) to minimize the misclassification. Next, more sophisticated subtypes of green space were not examined in this research. Future studies may take into account other vegetation types (e.g., flowers), and quality of green space (e.g., wild vegetation vs. cultivated and well-maintained vegetation). Further, because the sampling points were extracted along the road, and the density and pattern of street networks could vary across different regions. Thus, the study findings need to be interpreted with caution, particularly in large rural areas. Nonetheless, the street level images, even though having sparse road network in rural areas, still represent publicly available eye-level green space. The “private” or not accessible greenery in both rural and urban areas may have less impact on human behaviors due to the lack of accessibility. In addition to the amount of green space, perceived quality and accessibility of green space may play an important role, because they could affect the use of green space (de la Barrera et al., 2016; Zhang et al., 2017). Further research is needed considering more information on the use of green space and individual activity patterns, especially for epidemiological studies linking green space to health outcomes.

2.5 CONCLUSION

This study provides a unique understanding of the relationship between green space and neighborhood SES. Compared to remote sensing data, street view data reflect different aspects of natural environments. Street view images coupled with deep learning approach can accurately and efficiently extract street green space and recognize different vegetation types, which can contribute to methodological development and mechanistic understanding of green space-related health studies. Results from this study indicate that green spaces were inequitably distributed in populations with different SES in Los Angeles County. Communities with a higher percentage of low SES and racial/ethnic minority communities had substantively lower street green space level. Governments and urban planners may consider not only the size or density of green space, but also the type and visibility of street green space from pedestrian’s perspective.

Chapter 3. Green Space, Physical Activity and Postpartum Depression

3.1 Objective of Present Study

In this chapter, I aimed to: 1) investigate the relationships between PPD and both neighborhood and individual residential green space exposure (i.e., street view green space, NDVI, land-cover green space, and proximity to park) and by vegetation types (i.e., tree, low-lying vegetation, and grass); and 2) examine the mediation effect of PA on the association between PPD and green space.

3.2 METHODS

3.2.1 Study population

This retrospective cohort study used electronic health records (EHRs) obtained from nearly 430,000 women who gave singleton live births between 2008 and 2018 at Kaiser Permanente Southern California (KPSC) facilities. KPSC serves approximately 19% of the population in Southern California and validly represents the sociodemographic diversity of the Southern California Census population (Chen et al., 2019; Koebnick et al., 2012). In total, 415,020 pregnancies were included after a series of exclusions, including women who were not KPSC members or with gestational age < 20 or >47 weeks (n=8,912), with multiple birth (n=7,454), with stillbirth (n=1,961), without address data (n=680), or lived in rural areas (n=14,819). All maternal residential addresses were geocoded with the Texas A&M, NAACCR, Automated

Geospatial Geocoding Interface Environment Geocoder. Urban areas were defined as those with a rural-urban commuting area code of 1.0, which indicates the metropolitan area core with primary flow of the population within an urbanized area (2010 version, https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/). A wide range of information on demographic characteristics, medical records, birth records and self-reported individual lifestyle was extracted from KPSC EHRs. More details of this population have been described in my previous work (Sun et al., 2022). This study was approved by the Institutional Review Board of KPSC and the University of California, Irvine.

3.2.2 Outcome: Postpartum depression (PPD)

Our previous work suggested that the completeness and accuracy of PPD diagnosis solely based on diagnostic codes in EHRs is not reliable, and the accuracy of PPD identification can be improved by supplementing clinical diagnosis with pharmacy utilization records. Thus, PPD was defined by using both PPD diagnosis and prescription medications in this study. PPD diagnosis codes and related pharmacy records were identified and extracted from KPSC EHRs.

3.2.3 Green space exposures

I characterized green space exposure using five main indicators, including a novel measure of street view-based green space and vegetation types, three commonly-used satellite-based measures (i.e., NDVI, land-cover based green space and tree canopy cover), and another common measure of proximity to the nearest park. Both individual-level and neighborhood-level green space exposures were considered in this analysis. Individual residential green space exposures were measured within 200 m and 500 m buffers around the maternal residence at delivery for all but distance to the nearest park. The neighborhood-level green space exposure was calculated by averaging all individual residential green space values within a given zip code (median area: 18.2 km2). The main analysis focused on 200 m buffer as I aimed to examine between- and within- effects of green space and the larger buffer sizes make the individual-level exposure more similar to the neighborhood-level exposure. Zip Code Tabulation Areas (2010 version, https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html) defined by the U.S. Census Bureau were used to represent zip codes.

- ***Street view green space***

I requested street view images using Microsoft Bing Maps Application Programming Interface. The street network shapefile for Southern California were obtained from the U.S. Census Bureau (U.S., 2015). Sampling points for street view images were constructed along the road network with a 200 m space interval between each point and geocoded with ArcMap 10.5 (Esri, Redlands, CA, USA) (Li et al., 2015). Four main cardinal directions at each point were retrieved to include the entire streetscape (e.g., 0, 90, 180, and 270 degrees) (Helbich et al., 2019; Wang et al., 2018).

I applied a machine learning model using semantic segmentation to identify three different types of vegetation including tree (e.g., canopy), low-lying vegetation (e.g., shrub, bush), and grass based on high resolution street view image data. The accuracy of the deep learning model was high with 92.5% mean intersection over union (Sun et al., 2021). The proportion of different vegetation types in the image was predicted by the deep learning model. Total green space was defined as the sum of proportion of all types of green space in each image. For each address, the proportion of green space for all points within a circular buffer around the residential address were averaged to assess the street green space exposure. The number of sampling points (e.g., 500 m buffer: 83±27) per address varies depending on the buffer size and street density. Further details of the street view green space model have been previously described (Sun et al., 2021).

- ***Normalized difference vegetation index (NDVI)***

To compare the street view green space with satellite imagery-based green space, I used the NDVI (Tucker, 1979) to characterize green space exposure. Briefly, NDVI captures the vegetation density on the ground from satellite data based on different land surface reflectance between visible and near-infrared wavelength of vegetation. NDVI ranges from -1 to 1, with higher values indicating a higher density of greenness. Negative values, usually representing water bodies, were recorded to zero before further analyses were performed (Markevych et al., 2017). In this study, I used the Terra (MOD13Q1) satellite instrument of Moderate Resolution Imaging Spectroradiometer (MODIS) products from NASA, with a spatial resolution of 250 m × 250 m and a temporal resolution of every 16-days.

Previous study showed the NDVI values are highly correlated during the entire year in California and do not change substantially across seasons (Sun et al., 2020). Therefore, I calculated annual mean NDVI by averaging the NDVI values in all grids within a circular buffer for the year 2013 (the mid year of the study period).

- ***Land-cover based green space and tree canopy cover***

Land cover data were obtained from the National Land Cover Database (NLCD, version 2013, https://www.mrlc.gov/data/nlcd-2013-land-cover-conus). The NLCD provides nationwide data on land cover at a 30 m resolution with 16 classes (Homer et al., 2012). Greenness-related categories from the NLCD, including forest, shrubland, herbaceous, wetlands, developed - open space (i.e., >80% vegetation cover) were aggregated as one measure of green space. Additionally, I obtained the 2011 tree canopy data from the NLCD, which contains the percentage of total tree canopy cover at a 30 m resolution (https://www.mrlc.gov/data/nlcd-2011-usfs-tree-canopy-cover-conus). The percentages of area within or intersecting the circular buffers were assessed as land-cover based green space exposures.

- ***Proximity to the nearest park***

Using the California Protected Areas Database (CPAD, version 2021, https://data.cnra.ca.gov/dataset/california-protected-areas-database), I estimated proximity to parks as a straight-line distance to the nearest park based on the geocoded residential addresses at delivery. The CPAD, developed and maintained by the California Natural Resources Agency, provides GIS dataset depicting the wide diversity of parks and open spaces in California, ranging from large National Parks and Forests to small neighborhood parks. In this study, only parks and open spaces defined as "Open Access" were included. I converted the positive distance value to negative as proximity to the nearest park. A binary variable was also used to assess whether the maternal residential address was within a 500 m buffer (about a 5-minute walk) from boundaries of a nearest park.

I additionally explored the relationship between neighborhood walkability and PPD. Walkability scores at block-group level were obtained from the National Walkability Index dataset (https://www.epa.gov/smartgrowth/smart-location-mapping#walkability).

3.2.4 Mediator: Physical activity (PA) during pregnancy

The PA measurements were based on self-reported information on physical activity at the time of the visit encounter (7±4 times during the entire pregnancy) in KPSC EHRs. Participants were asked the following two questions to capture frequency and average daily time spent engaging in physical activity over the last seven days at the time of their visit: 1) number of days exercised per week and 2) number of minutes exercised per day. The date of questionnaire completed and total number of minutes exercised per week (number of minutes exercised per day × number of days exercised per week) were extracted and calculated. I then calculated trimester-specific and entire-pregnancy PA levels by averaging the self-reported PA data in each specific time period from conception to the end of the pregnancy: the first trimester (1st - 3rd gestational months), second trimester (4th - 6th gestational months), and third trimester (7th gestational month to delivery). PA during the entire pregnancy was calculated by averaging the PA measurements in three trimesters.

3.2.5 Statistical analyses

Distribution of selected population characteristics and green space indicators were assessed. Pearson's correlation was employed to examine the correlation between green space indicators. First, I used multilevel logistic regressions to examine the association between each green space indicator, PA and PPD separately. All green space indicators were treated as continuous exposures. Odds ratios (ORs) and 95% confidence intervals (CIs) were calculated per interquartile range (IQR) increment for each green space indicator. Moran's I was used to test the spatial clustering for PPD given the large spatial scale of the study region. The Moran's I was 0.0002 ($p < 0.001$). The spatial correlation is weak despite its statistical significance. I included zip code as a random effect to account for both within- and between- effects concurrently using the within-between random effects model (Bell et al., 2018):

$$y_{ir} = \beta_0 + \beta_{1W}(x_{ir} - \bar{x}_r) + \beta_{2B}\bar{x}_r + \beta_3 z_i + (\nu_r + \epsilon_{ir})$$

Here, for individual i and region r, β_{1W} represents the within region effect, while β_{2B} represents the between effect. The within effects reflect remaining individual-level effects after accounting for the between effects (i.e., individual observations clustered by zip code), while between effects reflect neighborhood-level effects (i.e., zip code in this study) with keeping the deviation constant. Confounder adjustments are denoted using simplified notation $\beta_3 z_i$, ν_r are the zip code random effects, the ϵ_{ir} are the model's residuals for individuals.

Multiple linear regression models were applied to estimate the difference in PA in each specific time period during pregnancy associated with green space exposure. PA levels were log-transformed. All results were expressed as the percent change in PA levels with 95% CIs relative to one unit increment of each green space indicator.

Furthermore, I conducted causal mediation analysis (R packages "mediation") to estimate the potential contribution of PA associated with green space on the risk of PPD (Tingley et al., 2014). Green space indicators with protective effects on the risk of PPD were identified and selected to further perform the mediation analysis. In the causal mediation analysis, multilevel models were used to take into account heterogeneity within and between groups simultaneously. In this case, the zip code-level neighborhood green space was a group-level exposure variable but PA and PPD were treated as individual-level mediator and outcome, respectively. The ‘‘proportion mediated’’, which is the proportion of the total effect explained by the mediator [mediation effect/ (mediation effect + direct effect) or mediation effect/total effect], was calculated. Given that the green space indicators were continuous variables, I specified two values of the exposure (Q3 vs. Q1) to make the contrast in the mediation models.

In the main analysis, I adjusted for a minimal set of potential confounders, including maternal age, race/ethnicity (African American, Asian, Hispanic, non-Hispanic white, and others including Hawaiian/Pacific Islanders, American Indian/Alaskan native and mothers with multiple race/ethnicities specified), educational level (<college, college < 4 years, and college ≥ 4 years), and median household income at census block group in 2013 (the mid year of the study period). Moreover, I performed sensitivity analyses to examine the influence of adjusting for maternal smoking status (never smoker, ever smoker, smoking during pregnancy, and passive smoker), season of conception (warm: May-October; cool: November-April), year of infant birth, and insurance type. Mediation analysis requires no unmeasured confounding between the exposure of interest, the mediator and the outcome. Therefore, I included all above covariates and pre-pregnancy BMI in the mediation models. Due to potential differential susceptibility of green space effects on health across populations with different demographic factors, socioeconomic status and health conditions (Rigolon et al., 2021), I performed stratified analyses by maternal age, race/ethnicity, educational level, neighborhood household income, and pregnancy-related comorbidities (preeclampsia, gestational hypertension and gestational diabetes) to explore the differences between population subgroups. Cochran Q tests were applied to measure the heterogeneity among subgroups. All analyses were conducted with SAS version 9.4 (SAS Institute, Inc., Cary, NC) and R software (version 4.0.5).

3.3 RESULTS

Among 415,020 births included in this study, 43,399 (10.5%) cases of PPD cases were identified. The description of the sociodemographic characteristics of study participants, green space exposures, and PA levels are presented in Table 3.1. The mean (standard deviation) of maternal age in this study was 30.2 (5.8) years. Compared to the entire cohort, PPD cases were more frequent among older mothers, African American or non-Hispanic white mothers, mothers with college education < 4 years, mothers who live in middle- and high-income neighborhoods, smoking mothers, and mothers with less physical activity during pregnancy.

Differences were observed for residential street view green space exposure (200 m) by maternal characteristics. On average, total street green space levels were higher among older mothers, non-Hispanic white or Asian mothers, mothers with higher education, and mothers who live in high-income neighborhoods. Overall, a similar distribution occurred for street tree and low-lying vegetation, while grass levels showed an opposite trend. For satellite-based green space indicators, NDVI, land-cover green space and tree canopy cover had a similar pattern with street view total green space.

- ***The relationship between multiple green space indicators***

Table 3.2 provides summary statistics and Pearson correlation coefficients between individual residential green space exposures (200 m). Street total green space was positively correlated with all green space types, and the correlations were most pronounced with tree (r = 0.89), followed by grass (r = 0.22) and low-lying vegetation (r = 0.07), while street tree coverage were negatively correlated with low-lying vegetation and grass; the correlations were similar across different buffer sizes. For satellite-based NDVI, it was moderately correlated with street total green space and trees (r=0.40 and 0.35, respectively), and the correlations with street low-lying vegetation and grass were weak. The tree canopy cover from satellite imagery was moderately correlated with street tree coverage (r=0.55), street total green space (r=0.55), and NDVI (r=0.48). Increased distance to park was correlated with decreased street tree coverage. Moreover, block group-level walkability score was negatively correlated with most green space indicators, except street tree levels and proximity to park. Additional summary statistics of green space indicators and PA levels are shown in Appendix 3.1.

- ***The association between green space, PA and PPD***

Overall, "between" effects of neighborhood green space exposures were stronger than "within" effects of individual residential green space exposure, suggesting that the main effect of green space on the risk of PPD was due to neighborhood-level (i.e., zip code) green space exposure (Appendix 3.2). Figure 3.1 illustrates the associations between exposure to neighborhood-level green space and the risk of PPD. For the zip code-level street view-based green space, exposure to total green space showed protective effects on PPD (OR=0.960, 95% CI: 0.934–

0.987) (Appendix 3.2). For different types of street green space, higher street tree coverage was associated with a decreased risk of PPD, indicating approximately 5.4% lower PPD risks for an IQR increase in street tree exposure. However, the association of neighborhood low-lying vegetation was not statistically significant in this analysis, and increased ORs were found for grass. For satellite-based green space indicators, zip code-level NDVI and land-cover based green space were associated with increased risk of PPD, except tree canopy cover for which a decreased risk of PPD was observed (OR=0.969, 95% CI: 0.945–0.994). No clear trend was observed between proximity to parks and PPD risk, while higher neighborhood walkability was associated with a lower risk of PPD (OR=0.920, 95% CI: 0.897–0.944). After accounting for the between effect of zip code-level neighborhood green space, I observed potential within effect of individual street low-lying vegetation, which was associated with a reduced PPD risk (OR=0.985, 95% CI: 0.974–0.996). Moreover, PPD was negatively associated with PA during the entire pregnancy (within effect: OR=0.929, 95% CI: 0.917–0.940).

In sensitivity analyses (Appendix 3.2), overall, associations between zip code-level green space and PPD were slightly stronger after further adjusting for smoking during pregnancy, season of conception, year of infant birth, and insurance type. The pattern of results within a 500 m buffer zone was similar to the 200 m buffer. In subgroup analyses (Appendix 3.3), the protective associations of PPD and street green space were significantly stronger among older mothers, non-Hispanic white mothers and Asian mothers, and mothers with higher education.

- ***The association between green space exposure and PA mediator***

I estimated the percent change of PA levels associated with green space exposures. The PA data were log-transformed, while the green space indicators were in its original metric. Overall, PA levels were positively associated with most green space indicators, including neighborhood street view-based total green space, tree, and low-lying vegetation, satellite-based tree canopy cover, distance to the nearest park, and walkability score (Figure 3.2, Appendix 3.4). For example, each one unit increase in street tree (percentage) was associated with a 1.43% increase in PA during the entire pregnancy (95% CI: 1.03%-1.82%). The positive associations were stronger during the second trimester. In contrast, exposures to more grasses and higher proportion of land-cover based green space were associated with decreased PA during pregnancy.

- ***Relative contribution of PA mediator***

Table 3.3 shows results from the mediation analysis that included green space indicators (200 m) that were significantly associated with decreased risk of PPD, including street view-based total green space and tree, satellite-based tree canopy cover and walkability score. For the associations between neighborhood-level green space exposure and PPD, the proportions of mediation effects attributable to PA during the entire pregnancy ranged from 9.6% to 15.6%. Among all green space indicators, PA explained the largest portion of the association between PPD and exposure to total tree canopy cover (15.6%, 95% CI: 3.5%-30.7%). PA during pregnancy could also explain approximately 10% of the association between PPD and neighborhood street view green space, and 5% of neighborhood walkability. In addition, the mediation effects due to PA were higher during late pregnancy (i.e., second and third trimester) compared to early pregnancy (i.e., first trimester) (Appendix 3.5).

Table 3.1 Description of the study population and residential green space levels (mean, SD) by maternal characteristics, 2008-2018.

Characteristics	Total births, n = 415,020 (%)	Postpartum depression, n = 43,399 (%)	Total green space, %	Tree, %	Low-lying vegetation, %	Grass, %	NDVI	Land-cover green space, %	Tree canopy cover, %
Physical activity,	79.5 (80.8)	74.9 (76.3)	-	-	-	-	-	-	-
Maternal age									
< 25	80513 (19.4)	6758 (15.7)	24.6 (4.5)	15.0 (4.7)	4.2 (1.6)	5.4 (1.8)	0.16 (0.04)	8.2 (16.2)	1.5 (2.0)
25-34	245934 (59.3)	25936 (59.8)	25.3 (5.0)	15.6 (5.1)	4.4 (1.6)	5.3 (1.8)	0.16 (0.04)	8.5 (16.1)	2.0 (2.6)
≥ 35	88573 (21.3)	10705 (24.5)	25.9 (5.4)	16.2 (5.4)	4.5 (1.6)	5.2 (1.8)	0.17 (0.04)	8.2 (15.5)	2.5 (3.0)
Maternal race/ethnicity									
African American	31896 (7.7)	3602 (8.3)	24.5 (4.4)	14.6 (4.7)	4.3 (1.5)	5.6 (1.8)	0.15 (0.04)	6.5 (13.7)	1.3 (1.9)
Asian	52946 (12.8)	2639 (6.1)	25.9 (5.3)	16.2 (5.4)	4.6 (1.6)	5.1 (1.7)	0.17 (0.04)	7.7 (14.5)	2.6 (3.0)
Hispanic	213543 (51.5)	21525 (49.6)	24.7 (4.6)	15.3 (4.7)	4.1 (1.5)	5.3 (1.7)	0.16 (0.04)	7.0 (14.5)	1.7 (2.1)
Non-Hispanic white	105728 (25.5)	14308 (33.0)	26.4 (5.6)	16.3 (5.7)	4.8 (1.8)	5.3 (1.9)	0.17 (0.04)	12.0 (19.2)	2.7 (3.2)
Multiple/other	10865 (2.6)	1324 (3.0)	25.5 (5.2)	15.5 (5.3)	4.6 (1.7)	5.3 (1.8)	0.16 (0.04)	9.6 (17.0)	2.2 (2.7)
Maternal education									
< College	137387 (33.1)	13258 (30.6)	24.5 (4.6)	15.0 (4.7)	4.2 (1.6)	5.3 (1.8)	0.16 (0.04)	8.1 (16.0)	1.5 (2.1)
College (< 4 years)	93590 (22.6)	11342 (26.1)	25.0 (4.7)	15.4 (4.9)	4.2 (1.6)	5.4 (1.8)	0.16 (0.04)	7.9 (15.7)	1.8 (2.3)
College (≥ 4 years)	184043 (44.3)	11799 (43.3)	26.0 (5.4)	16.2 (5.5)	4.5 (1.7)	5.3 (1.8)	0.17 (0.04)	8.9 (16.1)	2.5 (3.0)
Block group median household income in 2013									
≤ $43,696	103493 (25.0)	9640 (22.3)	24.1 (4.3)	15.0 (4.4)	4.0 (1.4)	5.0 (1.7)	0.14 (0.04)	5.4 (13.3)	1.2 (1.6)
$43,696-$55,962	103411 (25.0)	10846 (25.0)	25.0 (4.7)	15.6 (4.9)	4.1 (1.5)	5.4 (1.8)	0.16 (0.03)	7.5 (15.4)	1.7 (2.1)
$55,962-$71,602	103473 (25.0)	11365 (26.3)	25.5 (4.9)	15.7 (5.2)	4.4 (1.7)	5.6 (1.8)	0.17 (0.04)	8.4 (15.4)	2.1 (2.4)
> $71,602	103431 (25.0)	11427 (26.4)	26.5 (5.8)	16.2 (5.8)	4.9 (1.8)	5.3 (1.8)	0.19 (0.04)	12.3 (18.6)	3.1 (3.5)
Smoking									
Never Smoker	346811 (83.6)	32546 (75.0)	25.3 (5.0)	15.6 (5.1)	4.4 (1.6)	5.3 (1.8)	0.16 (0.03)	8.3 (15.8)	2.0 (2.6)

Ever Smoker	47260 (11.4)	7305 (16.8)	25.5 (5.2)	15.8 (5.2)	4.4 (1.7)	5.3 (1.8)	0.16 (0.04)	8.9 (16.5)	2.1 (2.7)
Smoking during pregnancy	20915 (5.0)	3547 (8.2)	25.2 (4.9)	15.5 (5.0)	4.3 (1.6)	5.4 (1.8)	0.16 (0.04)	8.9 (17.1)	1.9 (2.5)
Passive smoker									
Yes	8789 (2.1)	1080 (2.5)	24.8 (4.7)	15.1 (4.9)	4.2 (1.7)	5.5 (1.8)	0.16 (0.04)	8.6 (16.4)	1.6 (2.2)
No	404119 (97.9)	42212 (97.5)	25.3 (4.0)	15.6 (5.1)	4.4 (1.6)	5.3 (1.8)	0.16 (0.04)	8.4 (16.0)	2.0 (2.6)
Insurance type									
Medical	40142 (9.8)	4996 (11.6)	24.6 (4.5)	15.0 (4.7)	4.2 (1.6)	5.4 (1.8)	0.15 (0.04)	8.2 (16.1)	1.5 (2.0)
Other	367918 (90.2)	37971 (88.4)	25.4 (5.1)	15.7 (5.2)	4.4 (1.6)	5.3 (1.8)	0.16 (0.04)	8.4 (16.0)	2.1 (2.7)
Season of conception									
Warm season	204728 (49.3)	20976 (48.3)	25.3 (4.0)	15.3 (5.0)	4.4 (1.6)	5.3 (1.8)	0.16 (0.04)	8.5 (16.0)	2.1 (2.7)
Cool season	210292 (50.7)	22423 (51.7)	25.3 (5.0)	15.6 (5.0)	4.4 (1.6)	5.3 (1.8)	0.16 (0.04)	8.4 (16.0)	2.0 (2.6)

SD, standard deviation; NDVI, normalized difference vegetation index.

Table 3.2 Summary statistics and Pearson correlation coefficients between green space indicators.

	Mean (SD)	IQR	Total street green space	Tree	Low-lying vegetation	Grass	NDVI	Land-cover greenness	Tree canopy cover	Distance to park	Walkability score
Total street green space, %	25.28 (5.04)	5.99	1.00								
Tree, %	15.62 (5.13)	6.35	0.89	1.00							
Low-lying vegetation, %	4.36 (1.63)	1.96	0.06	-0.26	1.00						
Grass, %	5.30 (1.79)	2.28	0.22	-0.13	-0.01	1.00					
NDVI, (0-1)	0.16 (0.04)	0.05	0.40	0.35	0.00	0.14	1.00				
Land-cover greenness, %	8.41 (16.00)	9.22	0.16	-0.08	0.44	0.28	0.25	1.00			
Tree canopy cover, %	2.03 (2.61)	2.35	0.55	0.55	0.08	-0.11	0.48	0.06	1.00		
Distance to park, km	0.52 (0.45)	0.47	0.01	-0.09	0.07	0.21	-0.09	0.18	-0.12	1.00	
Walkability score, (0-20)	12.59 (3.32)	4.33	-0.05	0.11	-0.27	-0.19	-0.25	-0.45	-0.03	-0.16	1.00

SD, standard deviation; NDVI, normalized difference vegetation index.

Exposures	OR 95% CI
Street view green space, %	
Total green space	0.960 (0.934, 0.987)
Tree	0.946 (0.921, 0.972)
Low-lying vegetation	1.011 (0.985, 1.037)
Grass	1.046 (1.021, 1.072)
Green space indicators	
Mean annual NDVI (0-1)	1.094 (1.067, 1.122)
Land-cover green space, %	1.041 (1.022, 1.060)
Tree canopy cover, %	0.969 (0.945, 0.994)
Proximity to the nearest park	0.989 (0.972, 1.006)
Walkability score (0-20)	0.920 (0.897, 0.944)

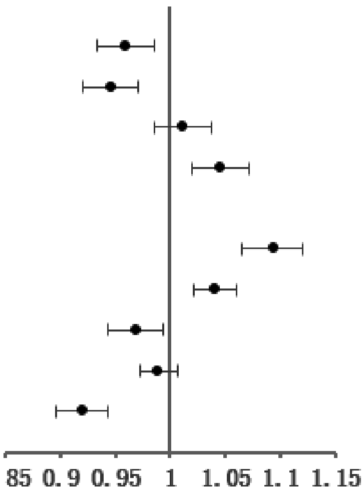

Figure 3.1 Adjusted odds ratios (ORs) and 95% confidence intervals (CIs) of maternal postpartum depression associated with residential green space and physical activity.

NDVI, normalized difference vegetation index.

ORs and 95% CIs were calculated for per interquartile range (IQR) increment for green space indicators; Models adjusted for maternal age, race/ethnicity, educational level, and block group household income.

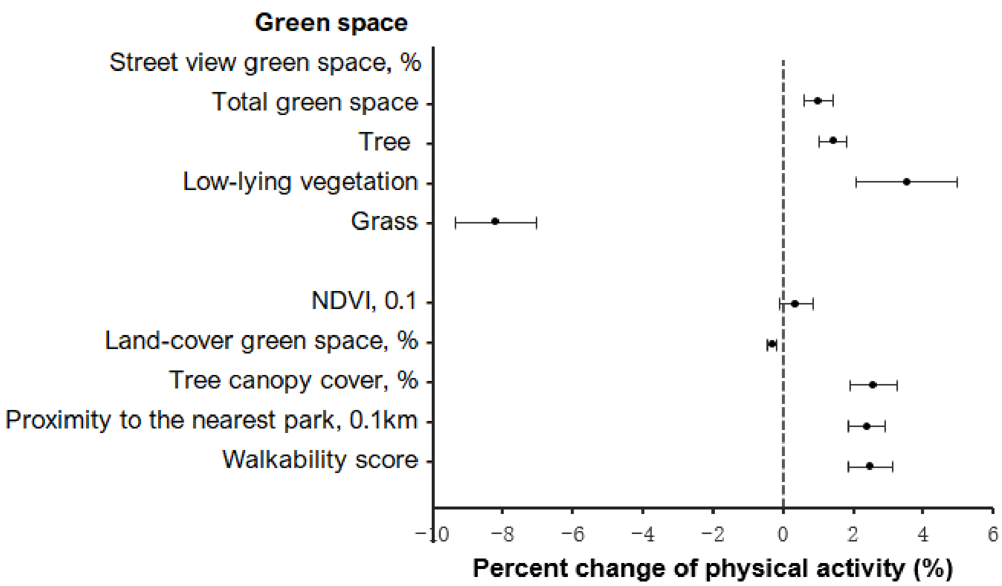

Figure 3.2 Percent change and 95% confidence intervals of the associations between residential green space and physical activity during the entire pregnancy.

NDVI, normalized difference vegetation index.

Models adjusted for maternal age, race/ethnicity, educational level, and block group household income.

Table 3.3 Proportions of the effects of green space exposure on postpartum depression due to mediation effects of physical activity during the entire pregnancy.

Green Space Indicators	Percentage mediated by physical activity and 95% CI, %
Street view green space	
Total green space	11.7 (5.9, 33.0)
Tree	10.0 (5.7, 18.0)
Tree canopy cover	15.6 (7.8, 84.0)
Walkability score	5.3 (3.5, 8.0)

Models adjusted for maternal age, race/ethnicity, educational level, block group household income, smoking during pregnancy, pre-pregnancy BMI and season of conception.

3.4 DISCUSSION

To the best of our knowledge, this is the first study to examine the relationship of diverse green space measurements, PPD, and the role of PA. In this large obstetric population residing in southern California from 2008 to 2018, I found that the main protective effects of green space on PPD were for the neighborhood-level green space exposure, rather than individual-level residential green space. Maternal exposure to neighborhood street green space, and tree coverage (i.e., street tree and total tree canopy cover), was associated with a reduced risk of PPD compared to NDVI, land-cover green space and proximity to park. A protective association between individual-level street low-lying vegetation and PPD was also observed. Moreover, our results revealed that the effects of green space on PPD was mediated by PA (9.6% -15.6%) during pregnancy.

Relationships between green space exposure and PPD has not been studied; previous research mainly focused on antenatal depression. While a possible protective effect of green space against depression during pregnancy has been reported (McEachan et al., 2016; Runkle et al., 2022), other findings were inconsistent (Nichani et al., 2017). Several limitations exist in previous studies, including potential outcome misclassification (e.g., solely self-reported questionnaires or diagnostic codes), and potential exposure misclassification due to the coarse measurements and limitations of remote-sensing imagery. In this study, I examined a comprehensive set of green space measures at both neighborhood- and individual-level, including the innovative street view-based green space and commonly-used satellite-based and park-related measures to facilitate comparison with other work. The individual-level residential green space and neighborhood green space might have different and independent impacts on health. For instance, neighborhood green space may contribute more to improve regional air quality by filtering air pollutants or reducing emission sources due to the competitive land use between green space and sources of air pollution, or provide cooling benefits for their surroundings. Neighborhood green space may also work more toward increasing social cohesion, or physical activities over longer distances (e.g., running). In this study, I found that the main effects of green space on PPD were for between-zip code effects of green space exposure, rather than individual green space within a small buffer around the maternal home.

For the between effect of neighborhood green space, consistent and protective associations between PPD and total green space based on eye-level street view images were observed, but not NDVI, land-cover green space, or distance to park. Unlike parks, street green space can be more frequently experienced and easily accessible in daily activities to all residents in a given neighborhood regardless of purposely using it or not (visual or presence). While the remote sensing images may better reflect the total amount of regional green space (including private green spaces or park and forest away from the road), street view green space may be more related to physical activity, social contacts, neighborhood safety and stress (Helbich et al., 2019; Lu et al., 2018; Shepley et al., 2019), which are important mental health-related factors. Although I observed increased PPD risk for NDVI and land-cover green space, I cannot conclude that green space is detrimental to PPD as such measures only reflect the top-viewed and total amount of greenness and miss valuable information on the type and quality of green space. For example, the most consistent results of crime reduction were among studies involving vegetated streets compared to large undeveloped green areas or other green spaces (Shepley et al., 2019). More land use dedicated to grass without tree canopy was associated with higher odds of incident fair to poor general health (Astell-Burt & Feng, 2019). Indeed, our findings showed that PPD was negatively associated with satellite-based tree canopy cover, but not total amount or other types of green space represented by NDVI or land-cover measures. For the land-cover green space exposure, total land cover or different landcover classes may have different roles in affecting mental health. For example, Tsai et al. found that closer distance to forest had lower prevalence of mental distress, whereas distance to shrubland had inverse correlation (Tsai et al., 2018). Therefore, the choice of exposure indicators can greatly impact the relationship between green space and health, at least for the mental health outcomes. Future studies should carefully select green space measures; analyzing green space-health associations using multiple indicators at multiple scales within a study is recommended.

While type of green space is important to understand potential mechanisms, develop targeted interventions and enhance urban planning, green space-related studies considering types of green space and mental health are sparse. A study in Singapore reported that tree canopy cover showed stronger associations with mental health than total green space cover or park area (Zhang & Tan, 2019). An Australia study associated exposure to higher total green space and tree canopy with lower incidence of psychological distress among adults older than 45 years, higher grass levels with higher risk, and low-lying vegetation with no consistent risk (Astell-Burt & Feng, 2019). However, no prior study has explored green space types and mental health among pregnant women, and existing studies were solely relied on satellite-based green space data. Green space from satellite data cannot fully reflect the vertical dimension of green space; vegetation beneath tree canopy is underestimated. Both satellite-based and street view-based green space types were considered in this study to overcome the constraints of remote sensing metrics, better classify eye-level green space types, and make a comparison. Results from this study are partially consistent with previous findings among general population. Consistently protective associations between PPD and neighborhood-level tree coverage from both satellite and street view imagery were observed; street tree showed the strongest association with PPD. In contrast, grass was positively associated with PPD risk, and no clear trend as observed for neighborhood low-lying vegetation. The larger associations of trees on depression compared to low-lying vegetation and grass might be partially explained by the tree canopy blocking the sun and providing shade to mitigate environmental nuisances caused by noise, heat and air pollution (Abhijith et al., 2017; Dzhambov & Dimitrova, 2015; Park et al., 2017); larger stature and biomass of trees on visual greenness; the aesthetic purpose of street trees (Nagata et al., 2020); the canopy ecosystem in relation to higher levels of biodiversity (Prevedello et al., 2017); and providing settings for recreation activities, such as physical activity and social interaction (Wang et al., 2019).

It is also noteworthy that the findings ought not be interpreted as evidence for reducing grassy areas (e.g., open grassland, grass playfield), which may bring possible health benefits for other populations (Taylor et al., 2001). Further, our machine learning model was not able to differentiate the quality of green space. For instance, the roadside weeds are usually not well-maintained as lawns in parks or communities to provide a valuable aesthetic use and recreation area; it may also imply other mental health-related confounders, such as traffic noise and air pollution. Indeed, despite the overall protective effect of total green space, higher quantities of grass relative to street tree coverage did not afford similar levels of benefit. Given a fixed amount of space, tree and grass may compete with each other on the land use. Decision-makers and city planners may consider increase the amount of tree coverage, especially street trees, to create a healthy living environment.

Regarding within-zip code effect of individual-level green space exposure, despite no significant association between neighborhood street low-lying vegetation and PPD, I found a clear negative relationship of individual residential low-lying vegetation and PPD, indicating that residential low-lying vegetation might have additional benefits on PPD with holding zip code average green space exposure remaining the same. Compared to trees and grass, the low-lying vegetation surrounding home (e.g., streets close to home, well-maintained yard) may provide better visual effect in the landscape with their unique physical characteristics, such as form, texture and color. The variety of eye-level bush, shrubs, even flowers, could be essential to provide interest and aesthetic appeal to a street scene, which can help release negative affect and improve mental health. More appealing landscaping of residential yard could discourage criminal behavior and increase the sense of security and calm among residents (Troy et al., 2016). Hedge, a tightly planted cluster of tall shrubs, can help provide homeowner shade and privacy. Further research of green space types is warranted to better understand what aspects of green space matter to maternal mental health.

The role of PA on the association of green space exposure and PPD was unclear. Two previous studies regarding green space and antenatal depression showed that PA may not (Nichani et al., 2017) or explain only a small portion (5.6% - 7.8%) (McEachan et al., 2016) of the effect of satellite-based green space exposures on depression during pregnancy. Results from this study suggest statistically significant mediation effect of PA between street view green space and PPD ranged from 9.6% - 15.6%. Relatively larger contributions of PA were observed for tree canopy cover and PPD. The proportion of the total effect of neighborhood walkability on PPD explained by PA was found (5.3%). Thus, it can be expected that PA could be a pathway of green space-depression relationship, especially in areas with better built environment (e.g., street intersection, sidewalks) and greener streets. Different data sources and types of green space metrics might be differently associated with PA during pregnancy. For example, unlike the consistent positive associations between PA and neighborhood street green space, higher NDVI and land-cover greenness may not increase PA during pregnancy; tree coverage and low-lying vegetation could promote PA during pregnancy, but not grass. Previous studies suggested that the physical activity levels of children and older adults was associated with the amount of space devoted to treed areas, not grass (Giles-Corti et al., 2005; Janssen & Rosu, 2015). Even though well-maintained grass fields (e.g., parks or playgrounds) can promote some lawn sports and activities, this is less relevant to PA during pregnancy. This evidence may be one possible reason that previous satellite-based green space studies without considering green space types reported no or very weak associations between green space exposure and maternal mental health. As yet, there was little research regarding street green space, vegetation types, PA and PPD. Further studies are warranted to investigate the role of PA on the relationships between green space and maternal mental health using multiple green space metrics.

A review study indicated that the associations of demographic factors with PPD are mixed and complex (Guintivano et al., 2018). In this study, higher incidence of PPD were observed among older mothers, African American or non-Hispanic white mothers, mothers with college education < 4 years, and mothers who live in middle- and high-income neighborhoods. Overall, results from stratified models suggest that the protective associations of street green space with PPD were stronger for population subgroups who were already at greater risk for depression disorders, including older mothers, non-Hispanic white mothers, and mothers with relatively higher education. Increasing exposure to street green space targeting the vulnerable subgroups could help reduce the burden of PPD in southern California.

The main strengths of this study include the use of street view-based green space data and vegetation types, as well as the comparison with the multiple green space indicators, including satellite-based metrics, parks, and walkability; data structures for both within- and between- effects of green space exposure; the large and diverse population from the KPSC pregnancy cohort; the high-quality clinical data from KPSC EHRs, especially PPD identification based on both clinical diagnosis and prescription rather than self-reported surveys or diagnostic codes; and comprehensive data that allowed us to test the mediation effect of physical activity and control for a wide range of potential covariates, including demographics, socioeconomic factors, individual lifestyles, and pregnancy comorbidities.

However, certain limitations should be considered when interpreting the study findings. First, given the temporal variations of green space levels were not taken into account, potential exposure misclassifications may exist. For example, most street view images from Bing Maps were randomly captured in different dates between 2014 and 2015 (99%). Thus, this database may not reflect seasonal or higher temporal resolution measurement, and I assumed the green space across the study region remained stable over the study period. Nevertheless, the variation of green space over seasons (Sun et al., 2020) and years (Appendix 3.1) tends to be small. I also included year of birth in my analyses to control for potential temporal confounding. Second, although a number of green space indicators were applied to reflect different aspects of green space exposures, perceived quality and use of green space, which might be more important than quantity (Feng & Astell-Burt, 2018), were not taken into account. Other potential confounders, such as psychiatric history and adverse life events, were unavailable in this analysis. Further, future research needs to consider physical activity in the postpartum period, which may have more immediate impacts on postpartum mental health compared to prenatal exercise. Finally, green space levels could vary in different regions, and attitudes of pregnant women toward physical activity could vary among cultures (Guelfi et al., 2015). Thus, there is also a strong need for studies conducting in other geographical settings and populations.

3.5 CONCLUSION

This large study based on clinical data provides a unique understanding of the relationship between green space and PPD. I found that the main protective effects of green space on PPD were observed for neighborhood-level green space compared to individual-level green space. Street view-based total green space exposure were associated with a decreased risk of PPD in southern California, not satellite-based NDVI, land-cover green space, or proximity to park. In addition, physical activity could be considered as one of the plausible pathways of green space and depression. Protection and restoration of tree specifically, rather than low-lying vegetation or grass, may translate into a more pronounced reduction of PPD and optimize the potential benefits of green space exposure for promotion of physical activity and maternal mental health.

Chapter 4. Physiological and affective responses to green space virtual reality among pregnant women

4.1 Objective of Present Study

In this chapter, I aimed to examine physiological and affective responses to green space in pregnant women, using simulated green space exposure through VR. I hypothesized that 1) exposure to green space in a VR immersive environment would improve short-term physiological and affective status on stress recovery among pregnant women; and 2) different levels of VR green space environments (i.e., low, medium, high) would have different effects on physiological and psychological responses.

4.2 METHODS

Overview

To examine the physiological and affective responses to different levels of urban green space and urban settings, 63 pregnant women were recruited for a laboratory experiment that lasted 60 minutes. Women first participated in the Trier Social Stress Test (TSST), a well-validated laboratory stress protocol (Kirschbaum et al., 1993), and were then randomly assigned to view one of three, 5-min, VR videos of an urban scene with different green space levels (i.e., low, moderate, and high). Stress responses to the TSST and VR immersion were measured via changes in blood pressure (BP), heart rate (HR), skin conductance level (SCL), salivary alpha-amylase (sAA), salivary cortisol (SC), and affect.

4.2.1 Procedures

The study visits of pregnant women occurred between 8-14 weeks' gestational age and included the TSST, serial physiological measurement (i.e., BP, HR, and SCL), saliva collection and questionnaire. All subjects participated in the experiment between 1:30 p.m. and 5:30 p.m. to control for diurnal variations of cortisol secretion (Weitzman et al., 1971). Study participants were instructed to avoid food intake for 2 hours before study onset.

The timeline and experimental procedures are summarized in Figure 4.1. First, participants completed informed consent, and sat for 10 minutes to rest, while a researcher introduced the experimental procedure, devices and questionnaires. Then, participants wore the biomonitoring sensors to conduct Measurement 1 (T0, baseline), including BP, HR, and SCL, sAA, SC and survey (i.e., demographic and health condition data, the Perceived Stress Scale, and affect). Next, Following Measurement 1, women participated in the TSST to induce a moderate level of stress, and then immediately completed Measurement 2 (T1, immediately after TSST). Next, participants were randomly assigned to watch one of the three 5-min green space VR videos. During the "virtual exposure" part, the 360-degree videos were projected on the VR headset for participants to watch freely. Neither participants nor investigators knew which video the participants would be watching. This double-blind experimental approach eliminated threats to internal validity that might have arisen from the unconscious behavior of the investigators or the desire to please the investigators on the part of the participants. Immediately after the VR immersive experience, the participants completed Measurement 3 (T7, +7 min after TSST/ immediately after the VR green space exposure). Finally, the sensors were removed and the participants were escorted to a waiting room where two additional saliva samples were collected for later cortisol assessment (15, and 30 minutes after TSST). Taken together, the experiment lasted approximately 60 minutes.

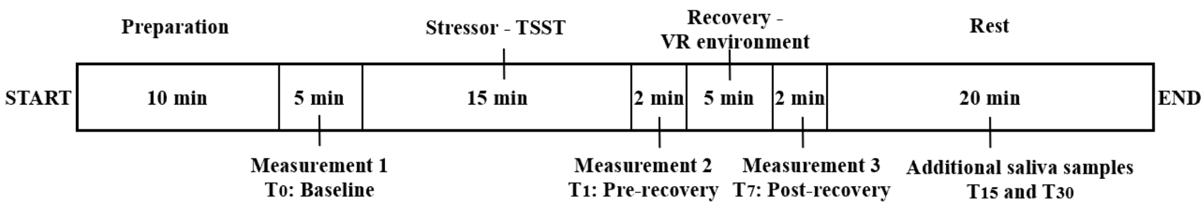

Figure 4.1 Timeline of experimental procedure.

Measurement 1: (T0, baseline) BP, EEG, sAA, SC, and survey (basic information, health status, Perceived Stress Scale questionnaire, and PANAS); Measurement 2: (T1, immediately after TSST) BP, EEG, sAA, SC, and survey (PANAS); Measurement 3: (T7, +7 min after TSST/ immediately after the VR green space exposure) BP, EEG, sAA, SC, and survey (PANAS, attitudes toward green space, and simulator sickness); T15 and T30: salivary cortisol; HR and SCL: real-time data throughout the experiment before the rest.

* BP: blood pressure, EEG: electroencephalogram, sAA: salivary alpha-amylase, SC: salivary cortisol, PANAS: Positive and Negative Affect Scale, HR: heart rate, SCL: skin conductance level.

4.2.2 Study population

From April to July in 2021, 63 healthy pregnant women were recruited from Beijing, China to participate in this study. To mitigate the influence of maternal hormone changes during pregnancy (Soma-Pillay et al., 2016), only individuals between 8-14 weeks' gestational age were eligible. For each participant, I gathered demographic, behavioral, and health-related data, including age, household income, taking medication or treatment, smoking, drinking, sleep quality, and current stress level in the baseline survey. Individuals who were younger than 18 years old, carried more than one fetus, taking medicine (e.g., psychoactive, beta-blockers, glucocorticoids), with a medical history of chronic diseases (e.g., endocrine, cardiovascular, psychotic disorder, and others), and who have used tobacco or alcohol within 24 h prior to the experiment were excluded from the study.

This study was approved by the Institutional Review Board of the Peking University and the University of California, Irvine.

4.2.3 Virtual reality green space exposure

To simulate virtual reality green space exposure in this laboratory experiment, I generated three 5-min 360-degree, three-dimensional (3D) VR videos of urban green environments. To create the videos, I first identified several streets and parks with varying levels of green areas in Beijing, China. At each site, I recorded the surrounding visual characteristics. To minimize the influence of other physical characteristics, such as building density, building quality, road surface, and general maintenance of the neighborhood, I compared 8 videos of streets and picked 2 sites with similar physical characteristics as the low and moderate green space environment. One video of urban park was picked as the high green space environment. For each selected site, I repetitively filmed for 5 times to collect the smoothest shot without detectable friction or waggle and with the least changes in sunlight intensity. All videos were taken on sunny days without strong winds in the summer (July to August, 2020) between 10:00 a.m. and 3:30 p.m. to reduce different sun angles and shadows (Ulrich et al., 1991). The videos were presented with low volume and similar background sounds without environmental noises, since a soundless visual feature renders an environment more fearful and more stressful for the participants (Annerstedt et al., 2013). People, animals, or moving vehicles were not contained in the videos to limit confounding characteristic and minimize distractions. Three 5-min videos with low, moderate, and high level of urban green space exposure were created. Equal-area projection and Semantic Segmentation method was used on the panoramic photos to calculate the area occupied by green space (e.g., trees, shrubs, and grasses), then divided it by the total area in the image to obtain the green areas ratio (Zhang et al., 2021). In this study, the level of green space exposure was defined as Low: 0%, urban street view without green space; Moderate: 12%, urban street view with green space; and High: 50%, open space with high green space level (e.g., urban park). Participants viewed the VR environments through a VR headset (iQIYI Qiyu 2Pro, iQIYI, Inc., Beijing, China).

Figure 4.2 Panoramic photos of the three VR environments, all located in Beijing: (a) High: 50%, urban park; (b) Moderate: 12%, urban street view with green space; (c) Non-green space: 0%, urban street view without green space.

4.2.4 Inducing stress

The TSST was used to induce psychological stress in a laboratory setting (Kirschbaum et al., 1993). The TSST is a standardized laboratory stress protocol, which consists of a preparation period in silence, a public speech as a mock job interview, and a mental arithmetic task (each of 5 min duration) in front of three interviewers and a video camera. The TSST has been widely used to induce mental stress under controlled conditions (Kudielka & Wust, 2010; von Dawans et al., 2011), and has reliable effects to induce stress across various age groups (Dickerson & Kemeny, 2004). It has been used in stress research to induce moderate psychological stress in pregnant women (Deligiannidis et al., 2016; Kofman et al., 2019; Nierop et al., 2006).

4.2.5 Outcome measurements

In order to assess the short-term physiological stress responses, I used immediate stress indicators, including BP, HR, and SCL in the experiment (Berto, 2014; Brown et al., 2013; Jiang et al., 2014; Klinkenberg et al., 2009; Yin et al., 2019; Yin et al., 2018). They were measured by two wearable biomonitoring sensors: Empatica E4 wristband (Empatica Inc., Boston, MA) and upper arm blood pressure monitor (HEM-7125J, Omron Healthcare (China) Co., Ltd, China). Blood pressure (in unit of mmHg) was measured 3 times (Measurement 1: T0, baseline; Measurement 2: T1, immediately after TSST; Measurement 3: T7, +7 min after TSST/ immediately after the VR green space exposure) during the experiment. The wristband collects data in real time, measuring the HR (beats per minute, bpm) and SCL [in unit of micro- Siemens (μS)] every second throughout the experiment. To represent the three stages of the experiment for real-time measurements (i.e., baseline, stressor, and recovery), the averages of HR and SCL were calculated internally at baseline (i.e., pre-stress, 5-min), TSST (15-min), and VR immersion (5-min), respectively. Furthermore, participants' alpha-amylase (N=3) and cortisol (N=5) (Deligiannidis et al., 2016; Dickerson & Kemeny, 2004; Thoma et al., 2012) were obtained from salivary samples collected at Measurement 1-3, T15 and T30 min. Each participant chewed on an oral swab for approximately 45 seconds until the swab (Salivette, SARSTEDT AG & CO. KG, Germany) was saturated with saliva.

In addition, I used the Positive and Negative Affect Scale (PANAS) (Watson et al., 1988) to measure self-reported affect three times during the experiment. The PANAS has been widely used as a self-reported measure of affect in both the community and clinical contexts (Clark & Watson, 1991) and has been validated in several languages, including Chinese (Huang et al., 2003). It consists of 20 items describing different emotions and feelings. Using a 5-point Likert-type scale, participants were asked to indicate the extent to which they "feel this way right now". The PANAS has two subscales, reflecting positive (i.e., attentive, active, alert, excited, enthusiastic, determined, inspired, proud, interested, and strong) and negative (i.e., hostile, irritable, ashamed, guilty, distressed, upset, scared, afraid, jittery, and nervous) emotions. Sum scores were used to create an overall score (range 10 to 50), as well as the positive and negative emotion subscale scores. Higher scores represent higher levels of positive/negative affect. The Perceived Stress Scale (10-item) (Cohen et al., 1983) was used in the baseline survey for measuring the perception of stress during the last month before the experiment. In Measurement 3, I also surveyed participants' attitudes toward green space and feelings of VR motion sickness, which may lead to potential bias in the physical and affective measurements.

4.2.6 Statistical analysis

Descriptive statistics were performed to describe demographic characteristics, physiological measurements and questionnaire data. Analyses of variance (ANOVA) was applied to test the effectiveness of randomization at baseline and after stressor. Required assumptions of ANOVA such as normality, sphericity, and equal-variance, were checked. In addition, SCL data was log transformed since they were right skewed. Paired t-test, or Wilcoxon signed-rank test was used to test the effectiveness of stressor to determine if participants' stress levels immediately after the TSST (T1) were significantly higher than their baseline measures.

I used the pre-post recovery differences (time-point data: T1 vs. T7, real-time data: TSST vs. VR immersion) among physiological measurements, including BP, HR, SCL, salivary alpha-amylase, and salivary cortisol, as the dependent variables in a linear model to analyze the differences of pre-post changes in VR environments of middle and high green groups versus those in non-green group. The mixed model for repeated measures was applied for salivary cortisol levels. For self-reported affect variables, I further conducted exploratory factor analysis to determine the internal structure of a list of positive or negative affect variables. The exploratory factor analysis is a statistical technique that seeks to reduce the dimensionality of a large number of measured variables by categorizing them into groups (latent underlying factors) according to the correlations between the measured variables (Watson, 2017). Scree plot was used to determine the number of factors to retain in the exploratory factor analysis. If self-reported affect variables of the PANAS questionnaire are classified together into one or more common categories, it suggests that those affects arise from similar underlying processes. These variables can be combined into a group or a "factor" (i.e., the sum score of the specific items) and then be used in the linear model to analyze the effect of VR green space exposure on stress recovery. All hypothesis tests were two-sided and P values <0.05 were considered as statistically significant. All analyses were performed with SAS version 9.4 (SAS Institute, Inc., Cary, NC).

4.3 RESULTS

Demographics, baseline measures and stressor

Table 4.1 presents the characteristic of the 63 participants at baseline. Participants had an average age of 32, with similar educational levels among three groups. Participants also reported similar scores for sleep quality and stress level. The average room temperature (25 ± 1°C) and relative humidity (40 ± 9%) indoors stayed consistent during the experimental periods. There were no statistically significant differences of demographics and indoor environmental quality among the three randomized groups, indicating the success of the randomization. No participant reported dislike of green space or severe motion sickness during VR immersion.

Table 4.1 Characteristics of study participants (n = 63) at baseline of the experiment by three randomized groups with low, medium and high exposures to green space.

Baseline characteristics	Green Space Environment		
	High	**Middle**	**Low**
Number of participants	21	21	21
Maternal age, years, mean (SD)	31.8 (2.4)	31.8 (2.7)	31.7 (3.0)
Maternal education, n (%)			
College or below	17 (81.0)	19 (90.5)	18 (85.7)
Higher than College	4 (19.0)	2 (9.5)	3 (14.3)
Gestational age, week	11.3 (2.2)	10.8 (1.7)	11.0 (2.1)
Sleep quality, 0-4	2.0 (0.6)	2.0 (0.5)	2.0 (0.7)
Self-reported stress level, 0-40	12.1 (5.7)	11.2 (5.4)	11.6 (6.7)
Indoor environment quality, mean (SD)			
Temperature, °C	24.8 (0.9)	24.7 (0.9)	24.6 (0.9)
Relative Humidity, %	39.5 (9.4)	40.2 (9.1)	41.0 (10.4)

SD, standard deviation.

Participants' physiological and psychological measures among three groups at baseline, pre-recovery (i.e., post-stressor) and post-recovery are shown in Figure 4.3. I observed that participants' physiological and affective stress levels increased significantly after the TSST, except DBP for the middle green space group. These results demonstrate that the TSST was an effective stressor for the participants. In addition, ANOVA results show no differences in effect sizes of the TSST between groups in BP, HR, SCL, salivary alpha-amylase, salivary cortisol, and self-reported affect, suggesting that there were no significant differences in stress level after the TSST between the three groups.

Different changes in stress indicators after VR immersion in different levels of green space exposure were observed.

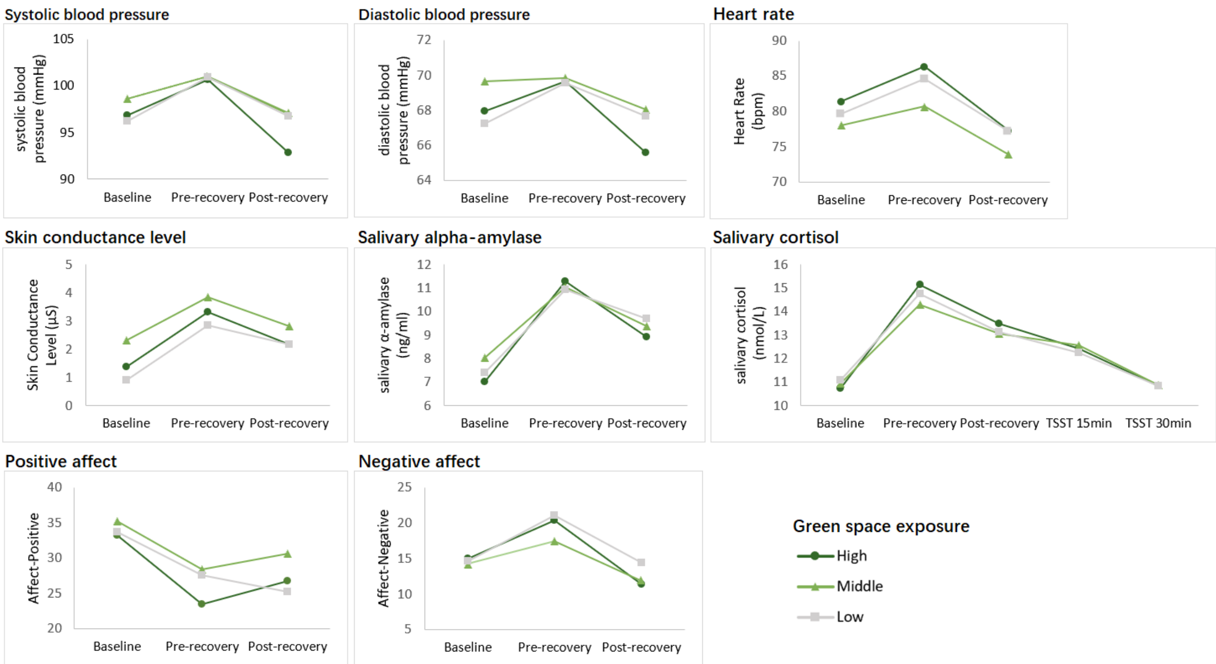

Figure 4.3 Average physiological and psychological measures at baseline, pre-recovery/post-stressor and post-recovery period in three environments.

Effect of green space environments on pre-post changes of physiological measures

In general, compared to the non-green environment (i.e., low group), participants experiencing green space environments during the recovery period had consistently greater decreases of systolic blood pressure (SBP), diastolic blood pressure (DBP), HR, SCL, salivary alpha-amylase, and salivary cortisol (Figure 4.4 and Table 4.2), especially for the high green space group. Specifically, high green space exposure was associated with 4.6 (95% CI: -8.5, -0.6) mmHg greater decrease in SBP as well as 1.2 (95% CI: -2.3, -0.2) ng/ml greater decrease in sAA concentration, respectively. However, I did not find substantial differences for DBP, HR, SCL (T7) and salivary cortisol (T30) compared to the non-green environment. Green space exposure did not show a significant effect on salivary cortisol levels as well, when considering multiple time points of salivary cortisol after the VR immersive experience (i.e., T7, T15 and T30).

Table 4.2 Estimated differences in pre-post changes in physiological and psychological measures in green space environments versus non-green environment during the 5-min recovery period.

Pre-post changes (95% confidence interval)	**High**	**Middle**
Physiological measures		
Systolic Blood Pressure (mmHg)	**-4.57 (-8.51, -0.64)**	-0.61 (-4.60, 3.37)
Diastolic Blood Pressure (mmHg)	-1.86 (-4.41, 0.69)	0.24 (-2.31, 2.79)
Heart Rate (1/min)	-1.77 (-5.52, 1.98)	-0.37 (-4.12, 3.39)
Log (Skin Conductance Level) (μS)	-0.20 (-0.67, 0.28)	0.12 (-0.35, 0.59)
Salivary Alpha-Amylase (ng/ml)	**-1.22 (-2.26, -0.18)**	-0.57 (-1.61, 0.46)
Salivary Cortisol (nmol/L)	-3.13 (-15.76, 9.51)	4.20 (-8.28, 16.68)
Positive and Negative Affect Scale (points)		
Overall positive affect	**6.62 (0.29, 12.95)**	5.67 (-0.66, 11.99)
Positive Factor 1	**6.38 (0.96, 11.80)**	4.24 (-1.18, 9.66)
Positive Factor 2	0.24 (-1.45, 1.92)	1.43 (-0.26, 3.11)
Overall negative affect	-3.29 (-8.36, 1.79)	0.90 (-4.17, 5.98)
Negative Factor 1	**-2.62 (-5.19, -0.04)**	0.62 (-2.07, 3.31)
Negative Factor 2	-1.33 (-3.49, 0.82)	-0.57 (-2.73, 1.59)
Negative Factor 3	0.67 (-0.90, 2.23)	0.86 (-0.70, 2.42)

Note: Reference: low green space group; Positive Factor1 "Happiness": excited, enthusiastic, determined, inspired, proud, interested, strong; Positive Factor2 "Attention": attentive, active; Negative Factor1 "Anxiety": afraid, scared, jittery, nervous; Negative Factor2 "Anger": hostile, irritable, distressed, upset; Negative Factor3 "Shame": ashamed, guilty. SCL data were log-transformed in the regression model. Significant results were bolded.

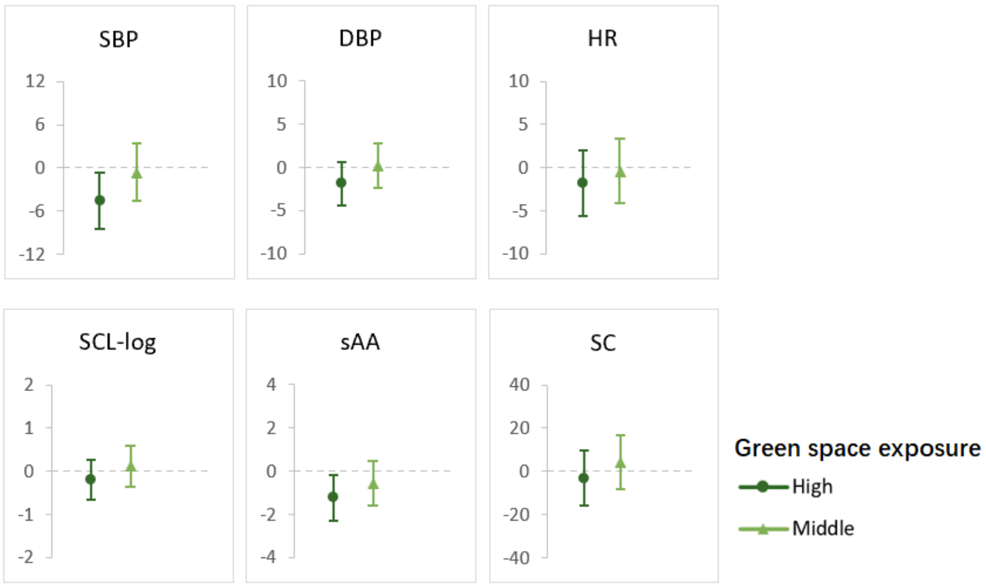

Figure 4.4 Estimated differences in pre-post changes in physiological measures in green space environments versus non-green environment during the 5-min recovery period.

Note: SBP: Systolic blood pressure (mmHg); DBP: Diastolic blood pressure (mmHg); HR: Heart rate (bpm); SCL: Skin conductance level (μS); sAA: Salivary alpha-amylase (ng/ml); SC: Salivary cortisol (nmol/L). SCL data were log-transformed in the regression model. Error bars depict 95% confidence interval.

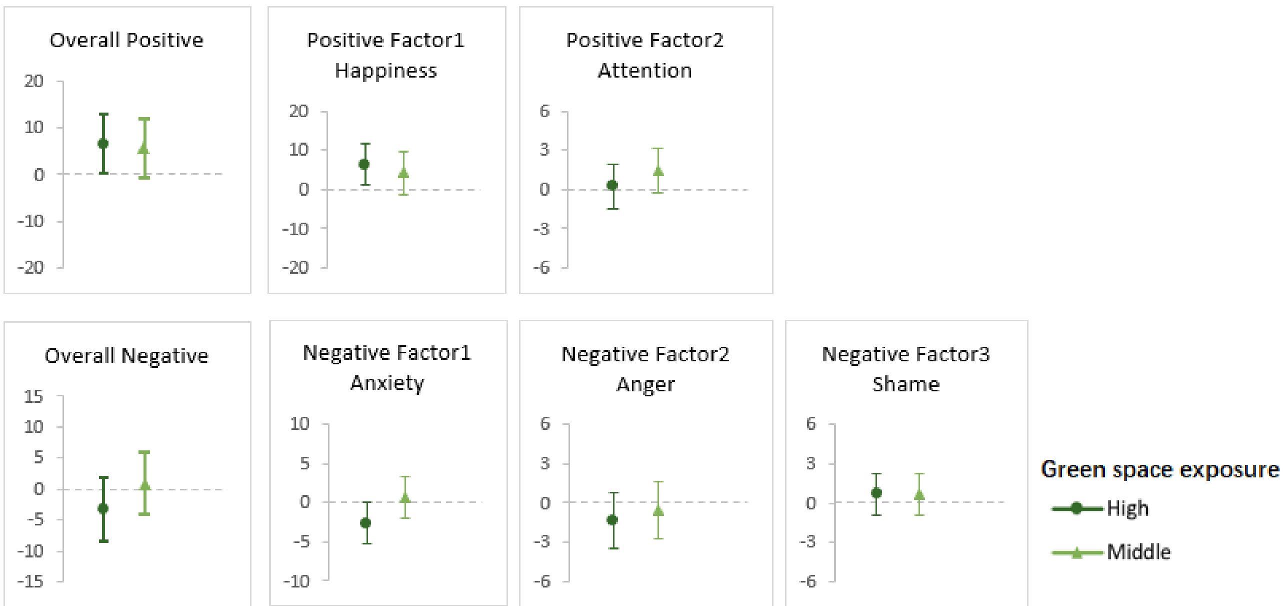

Figure 4.5 Estimated differences in pre-post changes in psychological measures in green space environments versus non-green environment during the 5-min recovery period.

Note: Positive Factor1 "Happiness": excited, enthusiastic, determined, inspired, proud, interested, strong; Positive Factor2 "Attention": attentive, active; Negative Factor1 "Anxiety": afraid, scared, jittery, nervous; Negative Factor2 "Anger": hostile, irritable, distressed, upset; Negative Factor3 "Shame": ashamed, guilty. Error bars depict 95% confidence interval.

Effect of green space environments on pre-post changes of affective responses

According to the scree plot in the exploratory factor analysis, two factors from 10 items of the positive affect and three factors from 10 items of the negative affect were identified to sufficiently explain the sample correlations, respectively (Appendix 4.1). The variables "excited, enthusiastic, determined, inspired, proud, interested, strong" had the highest rotated loadings on "Positive Factor1- Happiness", accounting for 75.6% of the variance. "Afraid, scared, jittery, nervous" had the highest loadings on "Negative Factor1 - Anxiety", explaining 37.1% of the variance in the data.

In general, participants reported higher overall positive scores after recovery compared to their scores before recovery (i.e., after stressor) in both high and middle green space groups. Compared to the change of positive scores in the low green space environment, participants in the high green space group had significant increase in overall positive score (6.6, 95% CI: 0.3, 13.0). Furthermore, the results from factor analysis show that participants were recovered from stress by feeling more positive emotions regarding happiness, but not the subscale of attention (Figure 4.5 and Appendix 4.1).

For the negative affect scale, the difference of the overall negative score between green vs. non-green exposure groups was similar. However, the high green space group had a mean value of "Negative Factor1 - Anxiety" that was 2.6 points lower (95% CI: -5.2, -0.04) than that of the non-green exposure group, suggesting that high green space environment effectively relieved stress by reducing nervousness and fear. No substantial difference was found among the affect subscales of anger and shame between green space groups.

4.4 Discussion

This study investigated the physiological and affective responses to green space exposure on stress recovery among 63 pregnant women. Participants were randomly assigned to explore one of three virtual urban scenes with different green space levels (Low: urban street view without green space; Middle: urban street view with a moderate level of green space; and High: urban park). Overall, these findings indicate that short-term exposure of pregnant women to VR green space environments had better post-stress restorative effects both physiologically and psychologically compared to those exposed to the non-green space environment. Exposure to high green space environment in park-like setting had the strongest impacts on stress recovery in this study.

For the general population, benefits of green spaces on stress reduction have been shown in previous VR-based studies. An experimental study in Canada found that 69 students who explored a virtual nature environment with dense vegetation had significantly improved self-reported affect and significantly lower skin conductance levels compared to those who explored a virtual urban or geometric environment (Valtchano & Ellard, 2010). VR immersion in a park and forest environment in Sweden, but not an urban area without green space, was associated with significant stress reduction as indicated by reduced skin conductance levels (Hedblom et al., 2019). Another study of 100 healthy adults from Boston reported reduced blood pressure and anxiety among participants viewing outdoor green space through VR versus those viewing a non-biophilic environment (Yin et al., 2020).

Most existing experimental research involving responses to natural environments and VR studied college students or healthy adult populations. It cannot be assumed that similar effects would be seen in other populations, such as younger or older populations, clinical populations, or individuals with limited access to outdoor nature (Li et al., 2021). For pregnant women, maternal hormone activity and psychological changes during pregnancy may lead to different stress responses compared to the general population (Mastorakos & Ilias, 2003; Newham & Martin, 2013). To the best of our knowledge, no study has explored virtual green space effects on stress recovery among pregnant women who might benefit more from mental health promotion during pregnancy.

Our results of the beneficial impacts of visual exposure to green space are partially consistent with previous findings in the general population, including improved blood pressure and self-reported affect. Importantly, I explored the research gap regarding affective responses to green space among pregnant women; the results indicate that exposure to high green space environment results in increased overall positive affect and decreased negative affect. Having lasting sad or anxious moods are major symptoms of depression, as well as perinatal depression. In this study, high green space exposure contributed to better stress recovery by increasing happiness and decreasing anxiety, suggesting significant acute improvement in depression-related affective responses in the short-term experiment setting. Future research is needed to investigate whether such short-term impacts can lead to longer term improvement of affective responses during pregnancy.

In terms of skin conductance level, electrodermal activity has largely been used to measure the impacts of environments on acute stress recovery (Frumkin et al., 2017). While we would expect a drop in arousal levels as the sympathetic nervous system recovers from the stressful task in nature environments (Hedblom et al., 2019; Jiang et al., 2014), other findings are inconsistent (Browning et al., 2019; Yin et al., 2020). In this study, no significant differences were observed for skin conductance levels between three green space environments. Gender difference might be one of the potential reasons that may partially explain the inconsistent results in terms of skin conductance levels. Green space may induce more pronounced recovery from a stressful event in males compared to females (Jiang et al., 2014). In addition, skin conductance levels did not recover back to baseline in all VR environments, suggesting that the sympathetic activation may need more time to completely recover (i.e., 5-min recovery period in this study). Furthermore, during the recovery phase, participants' feelings of interest and engagement in green space environments may cause increased physiological arousal and support positive affect maintenance. On the contrary, reduction of physiological arousal may reflect negative affect, such as boredom and disengagement. Thus, a single metric of electrodermal activity might not be a good indicator of affective arousal and may produce mixed findings (Felnhofer et al., 2015). The link between arousal and emotional reaction to different VR environments, including subjective (e.g., self-reported affect) and objective (e.g., skin conductance), is still a conflicting theoretical debate. Further research is needed to enhance our understanding of the link between electrodermal activity and VR green space exposure in a comprehensive discussion, such as designing longer recovery period and/or monitoring period, considering more emotional states, combining physiological measurements and subjective feelings, and using comparable technologies (e.g., standard questionnaire) to improve cross-study comparability.

Both sAA and salivary cortisol serve as valid and reliable indicators of stress (Ali & Nater, 2020). However, only few studies have used sAA (X. Wang et al., 2019) and salivary cortisol (Annerstedt et al., 2013; Jiang et al., 2014) to examine the associations between stress recovery and green space exposure after an acute stressor. In previous studies, post-recovery salivary cortisol changes were not observed (Annerstedt et al., 2013) or only observed for male, not for female participants (Jiang et al., 2014). Moreover, the study involving sAA only focused on forest environments rather than urban environment (X. Wang et al., 2019). In this study, I used both sAA and salivary cortisol and compared their responses. It is noteworthy that significant pre-post changes between the three green space environments were observed for sAA, but not for salivary cortisol. The different responses between sAA and salivary cortisol may be partly explained by the different biological systems of stress responses: 1) the sympathetic nervous system (part of the autonomic nervous system), which is activated immediately after stressor occurs, and 2) the HPA axis, which is activated minutes after certain types of stressors occur. In response to stress, sAA and salivary cortisol are produced respectively by the sympathetic nervous system and the HPA axis (Maruyama et al., 2012). The sAA is sensitive to momentary emotional arousal (Giesbrecht et al., 2013), which can reflect acute stress challenge and short-term recovery, and be captured during a short time after the exposure. On the other hand, it appears as though the VR manipulation was too subtle to manipulate cortisol trajectories through HPA axis among pregnant women, and future research should test whether cortisol trajectories in non-pregnant women may be moderated by this intervention. In addition, the TSST elicits a prompt and high stress-related cortisol increase. Subsequently, the relief in ending the stressful task may lead to a large cortisol drop for every participant; the magnitude of decrease may mask small differences in the change of cortisol levels due to different green space exposure (Annerstedt et al., 2013). Moreover, there is evidence suggesting that some of the health benefits of participation in restorative activities may not be immediate but can be delayed (Bershadsky et al., 2014). Future research regarding the stress response and green space exposure is necessary.

Studies of urban green space are of interest for city planners aiming to create a safe and healthy living environment. To make the results more generalizable, the selected sites in the VR videos are all common environments in cities and parks. Results from this study suggest that, in comparison to non-green space environments or small green space features (e.g., street trees and roadside vegetation), open space with high green space levels (e.g., urban parks, community gardens, private yards) may lead to a more pronounced reduction of stress among pregnant women. A previous study focused on general population reported similar results that the VR photo of park and forest, but not the non-green urban street, provided significant stress reduction (Hedblom et al., 2019). In addition, the results showed that even a short immersion in VR green space environment can be considered a potential surrogate for real nature exposure to ease stress and promote mental health during pregnancy, in particular when actual nature exposure may not be possible.

This study has several strengths. First, the employment of 3D 360-degree VR video could provide a more immersive experience of exposure to a green space environment compared to traditional visual stimuli. Second, a wide range of physiological measurements and biomarkers in combination with psychological questionnaires was used in this study to comprehensively monitor participants' physiological and affective stress responses. Furthermore, double-blinding and the randomization design minimized potential bias and confounding factors. Moreover, exploratory factor analysis was applied in the affective analysis to identify the hidden from high dimensional data with inter-related affect variables, which provided more nuanced insights about emotional effects of green space on stress recovery.

However, this study has limitations, which suggest avenues for further research. First, although VR technology provides the participants' immersive experience of exposure to virtual urban scenes, it is not the same as the real world. Nevertheless, studies have shown that the physiological and cognitive responses are consistent between VR environments and real physical exposure (Browning et al., 2019; Yin et al., 2018). Future studies may use computer-generated scenarios (Yeo et al., 2020) or actual nature environments to induce a greater sense of presence. In addition, solely visual connection with the environment were presented in the VR simulations without considering auditory, olfactory, and their interactions, which may strengthen the overall effects due to the potential multisensory benefits (Browning et al., 2019; Hedblom et al., 2019). As a counterpoint, however, using VR allowed us to isolate visual impacts from the mix of other sensory factors and study a specific pathway between green space and stress recovery. Moreover, the psychological state in pregnancy is not a stable construct, but is dynamic and fluctuates as gestation progresses (Newham & Martin, 2013). Future studies may explore the impact of green space on stress during late pregnancy rather than early pregnancy. Lastly, only three conditions of urban scenes in Beijing were included in this study: an urban street without green space, an urban street with moderate-level green space, and an urban park with high-level green space. Further studies may consider different dosages of urban green space as well as various kinds of landscapes in other regions.

4.5 CONCLUSION

In this study, I found that visual exposure to a green space environment in VR was associated with lower systolic blood pressure, reduced salivary alpha-amylase, improved positive affect and decreased negative affect compared to non-green space environment, suggesting that even short exposure to a green space environment resulted in both physiological and affective stress reduction among pregnant women. VR nature experiences, especially in parks with higher green space, could be an effective way to reduce stress and improve mental health and well-being during pregnancy. Urban planners may consider that improved urban parks may optimize the benefits of green space to stress recovery during pregnancy.

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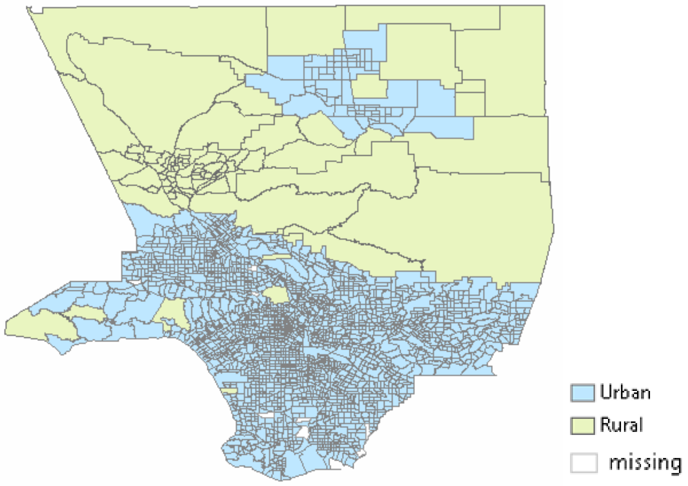
Appendix 2.1 Summary statistics of green space indicators and socioeconomic factors.

Exposures	Mean	SD	Min	25th	50th	75th	Max
Tree, %	16.9	4.4	6.6	13.6	16.0	19.5	33.1
Low-lying vegetation, %	4.6	1.4	2.2	3.7	4.3	5.1	12.7
Grass, %	4.9	1.4	1.3	4.0	4.8	5.7	13.8
Total green space, %	26.3	4.9	17.7	22.8	25.3	28.8	46.7
NDVI	0.13	0.04	0.03	0.11	0.13	0.16	0.31
Educational Attainment, %	24.3	17.9	0	8.0	21.5	38.2	74.8
Linguistic Isolation, %	15.0	11.6	0	5.6	12.5	21.3	67.9
Poverty, %	40.8	21.0	0	22.0	40.1	57.9	94.9
Unemployment, %	10.3	4.7	0	7.2	9.7	12.8	100.0
Housing Burden, %	23.3	9.6	2.4	16.2	22.5	29.8	67.2
Population Characteristics Score, 0-10	5.8	2.1	0.3	4.2	6.1	7.5	9.7
CalEnviroScreen3.0 score, 0-100	36.5	16.3	1.3	23.3	36.4	49.3	80.7
Non-white population, %	71.4	26.6	0	48.9	81.0	95.2	100.0
Sampling points per tract	103	231	0	28	63	115	5269

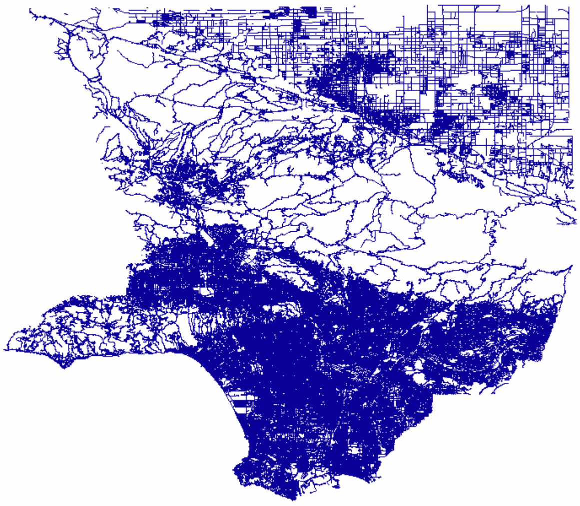
SD, standard deviation. NDVI, normalized difference vegetation index.

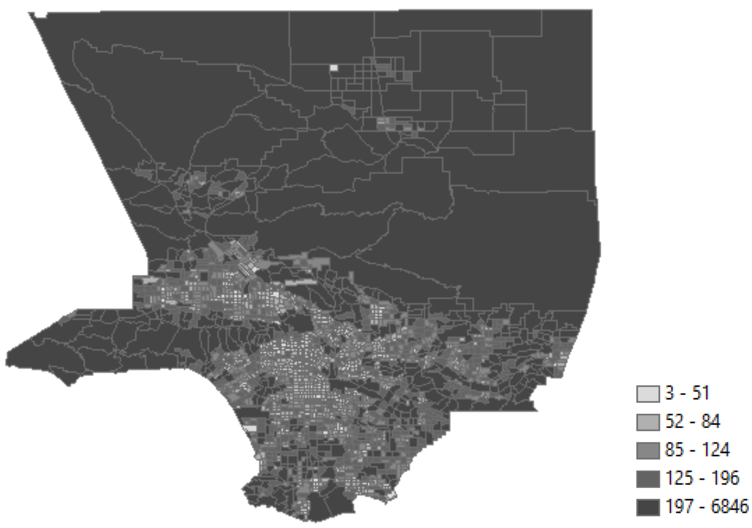
Educational Attainment: Percent of population over 25 with less than a high school education; Linguistic Isolation: Percent limited English speaking households; Poverty: Percent of population living below two times the federal poverty level; Unemployment: Percent of the population over the age of 16 that is unemployed and eligible for the labor force; Housing Burden: Percent housing burdened low income households.

Appendix 2.2 The urban/rural status, street network and the number of sampling points along the street per census tract, Los Angeles County.



Urban areas: the rural-urban commuting area (RUCA) code = 1; Rural areas: RUCA code >1; Missing: RUCA code = 99.





Appendix 2.3 Popular Semantic segmentation models.

Cityscapes 2020 Rank	Model/Method	Cityscapes 2020 mean IoU	Year	Type of Improveme nt	Description	Advantages
1	Hierarchical Multi-Scale Attention + HRNet-OCR [1]	85.1%	2020	Mechanism	A hierarchical attention mechanism by which the network learns to predict a relative weighting between adjacent scales to best combine predictions from multiple inference scales and get more refined segmentation results	Objects of different sizes are inferenced by networks of different resolutions
2/5	HRNetV2+OCR+ [2]	84.5%	2019	Architecture	A high-resolution representation model with object-contextual representation technique to enhance the semantic segmentation performance on high-resolution images	Connect high-to-low resolution convolutions in parallel; Maintain high-resolution representations through the whole process; Repeat fusions across resolutions to strengthen representations
3	EfficientPS [3]	84.2%	2020	Architecture	A panoptic segmentation model with: 1. Backbone-network：EfficientNets 2. 2-way Feature Pyramid Network 3. semantic segmentation: Separable Convolution 4. instance segmentation: Mask RCNN	More Efficient; Better Performance; Panoptic Segmentation is a new trend
4	Panoptic-DeepLab [4]	84.2%	2019	Architecture	A panoptic segmentation model with: The semantic segmentation branch: DeepLab The instance segmentation branch: class-agnostic. bottom-up	1-stage is faster than 2-stage; Bottom-up instance segmentation branch; Panoptic Segmentation is a new trend

6	Densely Connected Neural Architecture Search (DCNAS) [5]	83.6%	2020	Architecture Search	The NAS approach is used to solve the search problem of network width, named DenseNAS: to construct a new intensively connected search space, and to design a super network as a continuous representation of the search space	Automatically search for the best model fit for current dataset
7	DeepLabV3Plus + SDCNetAug [6]	83.5%	2018	Architecture	A novel boundary label relaxation technique that makes training robust to annotation noise and propagation artifacts along object boundaries	Better classify the points at the boundary
8	Global Aggregation then Local Distribution (GALDNet) [7]	83.3%	2019	Architecture	A method to first use Global Aggregation and then Local Distribution, because traditional Global Aggregation is often dominated by features of large patterns and tends to oversmooth regions that contain small patterns.	Better use global information
9	Split-Attention Networks (ResNeSt) [8]	83.3%	2020	Architecture	A modular Split-Attention block that enables attention across feature-map groups. By stacking these Split-Attention blocks ResNet-style, we obtain a new ResNet variant which we call ResNeSt.	A novel model for a wide range of application scenarios
32	PSPNet [9]	81.2%	2017	Architecture	A classical model based on the proposed Pyramid Pooling Module to aggregate contextual information at different scales	Aggregate contextual information at different scales
71	Fully Convolutional Networks (FCN) [10]	65.3%	2015	Architecture	A classical model which replaces the fully connected layers in the traditional CNN network with convolution layers to obtain a 2-dimensional feature map, and followed by softmax to obtain the classification information of each pixel	From Image Classification to Semantic Segmentation

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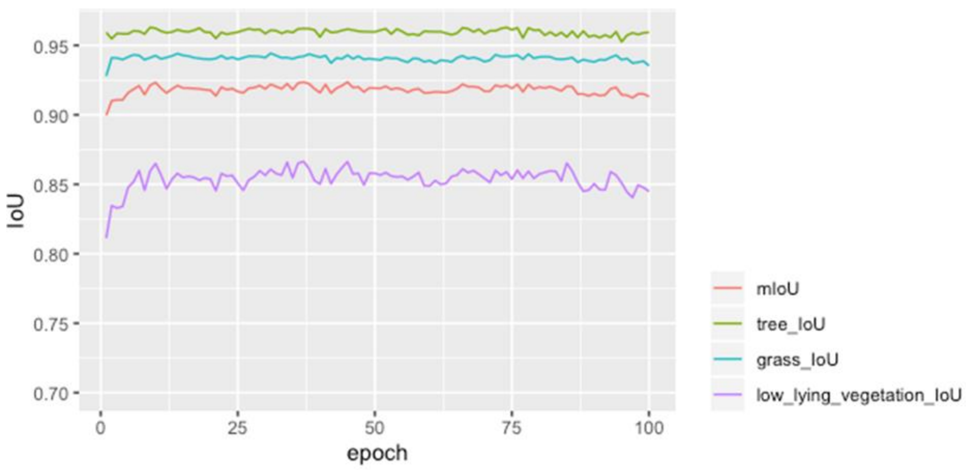
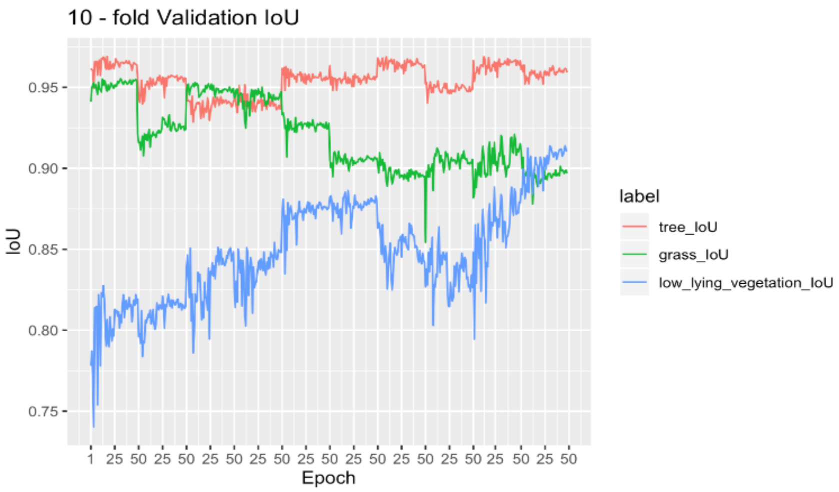
Appendix 2.4 Model validation



IoU, Intersection over union.

Appendix 2.5 Accuracy of each fold of HRNetV2+OCR+ model.



IoU	Tree	Low-lying vegetation	Grass	Mean IoU
Fold 1	96.4	80.6	95.1	89.4
Fold 2	95.3	81.1	92.3	89.5
Fold 3	93.9	83.2	94.9	90.7
Fold 4	94.0	83.7	94.3	90.7
Fold 5	95.6	87.3	92.6	91.8
Fold 6	95.5	87.7	90.5	91.2
Fold 7	96.4	85.0	89.7	90.4
Fold 8	94.9	83.5	90.3	89.6
Fold 9	96.4	86.3	90.5	91.0
Fold 10	95.9	90.3	89.6	91.9
Average	95.4	84.9	92.0	90.6

IoU (%), Intersection over unions.

Appendix 2.6 Associations between neighborhood socioeconomic status and green space in urban areas of Los Angeles County, census tracts.

	IQR	Tree		Low-lying vegetation		Grass		Total green space		NDVI	
Socioeconomic status		regression coefficient	95% CI	regression coefficient	95% CI	regression coefficient	95% CI	regression coefficient	95% CI	regression coefficient	95% CI
CalEnviroScreen 3.0 Score, 0-100	26.0	-2.31	(-2.69, -1.92)	0.07	(-0.05, 0.19)	-0.43	(-0.56, -0.3)	-2.67	(-3.08, -2.25)	-0.023	(-0.026, -0.019)
Population Characteristics Score, 0-10	3.3	-1.98	(-2.36, -1.6)	-0.18	(-0.29, -0.06)	-0.48	(-0.6, -0.35)	-2.63	(-3.03, -2.23)	-0.019	(-0.022, -0.015)
Educational Attainment, %	30.2	-1.82	(-2.22, -1.42)	-0.08	(-0.2, 0.04)	-0.45	(-0.58, -0.32)	-2.35	(-2.78, -1.93)	-0.014	(-0.018, -0.01)
Linguistic Isolation, %	15.7	-0.77	(-1.01, -0.52)	-0.03	(-0.1, 0.05)	-0.25	(-0.33, -0.17)	-1.05	(-1.31, -0.79)	-0.009	(-0.012, -0.007)
Poverty, %	35.9	-1.90	(-2.23, -1.56)	-0.03	(-0.13, 0.07)	-0.51	(-0.62, -0.4)	-2.44	(-2.79, -2.09)	-0.018	(-0.02, -0.014)
Unemployment, %	5.6	-0.16	(-0.31, -0.01)	0	(-0.04, 0.05)	-0.01	(-0.06, 0.04)	-0.17	(-0.33, -0.01)	-0.001	(-0.002, 0)
Housing Burden, %	13.6	-0.62	(-0.83, -0.4)	-0.02	(-0.08, 0.05)	-0.21	(-0.28, -0.14)	-0.84	(-1.07, -0.62)	-0.006	(-0.008, -0.004)
Disadvantaged community, yes	-	-0.98	(-1.3, -0.66)	-0.01	(-0.1, 0.09)	-0.27	(-0.37, -0.17)	-1.26	(-1.6, -0.92)	-0.010	(-0.013, -0.007)
Racial/ethnic minority groups, high	-	-0.91	(-1.32, -0.5)	-0.11	(-0.23, 0.02)	-0.23	(-0.37, -0.1)	-1.25	(-1.69, -0.82)	-0.006	(-0.01, -0.003)

IQR, interquartile range; CI, confidence interval; NDVI, normalized difference vegetation index.

All models adjusted for population density.

Appendix 3.1 Summary statistics of green space indicators and physical activity levels.

Exposures	Mean	SD	Min	25th	50th	75th	Max	N
Individual-level green space exposure								
Street view green space 200m, %								
Total green space	25.28	5.04	12.79	21.71	24.19	27.70	64.41	412616
Tree	15.62	5.13	2.44	12.03	14.77	18.37	47.33	412616
Low-lying vegetation	4.36	1.63	0.35	3.22	4.08	5.18	22.11	412616
Grass	5.30	1.79	0.10	4.03	5.08	6.32	23.09	412616
Street view green space 500m, %								
Total green space	25.15	3.97	16.46	22.41	24.34	27.04	64.63	414302
Tree	15.32	4.12	3.88	12.60	14.73	17.54	42.05	414302
Low-lying vegetation	4.53	1.41	1.10	3.55	4.29	5.22	17.80	414302
Grass	5.30	1.43	0.92	4.34	5.13	6.05	19.47	414302
Green space indicators								
Mean annual NDVI 200m, (0-1)	0.16	0.04	0.03	0.13	0.16	0.19	0.48	411059
Mean annual NDVI 500m (0-1)	0.16	0.04	0.03	0.14	0.16	0.19	0.51	412995
Land-cover green space 200m, %	8.41	16.00	0.00	0.00	1.12	9.22	99.93	415020
Land-cover green space 500m, %	12.24	17.47	0.00	1.07	4.75	15.99	99.97	415020
Tree canopy cover 200m, %	2.03	2.61	0.00	0.33	1.15	2.68	39.17	414950
Tree canopy cover 500m, %	2.00	2.27	0.00	0.50	1.28	2.64	35.66	414950
Distance to the nearest park, km	0.58	0.48	0.00	0.25	0.47	0.77	9.24	415020
Walkability score (block group, 0-20)	12.59	3.32	1.67	10.67	13.17	15.00	20.00	415020
Zip code-level green space exposure								
Street view green space 200m, %								
Total green space	26.31	3.97	18.56	23.42	25.78	28.51	45.36	583
Tree	16.57	4.02	7.43	13.71	16.05	19.12	31.41	583
Low-lying vegetation	4.67	1.19	1.96	3.83	4.45	5.30	10.90	583
Grass	5.06	1.23	1.52	4.18	4.97	5.74	10.33	583
Street view green space 500m, %								
Total green space	26.23	3.90	19.25	23.34	25.65	28.43	44.65	584
Tree	16.31	3.95	7.51	13.59	15.79	18.52	34.29	584
Low-lying vegetation	4.83	1.16	2.63	3.94	4.63	5.50	9.86	584
Grass	5.09	1.20	2.17	4.27	4.96	5.69	10.27	584
Green space indicators								
Mean annual NDVI 200m, (0-1)	0.17	0.04	0.04	0.15	0.17	0.19	0.30	580
Mean annual NDVI 500m (0-1)	0.17	0.04	0.04	0.15	0.17	0.19	0.32	581
Land-cover green space 200m, %	10.33	14.04	0.00	1.71	5.21	12.63	99.93	584
Land-cover green space 500m, %	14.12	16.07	0.00	3.17	8.35	18.60	99.97	584
Tree canopy cover 200m, %	2.56	2.45	0.00	0.93	1.83	3.66	19.31	568
Tree canopy cover 500m, %	2.57	2.43	0.00	0.95	1.85	3.52	18.08	568
Distance to the nearest park, km	0.50	0.40	0.00	0.33	0.43	0.57	7.55	584
Walkability score (block group, 0-20)	12.64	2.60	5.00	11.13	13.16	14.38	18.64	584

SD, standard deviation; NDVI, normalized difference vegetation index.

Appendix 3.2 Associations between residential green space and maternal postpartum depression among urban population.

Postpartum Depression	Model A		Model B	
Exposures	Between effect	Within effect	Between effect	Within effect
Street view green space 200m, %				
Total green space	0.960 (0.934, 0.987)	0.994 (0.983, 1.005)	0.956 (0.930, 0.982)	0.994 (0.982, 1.006)
Tree	0.946 (0.921, 0.972)	1.001 (0.998, 1.003)	0.944 (0.919, 0.969)	1.000 (0.997, 1.003)
Low-lying vegetation	1.011 (0.985, 1.037)	0.985 (0.974, 0.996)	1.012 (0.986, 1.038)	0.987 (0.976, 0.999)
Grass	1.046 (1.021, 1.072)	0.990 (0.978, 1.003)	1.041 (1.016, 1.066)	0.995 (0.982, 1.008)
Street view green space 500m, %				
Total green space	0.959 (0.932, 0.987)	0.992 (0.982, 1.003)	0.953 (0.926, 0.981)	0.994 (0.983, 1.005)
Tree	0.947 (0.924, 0.972)	1.000 (0.989, 1.011)	0.945 (0.921, 0.969)	1.000 (0.988, 1.012)
Low-lying vegetation	1.013 (0.986, 1.040)	0.987 (0.977, 0.998)	1.013 (0.986, 1.040)	0.989 (0.979, 0.999)
Grass	1.047 (1.024, 1.070)	0. 992 (0.981 1.004)	1.042 (1.019, 1.065)	0. 995 (0.983 1.006)
Green space indicators				
NDVI 200m, (0-1)	1.094 (1.067, 1.122)	0.987 (0.977, 0.998)	1.104 (1.077, 1.132)	0.990 (0.979, 1.001)
NDVI 500m, (0-1)	1.090 (1.064, 1.117)	0.992 (0.980, 1.004)	1.101 (1.075, 1.129)	0.996 (0.983, 1.008)
Land-cover green space 200m, %	1.041 (1.022, 1.060)	0.996 (0.992, 1.001)	1.038 (1.019, 1.057)	0.996 (0.992, 1.001)
Land-cover green space 500m, %	1.056 (1.035, 1.078)	0.994 (0.988, 1.000)	1.052 (1.031, 1.074)	0.995 (0.989, 1.001)
Tree canopy cover 200m, %	0.969 (0.945, 0.994)	0.995 (0.988, 1.002)	0.970 (0.946, 0.995)	0.995 (0.988, 1.002)
Tree canopy cover 500m, %	0.963 (0.940, 0.986)	0.993 (0.987, 1.000)	0.964 (0.941, 0.987)	0.993 (0.986, 1.000)
Proximity to the nearest park	0.989 (0.972, 1.006)	0.997 (0.987, 1.008)	0.994 (0.977, 1.012)	1.001 (0.989, 1.012)
Park<500m, yes vs. no	1.000 (0.999, 1.000)	1.003 (0.985, 1.021)	1.000 (0.999, 1.000)	1.000 (0.981, 1.019)
Walkability score	0.920 (0.897, 0.944)	1.020 (1.007, 1.033)	0.920 (0.896, 0.943)	1.016 (1.002, 1.030)
Physical activity				
During entire pregnancy	0.975 (0.954, 0.997)	0.929 (0.917, 0.940)	0.972 (0.950, 0.993)	0.923 (0.910, 0.935)
First trimester	0.995 (0.965, 1.026)	0.977 (0.964, 0.990)	0.992 (0.961, 1.023)	0.971 (0.957, 0.984)
Second trimester	0.961 (0.937, 0.986)	0.944 (0.931, 0.957)	0.958 (0.934, 0.983)	0.939 (0.926, 0.953)
Third trimester	0.964 (0.944, 0.985)	0.909 (0.897, 0.922)	0.962 (0.942, 0.983)	0.906 (0.893, 0.919)

NDVI, normalized difference vegetation index. ORs and 95% CIs were calculated for per interquartile range (IQR) increment for green space indicators.

Model A (within-between random effects models): Models adjusted for maternal age, race/ethnicity, educational level, and block group household income + maternal address ZIP code as a random effect.

Model B: Model A + further adjusted for smoking during pregnancy, season of conception, year of infant birth, and insurance type.

Appendix 3.3 Adjusted odds ratios (ORs) and 95% confidence intervals (CI) of postpartum depression associated with street view based total green space (500 m) among population subgroups.

Description		ORs per IQR air pollutant metrics	95% CI		p value for Cochrane's Q test
Maternal age					
	< 25	1.078	1.013	1.148	<0.001
	25-34	0.961	0.930	0.992	
	≥ 35	0.925	0.888	0.964	
Maternal race/ethnicity					
	African American	1.018	0.932	1.113	0.041
	Asian	0.954	0.911	0.999	
	Hispanic	0.997	0.959	1.036	
	Non-Hispanic white	0.926	0.893	0.960	
	Multiple/other	0.985	0.922	1.052	
Maternal education					
	< College	1.003	0.959	1.049	0.028
	≥ College	0.944	0.916	0.974	

ORs and 95% CIs were calculated for per interquartile range (IQR) increment for green space indicators; Models adjusted for maternal age, race/ethnicity, educational level, and block group household income.

Appendix 3.4 Percent change and 95% confidence intervals of associations between green space and physical activity in specific period of pregnancy.

Green space exposures	During entire pregnancy		First trimester		Second trimester		Third trimester	
	Percent change	95%CI	Percent change	95%CI	Percent change	95%CI	Percent change	95%CI
Street view green space 200m, %								
Total green space	1.00	(0.58, 1.42)	0.72	(0.34, 1.11)	0.90	(0.54, 1.25)	0.67	(0.30, 1.04)
Tree	1.43	(1.03, 1.82)	0.82	(0.45, 1.18)	1.14	(0.81, 1.47)	1.04	(0.70, 1.39)
Low-lying vegetation	3.54	(2.10, 4.98)	5.16	(3.88, 6.45)	3.56	(2.35, 4.76)	2.57	(1.30, 3.83)
Grass	-8.20	(-9.35, -7.05)	-5.89	(-6.99, -4.80)	-6.30	(-7.28, -5.32)	-6.59	(-7.61, -5.58)
Street view green space 500m, %								
Total green space	1.03	(0.59, 1.47)	0.79	(0.38, 1.19)	0.93	(0.55, 1.30)	0.65	(0.26, 1.04)
Tree	1.49	(1.08, 1.90)	0.86	(0.48, 1.24)	1.17	(0.82, 1.52)	1.07	(0.71, 1.43)
Low-lying vegetation	3.34	(1.90, 4.78)	5.02	(3.74, 6.30)	3.43	(2.23, 4.63)	2.34	(1.07, 3.60)
Grass	-8.42	(-9.69, -7.24)	-5.82	(-6.95, -4.70)	-6.30	(-7.31, -5.30)	-6.75	(-7.79, -5.71)
Green space indicators								
NDVI 200m, 0.1	0.37	(-0.12, 0.85)	1.03	(0.59, 1.47)	0.48	(0.06, 0.89)	0.29	(-0.13, 0.72)
NDVI 500m, 0.1	0.51	(0.39, 0.98)	1.17	(0.74, 1.60)	0.63	(0.23, 1.04)	0.37	(-0.05, 0.79)
Land-cover greenness 200m, %	-0.30	(-0.43, -0.17)	-0.07	(-0.20, 0.05)	-0.18	(-0.30, -0.07)	-0.29	(-0.41, -0.18)
Land-cover greenness 500m, %	-0.25	(-0.36, -0.14)	-0.04	(-0.15, 0.06)	-0.15	(-0.24, -0.06)	-0.24	(-0.33, -0.14)
Tree canopy cover 200m, %	2.57	(1.90, 3.24)	1.83	(1.20, 2.46)	2.12	(1.55, 2.69)	1.87	(1.28, 2.47)
Tree canopy cover 500m, %	2.69	(2.02, 2.35)	1.92	(1.29, 2.55)	2.21	(1.64, 2.78)	1.94	(1.35, 2.53)
Proximity to the nearest park, km	2.39	(1.89, 2.90)	2.32	(1.82, 2.81)	2.13	(1.69, 2.57)	2.23	(1.77, 2.69)
Walkability score	2.48	(1.85, 3.10)	0.96	(0.36, 1.56)	1.95	(1,42, 2.49)	2.19	(1.64, 2.73)

NDVI, normalized difference vegetation index. All models adjusted for maternal age, race/ethnicity, educational level, and block group household income. Unit: per 10 percent change in street view-based and land-cover green space, per 0.1 change in NDVI, per one unit change in park distance and walkability score.

Appendix 3.5 Proportions of the effects of green space exposure on postpartum depression due to mediation effects of physical activity during pregnancy.

Green Space Indicators	Percentage mediated by physical activity and 95% CI, %			
	First trimester	Second trimester	Third trimester	Entire pregnancy
Street view green space 200m				
Total green space	2.6 (-7.8, 20.0)	8.4 (0.1, 30.0)	13.1 (7.4, 25.0)	11.7 (5.9, 33.0)
Tree	1.8 (-3.2, 5.0)	7.6 (4.0, 15.0)	12.6 (7.2, 24.0)	10.0 (5.7, 18.0)
Street view green space 500m				
Total green space	-0.1 (-16.0, 15.0)	8.6 (1.6, 42.0)	11.7 (2.7, 25.0)	11.3 (3.3, 39.0)
Tree	0.7 (-4.1, 5.0)	6.9 (2.1, 14.0)	12.6 (4.1, 24.0)	9.6 (5.6, 18.0)
Tree canopy cover				
Tree canopy 200m	2.5 (0.0, 11.0)	12.9 (5.0, 43.0)	17.6 (6.5, 79.0)	15.6 (7.8, 84.0)
Tree canopy 500m	2.4 (-0.5, 16.0)	10.8 (5.7, 43.0)	14.7 (7.7, 36.0)	12.4 (7.6, 35.0)
Walkability score	-0.2 (-2.7, 0.1)	4.1 (0.2, 9.0)	9.5 (5.1, 15.0)	5.3 (3.5, 8.0)

Models adjusted for maternal age, race/ethnicity, educational level, block group household income, smoking during pregnancy, pre-pregnancy BMI and season of conception.

Appendix 4.1 Pattern matrix for Positive and Negative Affect Scale.

Rotated Factor Pattern (Standardized Regression Coefficients)			
Variables	**Factor1**	**Factor2**	**Factor3**
Positive affect scale			
Inspired	**0.91124**	-0.12198	-
Proud	**0.90725**	-0.10995	-
Strong	**0.80152**	0.09015	-
Excited	**0.77466**	0.12994	-
Interested	**0.73239**	0.06828	-
Enthusiastic	**0.72812**	0.15909	-
Determined	**0.67571**	0.16081	-
Attentive	-0.00895	**0.52332**	-
Active	0.30868	**0.49818**	-
Alert	-0.01822	0.15727	-
Variance Explained by Each Factor, %	75.6	24.4	-
Negative affect scale			
Scared	**0.78183**	0.08704	-0.04950
Jittery	**0.71818**	-0.04938	0.19774
Nervous	**0.54014**	0.04524	0.23550
Afraid	**0.53957**	0.03256	-0.00236
Irritable	-0.12598	**0.71313**	0.03039
Hostile	0.27328	**0.64531**	-0.14064
Upset	0.18101	**0.59222**	0.10550
Distressed	0.16855	**0.45297**	0.33006
Guilty	0.00230	0.01175	**0.73791**
Ashamed	0.05603	-0.01608	**0.76800**
Variance Explained by Each Factor, %	37.1	32.6	30.3

Note: Loadings greater than .40 were bolded and included in the factor.