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Associations between urban greenspace and depressive symptoms in Mexico's cities using different greenspace metrics

Maryia Bakhtsiyarava [a,*], Yang Ju [b], Mika Moran [c], Daniel A. Rodríguez [a,d], Iryna Dronova [e,f], Xavier Delclòs-Alió [g], Kari Moore [h], Marianela Castillo-Riquelme [i], Cecilia Anza-Ramirez [j]

[a] Institute of Transportation Studies, University of California, Berkeley, USA
[b] School of Architecture and Urban Planning, Nanjing University, Nanjing, China
[c] School of Public Health, University of Haifa, Israel
[d] Department of City and Regional Planning, University of California, Berkeley, USA
[e] Department of Environmental Science, Policy & Management, University of California, Berkeley, USA
[f] Department of Landscape Architecture & Environmental Planning, University of California, Berkeley, USA
[g] Faculty of Tourism and Geography, Universitat Rovira i Virgili, Tarragona, Spain
[h] Urban Health Collaborative, Drexel Dornsife School of Public Health, Philadelphia, USA
[i] School of Public Health, University of Chile, Santiago, Chile
[j] Laboratorio de Fisiología Comparada, Facultad de Ciencias y Filosofía, Universidad Peruana Cayetano Heredia, Lima, Peru

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ABSTRACT

Background: Greenspace has been shown to be positively associated with mental wellbeing, but studies from the global South have been scarce. We advance the understanding of the relationship between greenspace and depressive symptoms by using multiple clearly defined metrics describing neighborhood greenness and urban parks in an understudied region with rapid urban growth.
Methods: We linked individual-level health survey data for urban residents in Mexico (n = 17,258 respondents in 84 cities) with measures of greenspace such as satellite-derived normalized difference vegetation index (NDVI), percent green area, urban parks characteristics, and kernel-density-derived continuous greenspace indicator. We estimated the odds ratios of experiencing depressive symptoms associated with greenspace at residential neighborhoods adjusted for individual and area-level characteristics.
Results: Among the various measures of greenspace investigated, the amount of greenness measured by neighborhood NDVI was associated with smaller odds of depressive symptoms. An increase by one standard deviation in the median of annual maximum NDVI at neighborhood level is associated with 8.7 % (Odds Ratio [OR] = 0.913, 95 % CI 0.853–0.977) lower odds of experiencing depressive symptoms, adjusted for individual and area-level characteristics. We find some evidence that, when neighborhood-level greenness is accounted for, the broader availability of greenspace outside of the neighborhood may be associated with smaller odds of depressive symptoms. We found no statistically significant associations for the measures describing % greenspace in a neighborhood and urban parks, and the results were not sensitive to seasonal changes in greenness. Neighborhood-level particulate matter (PM2.5) may lessen the benefits of greenspace for depressive symptoms.
Conclusions: Higher neighborhood-level greenness as measured by NDVI is associated with smaller odds of depressive symptoms in Mexico's cities, whereas many other metrics are not. The influence of the choice of greenspace metrics on the subsequent associations highlights the importance of clear operational definitions of greenspace and the need to consider multiple complementary greenspace metrics in greenspace-health research.

1. Introduction

Mental health disorders are among the top ten causes of the global burden of disease, with depressive disorders in particular ranked as the 13th leading cause of disability-adjusted life-years (Global and regional, 2017). The prevalence of individuals susceptible to depressive disorders is anticipated to rise amid prevailing demographic, socioeconomic, and environmental shifts including the increasing population of youth in

* Corresponding author.
E-mail address: mariab@berkeley.edu (M. Bakhtsiyarava).

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low- and middle-income countries, ageing population in high-income countries, rising inequality, conflict, and escalating climate change (Charlson et al., 2019; Mathers & Loncar, 2006; Tuholske et al., 2021). As the United Nations designated mental health a priority for the sustainable development agenda and included it as one of the sustainable development goals (Votruba et al., 2016) (Sustainable development goal #3: Good health and wellbeing), the scientific community has taken on a more holistic approach to understanding the determinants of mental health that acknowledges not only individual-level factors but also the role of the environment – including the built and natural environment.

Among the findings of this more holistic research is increasing evidence that exposure to abundant greenspace may be beneficial for mental health (Dzhambov et al., 2018; Gascon et al., 2018; Wood et al., 2017; Zhang & Tan, 2019). However, the majority of this evidence is derived from studies conducted in the global North (Collins et al., 2020). As a result, the understanding of the relationship between greenspace and mental health is much more limited beyond the global North, including Latin America and other low- and middle-income countries/regions (LMICs) because of the mere paucity of studies focusing on these locations (Nawrath et al., 2021; Zhang et al., 2021). These understudied global South areas are where escalating climate change and rapid urbanization trends converge, (Tuholske et al., 2021) putting a high number of people at risk for negative health impacts (Kephart et al., 2022). Cities in the global South are also different from those in the global North cities because of a range of characteristics, including warmer tropical and subtropical climates, greater biodiversity, more constrained financial resources, lack of city planning, and high levels of urbanization, population density, and socioeconomic inequality (Busso & Messina, 2020; Dobbs et al., 2019; United Nations Department of Economic and Social Affairs Population & Division, 2018). These characteristics present implications and challenges for the provision of greenspace and its ability to provide mental health benefits, (Rigolon et al., 2018) but this has rarely been examined in empirical research. For greenspace to be an effective resource for mental health, more research is needed from these understudied regions. Therefore, our knowledge of the relationship between greenspace and mental health cannot be complete without studies in these diverse settings with unique urban challenges.

This study addresses the dearth of the information from the cities in the global South by analyzing the relationship between greenspace – as defined by multiple clearly articulated greenspace metrics – and depressive symptoms in 84 Mexico's cities. Our work fills a geographic gap in the literature by investigating the relationship between greenspace and mental health in an understudied region of the world while also highlighting the importance of clear operational definitions of greenspace and the need to consider multiple complementary greenspace metrics. In particular, the study is guided by the following research questions.

1) How do the associations between depressive symptoms and greenspace vary between different greenspace metrics, including NDVI, % greenspace, measures describing urban parks, and greenspace measured across continuous space in Mexico's urbanized areas?
2) What are the implications of considering the timing and duration of exposure to greenspace for the association with depressive symptoms?

To address these questions, we combine individual-level adult health survey data with data on satellite-derived vegetation greenness, greenspace coverage from a land cover map, and urban parks data derived from a combination of web data mining and remote sensing. This work contributes to a more comprehensive understanding of the relationship between greenspace and mental health across diverse geographical contexts, which can promote global mental health equity and help inform greenspace-related strategies to improve mental health.

2. Background

The research on mental health and greenspace in Mexico has been limited, in contrast to the global North where the relationship between greenspace and mental health has been established (Collins et al., 2020; Liu et al., 2023; Nawrath et al., 2021). Specifically, the main connection between greenspace effect on mental health lies in its ability to reduce stress and restore attention, (Markevych et al., 2017) as we review below. Establishing this connection in Mexico – especially across multiple geographical locations – can be challenging because of the lack of readily available greenspace data, despite it being particularly critical due to Mexico's rapid urbanization and the resulting displacement of greenspace (Aguilar et al., 2022). To do so, however, it is important to contend with the selection of greenspace metrics as no universal agreement exists about the most appropriate metric associated with mental health. Below we review several commonly used options as well as considerations related to measuring exposure to greenspace.

2.1. Linkages between greenspace and mental health

Several causal pathways between greenspace and human wellbeing, including mental health, have been suggested in the literature. The first pathway involves harm mitigation, which is facilitated by the ability of greenspace to remove pollutants from the air, reduce noise, and regulate temperature (Markevych et al., 2017; Nieuwenhuijsen et al., 2017). The second pathway through which greenspace may improve wellbeing is the reduction of stress and attention restoration. Specifically, the Stress Reduction Theory (SRT) posits that viewing green vegetated areas and being exposed to natural environments can shut down or ameliorate an individual's psychophysiological stress because of the ability of natural environments to elicit positive thoughts and block negative emotions (Hartig, 2021; Kaplan & Kaplan, 1982; Ulrich, 1983). Another mechanism within this pathway acts upon an antecedent state of attention fatigue, instead of stress, and is encapsulated in the Attention Restoration Theory (ART), wherein the ability of nature to effortlessly capture attention enables individuals to overcome mental attention fatigue and restore attention (Hartig, 2021; Kaplan & Kaplan, 1982; Ulrich, 1983). Finally, another set of pathways focuses on instoration, or the capacity of greenspace to facilitate social cohesion (e.g., greenspaces such as urban parks are places where local residents gather, which encourages social contacts and interaction) and promote physical activity (through providing a physical space to engage in physical activity) (Markevych et al., 2017). While the potential of greenspace to improve the quality of the natural environments and human health through the harm mitigation pathway has been established (Tallis et al., 2011; Zhang et al., 2017) – albeit not without caveats (Zhang & Tan, 2019; Schinasi et al., 2023) – empirical evidence regarding greenspace and human health, including mental health, has been most consistent with the mechanisms described in the ART and SRT (Nieuwenhuijsen et al., 2017). Overall, multiple studies have reported positive associations between the amount of greenspace in individuals' neighborhoods and residential areas and mental health, (Beyer et al., 2014; Bojorquez & Ojeda-Revah, 2018; Braçe et al., 2020; Callaghan et al., 2021; Engemann et al., 2019; McEachan et al., 2016) some studies have reported inconsistent results, (Gascon et al., 2018) and recent reviews on the topic have characterized the state of the evidence for the associations between greenspace and mental wellbeing as limited (Callaghan et al., 2021; Houlden et al., 2018).

2.2. Mental health and greenspace in Mexico

While there is some evidence that greenspaces may support mental health in upper-middle-income countries, rapidly urbanizing and poorer middle-income countries are still underrepresented in this line of work (Collins et al., 2020). In Latin America in general and in Mexico in particular, data and research on both mental health and urban greenspace have been scarce (Flores et al., 2022).

On the one hand, there is no systematic register of mental health illnesses in Mexico, including depressive disorders, despite the fact that depressive disorders are the 4th leading cause of years of life lost to disability in Mexico (Agudelo-Botero et al., 2021). As a result, limited human and financial resources have been allocated for diagnosis and treatment of depressive disorders in the country, the type of and provision of care varies widely, and a large number of people with depressive disorders do not receive medical diagnosis nor treatment (Agudelo-Botero et al., 2021; Berenzon et al., 2013). On the other hand, little is known about the provision of greenspace in Mexico. The fast-paced urbanization accompanied by limited urban planning has led to the predominant emphasis on investing in the built environment, often at the expense of preserving and enhancing urban greenspaces (Aguilar et al., 2022). In Mexico City, for example, urban planning concerning new urban sprawl in the city peripheries has been limited to laying out a street grid and ensuring the maximization of land sales with little attention to infrastructure, including greenspace infrastructure (Aguilar et al., 2022; Delgado Ramos, 2019). The lack of attention to greenspace is especially pronounced in informal settlements and marginalized communities, which are characterized by a lack of greenspace and its poor quality (Dobbs et al., 2019; Sandoval & Sarmiento, 2020). Because of their limited participation in decision-making and grass root efforts, these communities also have little capacity to ensure the preservation and maintenance of greenspace (Breen et al., 2020). These issues are exacerbated by climate change – the removal of greenspace in the low-lying and densely-populated floodplains to accommodate urban sprawl increases the vulnerability to floods, landslides, and fires and further undermines greenspace quality and quantity (Benítez et al., 2012; Biggs et al., 2015; Sandoval & Sarmiento, 2020).

According to a recent study, 72 % of neighborhoods in Mexico City do not have access to any urban greenspace within 300 m, and policy efforts to ensure a more equitable distribution of greenspace across the city have been hampered by a lack of central inventory on the availability and characteristics of greenspace (Mayen Huerta, 2022). Our literature review revealed an extremely limited number of studies linking greenspace in Mexico and mental health or other indicators of wellbeing such as self-rated health. The existing studies from Mexico demonstrate that the use of urban greenspaces is associated with improved subjective wellbeing, (Mayen Huerta & Utomo, 2021) whereas the coverage and closer proximity to urban parks, especially well-maintained parks with ample vegetation and amenities, are associated with life satisfaction and better physical health, (Ayala-Azcárraga et al., 2019) and improved mental health (Bojorquez & Ojeda-Revah, 2018).

2.3. Greenspace metrics in research on mental health

In addition to the narrow geographic focus of the existing studies on greenspace and mental health, another challenge is a predominant use of metrics describing a single aspect of greenspace within a single study. Most studies use metrics describing either quantity, accessibility, or some characteristics of urban parks and visits to them, (Callaghan et al., 2021; Houlden et al., 2018; Nguyen et al., 2021) often under the umbrella term of “greenspace” (Taylor & Hochuli, 2017).

Some of the most widely used metrics describing greenspace quantity are represented by remote sensing-based vegetation indices such as Normalized Difference Vegetation Index (NDVI), (Tucker, 1979) which is usually used as a measure of the abundance and physical properties of greenspace and has been frequently used in the studies of mental health (Collins et al., 2020; Gascon et al., 2018; Markevych et al., 2017). Other metrics are derived from the satellite-based (e.g., Landsat (Loveland & Dwyer, 2012; Williams et al., 2006)) land use/cover maps, which use spectral properties of different landscape features to label the landscape with categories such as built-up, shrublands, forests, wetlands, and others. Researchers can use these maps to compute measures such as the land area covered by greenspace. Another measure of greenspace quantity that has been increasingly used in greenspace-wellbeing research describes the amount of and/or visibility of greenspace within eye-level panoramic view (Biljecki & Ito, 2021; de Vries et al., 2013; Labib et al., 2021; Lu et al., 2019). Greenspace can also be characterized based on its human use or specific type – parks, golf courses, gardens – with the resulting metrics describing the availability and accessibility of those types of human greenspace uses (Wood et al., 2017).

Considering multiple greenspace metrics and clearly defining them is important for several reasons. When studies rely on widely different greenspace metrics to investigate associations between greenspace and a particular health outcome and find inconsistent or contradictory relationships, some of these inconsistencies between studies may be attributed to the differences in the underlying definitions of what is tacitly described as greenspace. Analyzing multiple metrics in relation to a health outcome leads to a more detailed understanding about which aspects of greenspace are associated with wellbeing. They also allow for targeted policy recommendations (e.g., which type of greenspace is the most beneficial for reducing the urban heat island effect and which for promoting physical activity?).

2.4. Exposure to greenspace and its associations with depressive symptoms

In addition to the choice and definition of greenspace metrics, another important consideration is related to how exposure to greenspace is measured and modeled. Apart from the Modifiable Areal Unit Problem (MAUP), (Openshaw, 1984; Openshaw and Taylor) which has investigated the implications of measuring greenspace exposure at varying spatial scales, (Labib et al., 2020a, 2020b; Reid et al., 2018; Su et al., 2019; Tan & Samsudin, 2017) other empirical considerations are grounded in the uncertain geographic context problem (Kwan, 2012). This problem highlights two issues: 1) uncertainty in the relevant geographic context over which exposure is measured in relation to an outcome (spatial uncertainty) and 2) uncertainty in the temporal dimension and accuracy of exposure (temporal uncertainty) (Kwan, 2018). The spatial uncertainty problem grapples with the fact that measuring exposure through buffers or administrative units is only a rough proxy of an individual’s actual exposure. Most of the greenspace measures mentioned above are usually described within some distances or buffers around a residential location or at the level of neighborhoods, districts, and other administrative units. Dynamic measures of exposure such as greenspace characteristics encountered by individuals during their daily movements across space are starting to be used in research on greenspace and mental health (Wang et al., 2021). Overall, however, most greenspace-mental health relationship studies ignore the distribution of greenspace across space and measure it within a vantage point of human observation or within an area of interest, thus imposing a rigid boundary on an otherwise complex human activity space whose size can vary widely and across seasons (Järv et al., 2014). The temporal uncertainty of the uncertain neighborhood problem highlights the need to carefully match the time when an outcome was measured relative to when the exposure was measured and consider the duration of exposure, all of which have received limited attention in the current greenspace-health research (Gascon et al., 2018).

Ignoring the temporal complexity may obscure certain pathways between greenspace and mental health. For example, if the beneficial effect of greenspace exposure on mental health occurs via viewing greenery and being exposed to it – as is postulated in the SRT/ART – then it is reasonable to suggest that the largest boost greenspace provides to mental health may occur when vegetation is the most abundant, which itself is related to the seasonal patterns of vegetation growth. On a practical side, this seasonality of greenspace can be captured by greenspace metrics like NDVI, which are provided at monthly or biweekly intervals (Didan, 2015). However, NDVI-based greenspace metrics in health research usually represent static annual, monthly or other cross-sectional summaries as opposed to longitudinal, repeated measurements during an extended period (Helbich, 2019). Other metrics such as the percentage of greenspace and the metrics describing vegetated land use classes (forests, pastures, parks) are usually available and used as static, though this is unlikely to be problematic because they describe stable characteristics of the greenery and are unlikely to vary much within a given year. Still, depending on the underlying hypothesis connecting greenspace and mental health, cross-sectional measures of greenspace may be crude as they ignore the variability of greenspace quantity in time as well as how long individuals have been exposed to it.

3. Data and measures

3.1. Sample

We used Mexico's National Survey on Health and Nutrition (Encuesta Nacional de Salud y Nutrición, or ENSANUT) from 2012. The ENSANUT survey is conducted every six years by Mexico's National Institute of Public Health and collects data on individual health, including diet, nutrition, sleep, depression, health care use and access, and individual and household sociodemographic characteristics (Romero-Martínez et al., 2013). The survey uses a probabilistic multistage design and is representative at the national and state levels, as well as rural and urban strata. The original ENSANUT 2012 sample included 72,867 individuals residing all over Mexico. The ENSANUT 2012 participants were surveyed between January 2011 and March 2012. Survey participants were sampled from "neighborhoods" – defined as basic geostatistical areas (áreas geoestadísticas básicas urbanas) according to Mexico's National Institute of Statistics and Geography, akin to census tracts in the US context (Montejano Escamilla et al., 2020). Neighborhoods are comprised of 1–50 blocks that are clearly delimited by streets, avenues, walkways, or any other easily identifiable features on the land, and are the most detailed geographical unit in the survey (Montejano Escamilla et al., 2020). Neighborhoods were nested within cities, which are defined as explained below.

This study is part of the SALURBAL (Salud Urbana en America Latina) project, which is a multi-university collaboration investigating the social and environmental determinants of health in 371 cities in thirteen Latin American countries (Quistberg et al., 2019). SALURBAL delineated cities' urban extent boundaries (i.e. city defined based on the urban built-up extent, henceforth referred to as "cities") by combining official administrative boundary data with the built-up area from the Atlas of Urban Expansion, followed by an inspection of satellite imagery from the Global Urban Footprint Dataset and identification of urban built-up clusters using a hierarchical agglomerative process (Quistberg et al., 2019). In this analysis we are interested in the relationship between urban greenspace and depressive symptoms, so we limited the sample to the respondents living in highly urbanized areas, which amounted to 17,258 respondents from 680 neighborhoods in 84 cities in Mexico.

3.2. Outcome measure

The outcome measure was a categorical variable based on dichotomizing a continuous depressive symptoms scale. This variable is based on the Center for Epidemiological Studies Depression Scale-Short Form (CESD-SF) screening survey, (Roberts & Vernon, 1983) which has been validated for Mexico (Salinas-Rodríguez et al., 2013). To compute a screening score, survey participants were asked a series of seven questions about the frequency of experiencing the following in the last two weeks before the survey: poor appetite, inability to focus on tasks, feeling of depression, things taking extra effort, restless sleep, sadness, and inability to get going. The responses range 0–3 on the Likert scale, with "0" meaning "rarely/none of the time/1 day" and "3" indicating "most of the time/all of the time/5–7 days". The responses were then summed up, and if the total score was equal or greater than nine, an individual was considered to screen positively for depressive symptoms (Roberts & Vernon, 1983).

3.3. Individual- and neighborhood-level covariates

Individual and household socioeconomic characteristics have been shown as determinants of depression in Mexico and beyond, with women, persons with lower education, no steady employment, unpartnered persons, and generally socioeconomically disadvantaged people experiencing higher rates of depression and depressive symptoms (Agudelo-Botero et al., 2021; Belló et al., 2005; Gascon et al., 2018). In line with this evidence, we extracted individual and household-level covariates that describe the socioeconomic environment and which may be predictive of depressive symptoms: participants' age group, sex, marital status, educational attainment, car ownership, household access to piped water, and a measure of the number of people per room. We also used the unemployment rate among those 15 and older in the labor force and percentage of the population aged 25 and older who completed primary school or above obtained from Mexico's 2010 census as measures of neighborhood-level socioeconomic conditions. Finally, because air pollution may be associated with mental health (Buoli et al., 2018) and may mediate or moderate the relationship between greenspace and mental health, (Dzhambov et al., 2020) we extracted mean neighborhood PM2.5 concentrations from the Atmospheric Composition Analysis Group (ATMOS) from 2011 (van Donkelaar et al., 2016).

3.4. Greenspace data

3.4.1. NDVI

The first source of greenspace data is NDVI obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument of the Terra satellite (Didan, 2015). To construct an area-level greenness measure, we computed a median of annual maximum NDVI for 2011 for every neighborhood because the majority of survey participants were interviewed in 2011. Specifically, we used the 250-m, 16-day NDVI product (MOD13Q1.006) to compute a neighborhood median of the annual maximum NDVI for the entire year of 2011 for Mexico's neighborhoods, masking out water. We computed a spatial median of the annual maximum to capture peak greenness (max annual NDVI) and ensure that the area-level NDVI measure is representative of greenness in an entire neighborhood and is not skewed by some particularly green areas within the neighborhood (median).

The second source of NDVI data is represented by longitudinal, or repeated NDVI measurements, over 12 months preceding the survey. First, we extracted information on the exact date (day, month, year) an individual's survey responses were collected. Then, for every individual we computed mean NDVI for every month in their neighborhood during the 12-month period before the survey. We chose 12 months as a time period that captures all the intra-annual fluctuations in vegetation intensity and vigor, as shown in Fig. S1 in the Supplementary Material. For a sensitivity analysis, we also computed mean NDVI for every month during 9 and 6 months before the survey. This approach is aligned with the objective of investigating the implications of the temporal resolution of the greenspace exposure measurement and its association with depressive symptoms.

3.4.2. Greenspace coverage

A second source of data on greenspace is a landcover classification map based on the 10-m resolution Sentinel-2 satellite images from 2017. This fine-resolution map of urban greenspaces (including green grass, shrubs, and forests) was created by combining a greenspace map focusing on main urban areas in a city produced by Ju, Dronova, & Delclòs-Alió (2022), (Ju, Dronova, & Delclòs-Alió, 2022.) and a global land cover map by FROM-GLC10 (http://data.ess.tsinghua.edu.cn/). The resulting greenspace map represented a binary image with every 10-m pixel classified as greenspace or not greenspace. The urban greenspace landcover map contained urban greenspace as represented by green grass, shrubs, forests, and urban cropland (Ju et al.). From this map, we computed a percentage of neighborhood area covered by greenspace (Table 1).

3.4.3. Urban parks

The third dataset used in this study describes urban parks. Urban parks were classified using a combination of web data mining and remote sensing. Specifically, Pina et al. (Pina et al.) used the Google Cloud collaborators database to search for tagged parks locations and Sentinel-2 satellite images to map the parks' boundaries. The final classification represented a map of urban parks in 371 cities in Latin America and was used as input to compute various metrics describing urban parks. We used the following metrics to describe urban parks in the neighborhoods: the number of parks per capita; park area per capita; percent neighborhood area covered by urban parks; distance to the nearest park in a neighborhood as calculated from the neighborhood centroid to the nearest vertex of the park.

3.4.4. Measures of greenspace over continuous space

The three types of greenspace metrics mentioned above (also in Table 1 and Fig. 1) describe the characteristics of greenspace present within a neighborhood administrative boundary. These metrics do not capture the greenspace outside of the neighborhood boundaries that individuals may also use. To complement the greenspace metrics that are based on the neighborhood boundaries and account for the relatively proximate greenspace that individuals can interact with but that is located just outside of their immediate neighborhood, we constructed a series of measures describing the amount of greenspace across continuous space with the help of kernel density maps. This approach complements the neighborhood-level exposure and provides new information regarding greenspace available outside of the neighborhood that may be accessible by walking.

Kernel density estimation (KDE) uses local information to compute densities of features at any given point in space. KDE produces a smooth continuous surface of probability density using a distance function (Gatrell et al., 1996; Silverman, 2017). In this study, a kernel density surface of greenspace was computed by fitting a smoothed surface to each point in space and represents the predicted density of greenspace (green pixels) across space. The KDE-derived greenspace measures provide an advantage over metrics rigidly constrained by artificial administrative boundaries because they consider the continuous distribution of green areas in space.

Using the landcover classification map of greenspace (resampled to 30 × 30 m because of computational complexity), we created continuous kernel density surfaces of greenspace. A key component of KDE is bandwidth, or a spatial search radius, which determines the search radius for computing density. Some greenspace studies showed that there is no empirical support for the idea that the benefits of greenspace disappear with an increase in distance between a subject residence and green areas, partly because residential proximity to greenspace is a poor approximation of one's activity space (Ekkel & de Vries, 2017). Therefore, we used the following search radii for KDE surfaces to consider both localized and broad spatial effects: 250, 500, 1000, 2000, and 3000 m. We created density surfaces with the same cell size as the input greenspace map – 30 × 30 m. The resulting KDE surfaces represented the density of green pixels at any given point in space. After creating the kernel density surfaces, we summarized the mean density of continuous greenspace at the neighborhood level and linked them to the individual survey respondents. The literal interpretation of these KDE-derived variables is the number of 30 × 30 m green patches per km^2 within any 250 m (or 500 m, 1, 2, or 3 km) of a neighborhood. The kernel density estimation was carried out using the "arcpy" module in Python.

Table 1
Description of the neighborhood greenspace metrics used in the study.

Domain	Variable	Description	Data source
Quantity of greenspace	Median annual maximum NDVI	Vegetation greenspace and vigor. Higher NDVI indicates more vigorous greenery and larger vegetated areas.	Remote sensing data from MODIS
	% Greenspace	Percent neighborhood area covered by greenspace.	A 10 × 10 m binary map of greenspace
Urban parks	Number of parks per capita	The number of urban parks per 1000 residents.	Web scraping from Google Cloud Collaborator platform + Sentinel-2 satellite images
	Park area per capita	Total area of urban parks per 1000 residents.	
	% Area covered by parks	% Neighborhood area covered by urban parks.	
	Distance to nearest park	Distance to the nearest park from the neighborhood's centroid.	
Greenspace measured across continuous greenspace	Density of greenspace at different distances	Kernel density of greenspace pixels (30 × 30 m) per km^2 within 250, 500, 1000, 2000, and 3000 m of each output kernel density surface cell, summarized at neighborhood level.	Computed by authors using a 30 × 30 m binary map of greenspace

4. Statistical Analysis

4.1. Models with cross-sectional greenspace metrics

We used logit mixed effects models to estimate the odds of an individual experiencing depressive symptoms in relation to various greenspace metrics (equation in the Supplementary Material). We estimated separate models for each type of greenspace metrics – NDVI, urban parks, and the measures of continuous greenspace based on the KDE described above. All the models were adjusted for individual age, sex, marital status, educational attainment, car ownership, household access to piped water inside dwelling, number of people per room, and neighborhood-level unemployment rate, neighborhood primary educational attainment, and neighborhood air pollution (PM2.5). The models included random intercepts for neighborhood and city. No multicollinearity issues were identified as the Variance Inflation Factors (VIFs) did not exceed 1.8.

For a sensitivity analysis based on the depressive symptoms total score (continuous variable), we estimated a zero-inflated Poisson model with the same mixed fixed effects and covariates as described above. The continuous total depressive symptoms score varied from 0 to 21, and a large number of respondents (37 %) had a total score of zero (negative answers to all the questions about the presence and frequency of depressive symptoms), and a zero-inflated model accommodated the distribution of the total score.

To investigate whether associations between the greenspace metrics and depressive symptoms are modified by individual and neighborhood-level characteristics, we included interaction terms between the greenspace variables and individual- and neighborhood-level covariates. Separate models were estimated to evaluate each interaction. Finally, we estimated a cross-level interaction between neighborhood and city greenspace to explore if the broader (city-level) availability of greenspace bears any influence on the association between local, neighborhood greenspace and depressive symptoms – since exterior (to neighborhood) greenspace at large may still provide harm-mitigating, stress- and attention-restoring, and other benefits to individuals, which in turn could be associated with the likelihood of experiencing depressive symptoms.

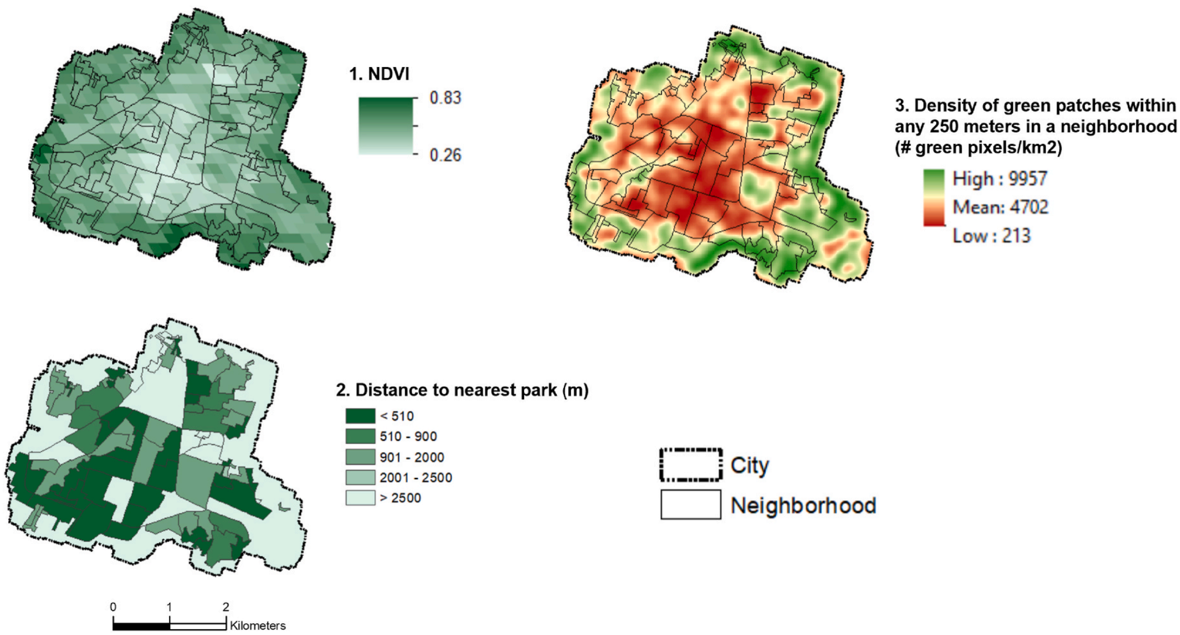

Fig. 1. Illustrative example of the three types of greenspace metrics/data used in this study, visualized for the city of Iguala (Mexico) and its neighborhoods (basic geostatistical areas): 1) Median of annual maximum NDVI obtained from the MODIS satellite; 2) Data on urban parks compiled from Google Cloud Collaborators database (tagged parks locations) and Sentinel-2 satellite images; 3) Data on the density of green patches across continuous space computed with the help of kernel density estimation using the 30 × 30 m binary landcover map.

4.2. Models with longitudinal NDVI

To model the relationship between depressive symptoms and time-varying NDVI, we used the distributed lag linear models (DLMs) (Gasparrini, 2011, 2014). These models have been widely used in temperature-mortality research as they provide a convenient quantitative framework for incorporating lagged and nonlinear effects (Gasparrini et al., 2015; Sera et al., 2019). In addition, they allow for an estimation of the cumulative effect of exposure – e.g., associations between greenspace and depressive symptoms that accumulated during a specific time period (Gasparrini, 2014). The DLMs also enable us to identify windows of (in)vulnerability, which represent specific periods in time when greenspace is negatively or positively associated with depressive symptoms. We fitted multi-level DLMs to estimate the odds of individuals experiencing depressive symptoms in relation to time-varying NDVI (equation in the Supplementary Material). The main difference between the multi-level DLMs and the logit mixed effects models has to do with how the time-varying NDVI is modeled. We first identified the best functional form of the greenspace-depressive symptoms relationship by estimating 1) a model with a linear term for NDVI and 2) a series of models where NDVI was modeled with natural cubic splines placed at different percentiles of the NDVI distribution. We then compared the AIC of the linear and various non-linear models and selected the final model as the one with the smallest AIC, which was the linear model. The model selection approach based on minimizing the AIC has been used in other studies that utilized DLMs (Sera et al., 2019). The second component of modeling the relationship between NDVI and depressive symptoms in the DLM framework includes specifying a lagged exposure-response association. The lag exposure-response component was specified with natural cubic splines equally spaced at 5.5 and 9.5 months before the survey. The lag component allows us to obtain month-specific associations between NDVI and depressive symptoms that are adjusted for NDVI during all other months. In sum, the effect of time-varying NDVI was modeled linearly with delayed effects (lag). When presenting results from the DLMs we will demonstrate 1) the overall, cumulative associations between average monthly NDVI during the entire 12-month period before the survey and depressive symptoms, and 2) associations between 1 (one) standard deviation higher NDVI and depressive symptoms during every month of the 12-month time period before the survey for each participant. To check the sensitivity of the results to the chosen period of NDVI measurement (12 months), we re-estimated the models with time-varying NDVI measured during the last 9 and 6 months before the survey for each respondent. All of the statistical analyses were carried out in R version 4.1.1.

5. Results

5.1. Sample characteristics

Table 2 contains descriptive statistics of the respondents from the analytic sample. Overall, our sample includes 17,258 respondents sampled in 680 neighborhoods in 84 cities in Mexico. According to the 2012 ENSANUT, 14 % of the respondents exhibited depressive symptoms as measured by the CESD depression score. The average total score for the 7-question depression screen was 3.84 (a total score >9 is considered a threshold for depressive symptoms). Overall, slightly more than a half of the respondents were female (57 %). However, among those with depressive symptoms women accounted for 76.9 %, whereas they totaled 54.3 % of the respondents who did not report depressive symptoms. The median respondent age in the sample was 41 years, and 30–39-year-olds comprised the largest age group. Most respondents were married/partnered (64 %) and had primary education as the highest educational attainment (48 %). Those with at least university education represented about one-eighth of the sample, while roughly 16 % of the respondents did not complete primary education. Those without reporting depressive symptoms in the last two weeks before the survey exhibited much higher rates of car ownership than those who experienced depressive symptoms – 36.8 % vs 24.6 %, respectively.

5.2. Greenspace metrics

Table 3 and Fig. 2 present descriptive information about the greenspace in the study area. Greenspace covers 19 % of any given neighborhood, on average, while urban parks on average cover a little more

Table 2
Descriptive statistics of the individuals and neighborhoods from the 2012 Mexico ENSANUT sample used in the study stratified by the status of depressive symptoms.

Dependent variable	Percentage/Mean	
Depression category based on the CESD-SF 7 questions score (yes, %)	13.80	
Continuous CESD-SF 7 questions total score	3.54	
	Those with depressive symptoms	Without depressive symptoms
Individual-level variables		
Male respondents (%)	23.10	45.70
Age groups (%)		
20-29	15.20	22.70
30-39	21.90	25.00
40-49	24.00	21.70
50-59	18.80	14.70
60+	20.10	16.00
Marital status (%)		
Married	57.00	65.20
Divorced/separated	16.50	9.82
Widowed	11.80	6.15
Single	14.70	18.8
Highest Educational Attainment (%)		
Less than primary	25.10	14.10
Primary education	53.50	47.40
Secondary education	15.80	25.30
University education	5.64	13.20
Piped water inside the dwelling (%)	81.90	86.00
Overcrowding (number of people per room)	1.57	1.51
Own a car (%)	24.60	36.80
Neighborhood-level variables		
Population	9725	8970
Neighborhood unemployment rate among the total population 15 years or above in labor force (%)	4.60	4.50
Neighborhood proportion of the population aged 25 or older who completed primary education or above (%)	91.70	90.90
Average annual PM2.5 concentration (μg/m3)	17.69	17.45
N (respondents)	2,375	14,883
N (neighborhoods)	631	680
N (cities)	84	84

than 1 % of a neighborhood area. The highest correlations are observed between the measures describing the density of greenspace measured over continuous neighborhood space. Pairs of these metrics at similar bandwidth distances exhibit stronger correlations. The metrics describing the density of greenspace over continuous space are also correlated with % green, which is not surprising given that both measures describe the extent to which greenspace fills the space, albeit the density metrics also take into account neighboring greenspace.

Apart from the high correlations among the density metrics, % greenspace and median annual maximum NDVI have a high correlation at 0.64. These measures are closely related because they both characterize the amount of greenspace (in addition, NDVI also measures greenspace intensity/vigor) but they are not identical. Fig. 2 also highlights a distinct difference between the urban park metrics and the rest of the metrics describing urban greenspace – the correlations between, for example, NDVI or % greenspace and the urban parks metrics are very low, meaning that the greenest neighborhoods do not necessarily have the most urban parks and vice versa. Overall, park metrics do not exhibit strong correlations with the other greenspace metrics.

Table 3
Descriptive statistics of greenspace metrics at respondents' neighborhoods.

Variable	Mean	SD	Min	Median	Max
Greenspace	19.43	17.21	0.04	14.35	86.09
Median of annual maximum NDVI	0.32	0.14	0.10	0.29	0.74
Number of urban parks per 1000 residents	0.29	0.54	0.00	0.00	6.32
Area covered by parks	1.11	2.66	0.00	0.00	29.01
Total area (m^2) of parks per 1000 residents	1573	4860	0.00	0.00	65,181
Distance to nearest park (m)	4834	8478	42.13	1346	60,286
Continuous-surface greenspace (KDE) (summarized at neighborhood level)					
Mean density of greenspace within 250 m[a]	2052	1688	11.43	1563	8579
Mean density of greenspace within 500 m	2184	1649	26.63	1777	8463
Mean density of greenspace within 1 km	2403	1597	76.14	2074	8189
Mean density of greenspace within 2 km	2640	1488	192.38	2503	7954
Mean density of greenspace within 3 km	2717	1402	268.42	2664	7949
N (neighborhoods)	680				
N (cities)	84				
Neighborhood area (km^2)	0.44	0.77	<0.01	0.33	88.90
City area (km^2)	184	343	18	89	2864

[a] The literal interpretation of this variable is the number of 30 × 30 m green patches per km^2 within any 250 m (or 500 m, 1, 2, or 3 km) in a neighborhood.

5.3. Associations between greenspace and depressive symptoms

Next, we present adjusted associations between the odds of experiencing depressive symptoms and greenspace. As explained in the Statistical Analysis section, the results are from single exposure models that included each greenspace metric separately. Neighborhood NDVI is associated with smaller odds of experiencing depressive symptoms after adjusting for individual and area-level variables (Table 4). A one standard deviation increase in the median of annual maximum NDVI in the neighborhood is associated with 8.7 % (Odds Ratio [OR] = 0.913, 95 % CI 0.853–0.977) lower odds of experiencing depressive symptoms. When, instead of NDVI, we consider another metric describing greenspace – neighborhood green coverage (% green) – it is also associated with reduced odds of experiencing depressive symptoms, but the confidence interval for the effect contains the null (95 % CI 0.904–1.015). Switching to the urban parks, we find that both higher % neighborhood area covered by parks and greater distance to parks are associated with smaller odds of experiencing depressive symptoms, but the estimates are imprecise and contain the null. The other park metrics – higher number of parks per capita and higher total area of parks per capita are associated with increased odds of depressive symptoms, albeit these associations do not reach statistical significance either.

We evaluated the relationship between depressive symptoms and greenspace across continuous space within neighborhoods – thus including both neighborhood greenspace and greenspace at different distances from the neighborhood – computed with the help of kernel density surfaces. We find that greater density, or availability of greenspace, in relative proximity to a neighborhood (250-2000 m from any point within the neighborhood) is not statistically significantly associated with depressive symptoms. However, when greenspace from within any 3 km of the neighborhood is considered, a one standard deviation increase in greenspace density within 3 km of the neighborhood is associated with a 6.6 % decrease in the odds of experiencing depressive symptoms (OR = 0.934, 95 % CI 0.878–0.994). Interestingly, regardless of their statistical significance, the direction of the associations for the greenspace density measures – smaller odds of depressive symptoms associated with greater greenspace availability – is consistent irrespective of the bandwidth used for the kernel density estimation. Also,

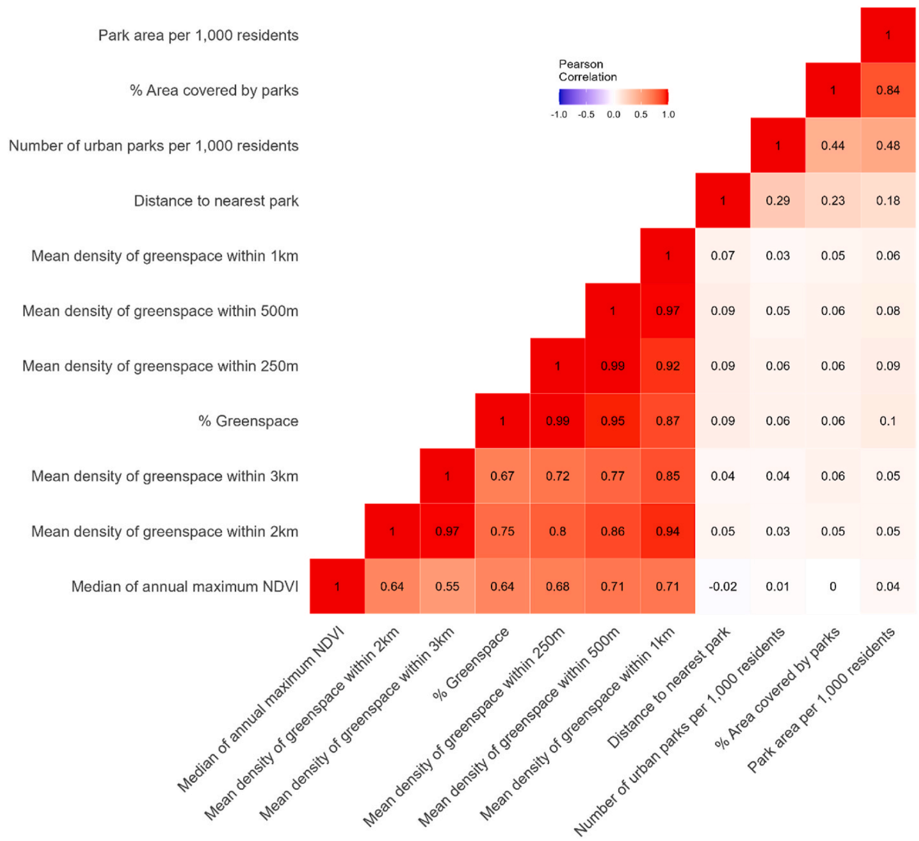

Fig. 2. Correlation between pairs of greenspace variables at the neighborhood level (n = 680).

Table 4
Adjusted multivariate associations between neighborhood greenspace metrics and the odds of experiencing depressive symptoms for adult respondents from the Mexico's Health and Nutrition Survey in 2012.

Part 1. Greenspace within neighborhoods								
Exposure[a]	OR	95 % CI	Variance (neighborhood)	Variance (city)	AIC	N (individuals)	N (neighborhoods)	N (cities)
Quantity of urban greenspace								
% Greenspace	0.958	0.904–1.015	0.113	0.072	12,870	17,258	680	84
Median of annual maximum NDVI	**0.913**	**0.853–0.977**	0.116	0.057	12,866	17,258	680	84
Urban parks								
Number of urban parks per 1000 residents	1.013	0.956–1.075	0.111	0.080	12,872	17,258	680	84
% Area covered by parks	0.991	0.933–1.053	0.111	0.080	12,872	17,258	680	84
Total area of parks per 1000 residents	1.002	0.943–1.064	0.111	0.080	12,872	17,258	680	84
Distance to nearest park	0.995	0.937–1.058	0.111	0.080	12,872	17,258	680	84
Part 2. Greenspace measured across continuous space in individuals' neighborhoods								
Mean density of greenspace within 250 m[b]	0.953	0.899–1.010	0.113	0.071	12,869	17,258	680	84
Mean density of greenspace within 500 m	0.949	0.895–1.006	0.113	0.069	12,869	17,258	680	84
Mean density of greenspace within 1 km	0.945	0.891–1.004	0.114	0.067	12,869	17,258	680	84
Mean density of greenspace within 2 km	0.941	0.885–1.000	0.115	0.065	12,868	17,258	680	84
Mean density of greenspace within 3 km	**0.934**	**0.878–0.994**	0.115	0.064	12,868	17,258	680	84

Results are from separate mixed effects models estimating the odds of experiencing depressive symptoms associated with neighborhood greenspace metrics among survey respondents residing in Mexico's cities (each row is a separate model). All models were adjusted for individual age, sex, marital status, educational attainment, car ownership, household access to piped water inside dwelling, number of people per room, and neighborhood-level unemployment rate, neighborhood primary educational attainment, and neighborhood air pollution (PM2.5). All models included random intercepts for neighborhood and city. Statistically significant coefficients are in bold. OR refers to Odds Ratio; 95 % CI is 95 % Confidence Interval.

[a] All of the exposure variables were standardized to z-scores, and the associations can be interpreted in relation to 1 standard deviation increase in the metric.

[b] The literal interpretation of the variables in Part 2 is the number of 30 × 30 m green patches per km^2 within any 250 m (or 500 m, 1, 2, or 3 km) in a neighborhood.

an estimated decrease in the odds of depressive symptoms increases numerically with spatial search radius distance – the smallest decrease in the odds of depressive symptoms is estimated at 4.7 % (OR = 0.953, 95 % CI 0.899–1.010) for the shortest bandwidth, 250 m, while for greenspace measured at 3 km they go down by 6.6 % (OR = 0.934, 95 % CI 0.878–0.994).

5.4. Time-varying NDVI

Here we present results from the distributed lag linear models estimating the cumulative association between monthly NDVI during the 12 months preceding the survey for each respondent and the odds of experiencing depressive symptoms. Overall, a one standard deviation increase in average monthly NDVI during the 12 months before the survey for every respondent is associated with smaller odds of depressive symptoms (Fig. 3A), which is consistent with the results from the cross-sectional analyses described above. An average monthly NDVI of 0.35 during the last 12 months before the survey is associated with a 16 % decrease (OR = 0.843, 95 % CI 0.756–0.940) in the odds of experiencing depressive symptoms, adjusted for individual and neighborhood characteristics (Fig. 3B and Supplementary Material Table S4).

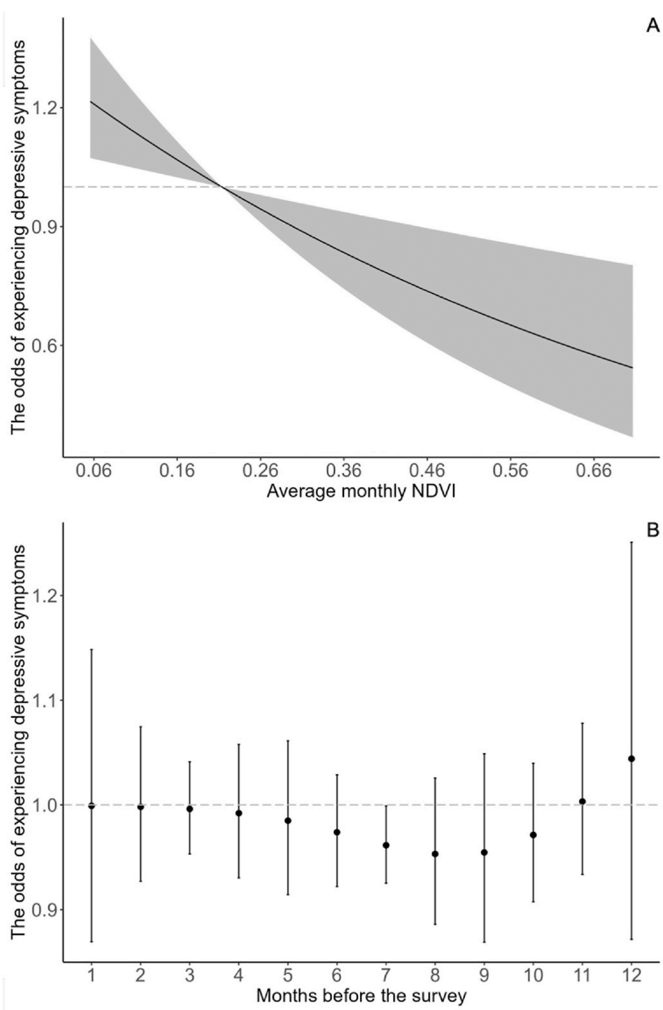

Fig. 3. Predicted cumulative (3A) and month-specific (3B) associations between average monthly NDVI during the 12 months before the survey and the odds of experiencing depressive symptoms among adults in the 2012 ENSANUT sample in Mexico. The curves are derived from the distributed lag linear models adjusted for individual age group, sex, educational attainment, marital status, the availability of piped water inside dwelling, car ownership, and the number of people per room, neighborhood-level unemployment rate, percentage of the neighborhood population aged 25 or older who completed primary education or above, and neighborhood air pollution (PM2.5). The curve in 3A depicts estimated odds (with 95 % confidence intervals) of experiencing depressive symptoms associated with average monthly NDVI during the 12 months before the survey. The estimates in 3B reflect the odds (with 95 % confidence intervals) of experiencing depressive symptoms associated with 1 (one) standard deviation higher NDVI in each month during the 12-month period before the survey, relative to the average monthly NDVI (0.214).

However, we do not find specific time windows within the last 12 months when higher-than-average NDVI is associated with a smaller likelihood of depressive symptoms (Fig. 3B). The same pattern was observed when we estimated the cumulative and month-specific associations between NDVI and depressive symptoms during the last 6 and 9 months before the survey (results not shown).

5.5. Additional analyses

To investigate whether individual or area-level characteristics modify the associations between greenspace and depressive symptoms, we interacted the greenspace variable that showed a statistically significant association with depressive symptoms – neighborhood NDVI – and the following: individual age, sex, marital status, educational attainment, car ownership, household access to piped water inside dwelling, number of people per room, and neighborhood-level unemployment rate, neighborhood primary educational attainment, and neighborhood air pollution (PM2.5) (Supplementary Material Table S1). The only statistically significant interaction was observed between NDVI and neighborhood-level PM2.5. Specifically, as can be seen in Fig. 4, the level of PM2.5 in the neighborhoods modified the magnitude, but not the direction, of the NDVI-depressive symptoms associations. For individuals residing in neighborhoods with higher-than-average levels of PM2.5, the reduction in the probability of experiencing depressive symptoms associated with higher neighborhood NDVI is much lower than for those residing in less polluted neighborhoods. We also estimated a cross-level interaction between neighborhood and city NDVI to analyze whether the amount of overall greenspace in a city modifies the association between local, neighborhood-level NDVI and depressive symptoms. No statistically significant interaction was observed (Supplementary Material Table S1).

To check the sensitivity of the results in Table 4 to the choice of an outcome variable, we re-estimated the models from Table 4 for the total depressive symptoms score (Table S2 in the Supplementary Material). We also re-estimated the models using an alternative measure of neighborhood NDVI – maximum of annual maximum NDVI to capture the highest (area-level) value of peak annual greenness in a neighborhood, as opposed to the median of annual max NDVI (which captures the spatial median of annual peak greenness) used in the main analysis (Table S3 in the Supplementary Material). The results from the sensitivity analyses are in line with the main results.

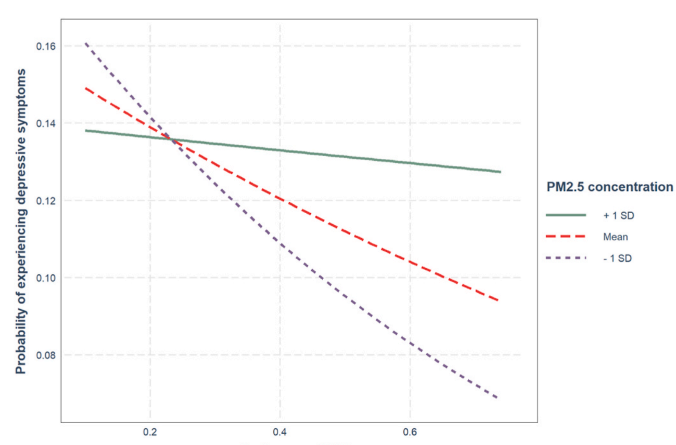

Fig. 4. Interaction between neighborhood-level PM2.5 and median max NDVI. The NDVI and PM2.5 variables were centered for the estimation. NDVI values on the x-axis are on the original scale. The interaction was estimated as part of the fully adjusted model described in the Statistical Analysis section and Equation 1 in the Supplementary Material.

6. Discussion

This work investigated associations between greenspace and depressive symptoms in Mexico's cities while considering greenspace metrics describing neighborhood vegetation greenness, greenspace coverage, and urban parks. We found that higher neighborhood NDVI is associated with smaller odds of depressive symptoms, and there is some limited evidence that the broader availability of greenspace outside the neighborhood may also be associated with smaller odds of depressive symptoms. We find no statistically significant associations between % neighborhood area covered by greenspace, the quantity and distribution of urban parks and individual-level depressive symptoms.

Our finding of higher levels of greenness associated with better mental health outcomes is in line with many previous studies (Dzhambov et al., 2018; Gascon et al., 2018; Wood et al., 2017; Zhang & Tan, 2019). Zhang et al. (Zhang & Tan, 2019) found that all three types of greenspace metrics considered – vegetation cover, canopy cover, park area – were associated with improved mental health, though canopy cover showed the strongest association. However, our results for the amount of greenspace contrast with findings from Chicago (Fan et al., 2011) and New York City, (Yoo et al., 2022) showing that neighborhood-level greenness was not associated with mental well-being. The Chicago study also found that park area positively impacted mental wellbeing, (Fan et al., 2011) which does not agree with our findings. Nonetheless, the same study showed that park distance was not associated with health outcomes, which is in line with our results. Interestingly, the study from New York City (Yoo et al., 2022) showed that park proximity was associated with increased emergency room visits for mental disorders. Among the studies from Mexico, our findings of no statistically significant relationships between urban park metrics and depressive symptoms are in contrast with 1) Bojorquez et al., (Bojorquez & Ojeda-Revah, 2018) who found a strong negative relationship between park coverage within residential buffers and depression score for adult women in Tijuana, and 2) Ayala-Azcárraga et al., (Ayala-Azcárraga et al., 2019) who found that park proximity was associated with improved life satisfaction among the users of nine Mexico City parks. Our finding of no association between park proximity and depressive symptoms are in line with Huerta and Utomo, (Mayen Huerta & Utomo, 2021) although the authors used a different outcome – subjective well-being. Differences between study designs and samples – in particular our multi-city study vs. smaller-scale studies for Mexico – may contribute to the divergent findings.

The association of NDVI with depressive symptoms, as opposed to % greenspace, is interesting and warrants future research into specific features of greenspace that can be beneficial for mental health. While % greenspace and NDVI are strongly correlated, they represent different aspects of greenspace. NDVI is characteristic of both vigor and the amount of vegetation in an area, whereas % greenspace area contains limited information about how healthy and verdant the vegetation may be. In our sample and in other studies NDVI showed weak correlations with urban park measures; (Gascon et al., 2016) and it only showed weak correlations with certain fine-grained types of land cover/use in other studies (Gascon et al., 2016; Rugel et al., 2017). Given that we found no associations for another set of greenspace metrics that do not explicitly describe vegetation intensity – urban parks – we speculate that it is the greenness, rather than only the amount, of vegetation that may be associated with reduced odds of depressive symptoms.

Our results showed no association between the amount and distribution of urban parks and depressive symptoms. The quality of urban greenspace, including parks, and such attributes as cleanliness and amenities, are important determinants of parks use (McCormack et al., 2010) and the psychological and physiological benefits they may confer. Therefore, future research should also consider parks' attributes and amenities and how they relate to depressive symptoms, in addition to considering park access and availability. As the reported correlations suggest, urban parks are not necessarily synonymous with greenness even though the urban parks in our data refer to green parks and even though parks are usually thought of as islands of nature in otherwise built-up urban areas (Jarvis et al., 2020). Directly considering the amount of vegetation in parks along with the quality of park maintenance may provide a deeper insight into the relationship between urban parks and depressive symptoms. Ultimately, urban parks and the other greenspace metrics used in the study are only weakly correlated. This is likely because urban parks are human-made, and their quantity is not necessarily correlated with abundant natural greenery in a city that is captured by NDVI or % green, which has also been reported in other cities (Jarvis et al., 2020). As such, park metrics describe fundamentally different aspects of greenspace from NDVI or % green and should be used as complementary indicators in future studies.

The results based on the continuous measure of greenspace revealed that more abundant greenspace measured within 3 km of any point in the neighborhood is associated with smaller odds of depressive symptoms. As the search radius distance goes up, the resulting metric unavoidably includes more greenspace from the neighboring units as evident by the summary statistics in Table 2 and findings from other studies (Reid et al., 2018; Zhang & Tan, 2019). This suggests that 1) the aggregation of units in space can impact the observed greenspace effect; 2) there might be thresholds or non-linearities in the relationship between greenspace and health. While these findings suggest that higher levels of greenspace outside of one's immediate neighborhood may be beneficial for mental wellbeing, the absence of an interaction between neighborhood and city greenness suggests that there may be a (most likely spatial) limit to that beneficial effect. Future studies should undertake a detailed exploration of exposure to greenspace in individuals' activity spaces, and how dynamic exposures may be associated with mental health.

We found little sensitivity of the greenspace-depressive symptoms associations to the temporal aspects of the exposure metric. Specifically, we did not identify critical time windows when higher-than-average NDVI during different periods before the survey is associated with smaller odds of depressive symptoms. This suggests that in Mexico's cities, it is not the intra-annual fluctuations in greenspace that are associated with depressive symptoms but rather the overall level of greenness. There has been extremely little research into the seasonal variability of greenspace and its impact on mental health, so this result should be verified in other settings.

While we found no evidence of effect modification of the association between greenspace and depressive symptoms by individual characteristics, we found that in more polluted neighborhoods the beneficial effects of greenspace may be diminished. This diminished benefit of greenspace may exist because air pollution can lead to oxidative stress, inflammation, and generally worse health, (Chuang et al., 2007; O'Neill et al., 2007) negating any benefits of greenspace exposure. However, the interplay between air pollution, greenspace, and mental health may be even more complex and include for example the mediating effect of greenspace on air pollution, (Dzhambov et al., 2020) the exploration of which is beyond the scope of this study.

Multiple cities have formulated their plans to increase greenspace coverage in terms of expanding percent tree coverage (de Barcelona, 2017; O'Neil-Dunne, 2016). In particular, an evidence-based guideline of 30 % neighborhood tree coverage has been suggested (Konijnendijk, 2023) – and adopted by many global North cities (de Barcelona, 2017; O'Neil-Dunne, 2016) – as a target. However, it is not clear what improvement in mental health the achievement of these targets would entail as most of the health impact assessments and simulation studies that evaluated the impact of increased greenspace on human wellbeing have been conducted in relation to temperature-related mortality (Iungman et al., 2023). Moreover, the % tree canopy target may not be suitable for Mexico because the country has a large area occupied by the arid climate zone with succulent vegetation that does not necessarily result in a conventional canopy as in deciduous/coniferous trees, so the target may need to be modified to 30 % vegetation coverage, for example. All of this underscores the importance of expanding research on greenspace and human health to diverse locations in the global South.

6.1. Limitations

Our study is not without limitations. First, our study did not include other alternative greenspace metrics that could be associated with depressive symptoms such as street-level greenery because of data availability. Such metrics would be extremely useful at small spatial scales – at individual residential level, for example – and we did not have such greenspace data nor residential address data available. Apart from urban parks, we did not have data on the availability of other specific types of greenspace (e.g., forests, grass, etc.). Relatedly, metrics describing the spatial configuration of greenspace (e.g., fragmentation, isolation, clustering of greenspaces) could provide insight into the importance of the spatial distribution and arrangement of greenery, but they could not be computed for the neighborhoods because of their small size. Second, survey respondents' answers to the depressive symptoms screening were self-reported and thus may suffer from subjectivity. Third, as this is a cross-sectional study, longitudinal data on depressive symptoms could provide more robust inference regarding the causal connections between greenspace and depressive symptoms. Fourth, our study may suffer from omitted variable bias resulting from unobserved individual-level covariates that could be associated with depressive symptoms such as income, even though we extracted as many individual and area-level socioeconomic variables from the survey data as possible, and it did not result in multicollinearity issues. Fifth, data on the duration of residence in a particular neighborhood was not available, so a certain degree of exposure misclassification is possible for individuals who moved shortly before the survey was conducted. Finally, as individuals move about the city, they are exposed to different levels of greenness through their activity spaces during the day. Unfortunately, we lacked data to compute mobility-based greenspace exposure metrics. Future research should consider using greenspace data collected at even finer geographical scales as well as data on specific greenspace types such as forests, grass, bushes (and others) to investigate how they relate to mental wellbeing.

6.2. Strengths

Our study is based on a large sample of individuals living across 84 large cities in Mexico, which is one of the few multi-site studies on the topic and which allows us enough statistical power to detect associations. The focus on Mexico extends the geographic extent in the evidence for the relationship between greenspace and mental health beyond the global North and several locations in Asia. We evaluated and compared heterogeneous types of greenspace data – NDVI, % greenspace, and urban parks – in relation to depressive symptoms. Moreover, we employed kernel density estimation to create continuous surfaces of greenspace, which allowed us to further explore the importance of broad (as opposed to local) greenspace which exists outside of the immediate residential neighborhood and which individuals can engage with. Another contribution lies in the exploration of the temporal resolution of greenspace data and its implications for depressive symptoms with the help of distributed lag models. Analyzing and comparing the relationship between greenspace and depressive symptoms using a wide array of metrics and approaches reveals the importance of the choice of metrics in studies of greenspace and human wellbeing.

7. Conclusion

Our study investigated associations between greenspace and depressive in Mexico's cities, which, along with other global South countries, is severely understudied in this line of work. Among a diverse set of metrics investigated, higher neighborhood-level greenness was associated with smaller odds of depressive symptoms, while other metrics were not. Overall, the magnitude of the associations between greenspace and depressive symptoms in Mexico's cities is small, although it is in line with what has been observed in other studies from other locations (Liu et al., 2023). As cities pursue greening as part of their efforts to regulate thermal comfort, reduce air pollution, provide communal spaces and increase social interaction, people's mental health will likely stand to benefit from those efforts. However, as our results show, more research using multiple complementary metrics of urban greenspace is needed, especially in the global South, to better understand specific features of greenspace associated with human health.

CRediT authorship contribution statement

Maryia Bakhtsiyarava: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Yang Ju:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **Mika Moran:** Conceptualization, Writing – original draft, Writing – review & editing. **Daniel A. Rodríguez:** Conceptualization, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Iryna Dronova:** Conceptualization, Writing – original draft, Writing – review & editing. **Xavier Delclòs-Alió:** Conceptualization, Writing – original draft, Writing – review & editing. **Kari Moore:** Data curation, Writing – original draft, Writing – review & editing. **Marianela Castillo-Riquelme:** Conceptualization, Writing – original draft, Writing – review & editing. **Cecilia Anza-Ramirez:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing interest

The authors state they have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2024.103219.

References

Agudelo-Botero, M., et al. (2021). Prevalence, incidence and years of life adjusted for disability due to depressive disorders in Mexico: Results of the Global Burden of Disease Study 2019. *J. Affect. Disord. Rep., 6*, Article 100206.

Aguilar, A. G., Flores, M. A., & Lara, L. F. (2022). Peri-urbanization and land Use fragmentation in Mexico City. Informality, environmental Deterioration, and Ineffective urban policy. *Front. Sustain. Cities, 4*.

Ayala-Azcárraga, C., Diaz, D., & Zambrano, L. (2019). Characteristics of urban parks and their relation to user well-being. *Landsc. Urban Plan., 189*, 27–35.

Belló, M., Puentes-Rosas, E., Medina-Mora, M. E., & Lozano, R. (2005). [Prevalence and diagnosis of depression in Mexico]. *Salud Publica Mex, 47*(Suppl 1), S4–S11.

Benítez, G., Pérez-Vázquez, A., Nava-Tablada, M., Equihua, M., & Álvarez-Palacios, J. L. (2012). Urban expansion and the environmental effects of informal settlements on the outskirts of Xalapa city, Veracruz, Mexico. *Environ. Urban., 24*, 149–166.

Berenzon, S., Lara, M. A., Robles, R., & Medina-Mora, M. E. (2013). Depresión: Estado del conocimiento y la necesidad de políticas públicas y planes de acción en México. *Salud Pública México, 55*, 74–80.

Beyer, K. M. M., et al. (2014). Exposure to neighborhood green space and mental health: Evidence from the survey of the health of Wisconsin. *Int. J. Environ. Res. Public. Health, 11*, 3453–3472.

Biggs, T. W., Anderson, W. G., & Pombo, O. A. (2015). Concrete and Poverty, vegetation and Wealth? A Counterexample from remote sensing of socioeconomic indicators on the U.S.–Mexico Border. *The Professional Geographer, 67*, 166–179.

Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. *Landsc. Urban Plan., 215*, Article 104217.

Bojorquez, I., & Ojeda-Revah, L. (2018). Urban public parks and mental health in adult women: Mediating and moderating factors. *Int. J. Soc. Psychiatry, 64*, 637–646.

Braçe, O., et al. (2020). Is a view of green spaces from Home associated with a lower risk of anxiety and depression? *Int. J. Environ. Res. Public. Health, 17*, 7014.

Breen, A., Giannotti, E., Flores Molina, M., & Vásquez, A. (2020). From "Government to Governance"? A systematic literature review of research for urban green infrastructure Management in Latin America. *Front. Sustain. Cities, 2*.

Buoli, M., et al. (2018). Is there a link between air pollution and mental disorders? *Environment International, 118*, 154–168.

Busso, M., & Messina, J. (2020). The inequality crisis: Latin America and the Caribbean at the Crossroads. *Inter-Am. Dev. Bank, 32*, Article 0002629.

Callaghan, A., et al. (2021). The impact of green spaces on mental health in urban settings: A scoping review. *Journal of Mental Health, 30*, 179–193.

Charlson, F., et al. (2019). New WHO prevalence estimates of mental disorders in conflict settings: A systematic review and meta-analysis. *The Lancet, 394*, 240–248.

Chuang, K.-J., Chan, C.-C., Su, T.-C., Lee, C.-T., & Tang, C.-S. (2007). The effect of urban air pollution on inflammation, oxidative stress, Coagulation, and Autonomic Dysfunction in young adults. *American Journal of Respiratory and Critical Care Medicine, 176*, 370–376.

Collins, R. M., et al. (2020). A systematic map of research exploring the effect of greenspace on mental health. *Landsc. Urban Plan., 201*, Article 103823.

de Barcelona, Ajuntament (2017). *Master plan for Barcelona's Trees 2017–2037*. https://ajuntament.barcelona.cat/ecologiaurbana/sites/default/files/Pla-director-arbrat-barcelona-ENG.pdf.

de Vries, S., van Dillen, S. M. E., Groenewegen, P. P., & Spreeuwenberg, P. (2013). Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. *Social Science & Medicine, 94*, 26–33.

Delgado Ramos, G. C. (2019). Real estate industry as an urban growth machine: A review of the political economy and political ecology of urban space production in Mexico city. *Sustainability, 11*, 1980.

Didan, K. (2015). MOD13Q1 MODIS/Terra vegetation indices 16-day L3 global 250m SIN grid V006. *NASA EOSDIS Land Process. DAAC, 10*, 415.

Dobbs, C., et al. (2019). Urban ecosystem Services in Latin America: Mismatch between global concepts and regional realities? *Urban Ecosystems, 22*, 173–187.

Dzhambov, A. M., Browning, M. H. E. M., Markevych, I., Hartig, T., & Lercher, P. (2020). Analytical approaches to testing pathways linking greenspace to health: A scoping review of the empirical literature. *Environmental Research, 186*, Article 109613.

Dzhambov, A. M., et al. (2018). Multiple pathways link urban green- and bluespace to mental health in young adults. *Environmental Research, 166*, 223–233.

Ekkel, E. D., & de Vries, S. (2017). Nearby green space and human health: Evaluating accessibility metrics. *Landsc. Urban Plan., 157*, 214–220.

Engemann, K., et al. (2019). Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. *Proc. Natl. Acad. Sci., 116*, 5188–5193.

Fan, Y., Das, K. V., & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health & Place, 17*, 1202–1211.

Flores, S., Van Mechelen, C., Vallejo, J. P., & Van Meerbeek, K. (2022). Trends and status of urban green and urban green research in Latin America. *Landsc. Urban Plan., 227*, Article 104536.

Gascon, M., et al. (2016). *Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city* (Vol. 19, pp. 88–94). Urban For. Urban Green..

Gascon, M., et al. (2018). Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study. *Environmental Research, 162*, 231–239.

Gasparrini, A. (2011). Distributed lag linear and non-linear models in R: The package dlnm. *J. Stat. Softw., 43*, 1.

Gasparrini, A. (2014). Modeling exposure–lag–response associations with distributed lag non-linear models. *Statistics in Medicine, 33*, 881–899.

Gasparrini, A., et al. (2015). Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *Lancet Lond. Engl., 386*, 369–375.

Gatrell, A. C., Bailey, T. C., Diggle, P. J., & Rowlingson, B. S. (1996). Spatial point pattern analysis and its Application in geographical Epidemiology. *Transactions of the Institute of British Geographers, 21*, 256–274.

Global, regional, and national disability-adjusted life-years (DALYs) for 333 diseases and injuries and healthy life expectancy (HALE) for 195 countries and territories, 1990–2016: A systematic analysis for the global burden of disease study 2016. *Lancet Lond. Engl., 390*, (2017), 1260–1344.

Hartig, T. (2021). Restoration in nature: Beyond the conventional Narrative. In *Nature and Psychology: Biological, Cognitive, developmental, and social pathways to well-being* (pp. 89–151).

Helbich, M. (2019). Spatiotemporal Contextual Uncertainties in green space exposure measures: Exploring a time series of the normalized difference vegetation indices. *Int. J. Environ. Res. Public. Health, 16*, 852.

Houlden, V., Weich, S., Albuquerque, J. P. de, Jarvis, S., & Rees, K. (2018). The relationship between greenspace and the mental wellbeing of adults: A systematic review. *PLoS One, 13*, Article e0203000.

Iungman, T., et al. (2023). Cooling cities through urban green infrastructure: A health impact assessment of European cities. *The Lancet, 401*, 577–589.

Järv, O., Ahas, R., & Witlox, F. (2014). Understanding monthly variability in human activity spaces: A twelve-month study using mobile phone call detail records. *Transp. Res. Part C Emerg. Technol., 38*, 122–135.

Jarvis, I., Gergel, S., Koehoorn, M., & van den Bosch, M. (2020). Greenspace access does not correspond to nature exposure: Measures of urban natural space with implications for health research. *Landsc. Urban Plan., 194*, Article 103686.

Ju, Y., Dronova, I., & Delclòs-Alió, X. (2022). A 10 m resolution urban green space map for major Latin American cities from Sentinel-2 remote sensing images and OpenStreetMap. *Scientific Data, 9*(1), 586.

Kaplan, S., & Kaplan, R. (1982). *Cognition and environment: Functioning in an uncertain world*. Greenwood.

Kephart, J. L., Sánchez, B. N., Moore, J., Schinasi, L. H., Bakhtsiyarava, M., Ju, Y., … Diez Roux, A. V. (2022). City-level impact of extreme temperatures and mortality in Latin America. *Nature medicine, 28*(8), 1700–1705.

Konijnendijk, C. C. (2023). Evidence-based guidelines for greener, healthier, more resilient neighbourhoods: Introducing the 3–30–300 rule. *J. For. Res., 34*, 821–830.

Kwan, M.-P. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers, 102*, 958–968.

Kwan, M.-P. (2018). The limits of the neighborhood effect: Contextual Uncertainties in geographic, environmental health, and social science research. *Ann. Am. Assoc. Geogr., 108*, 1482–1490.

Labib, S. M., Huck, J. J., & Lindley, S. (2021). Modelling and mapping eye-level greenness visibility exposure using multi-source data at high spatial resolutions. *Sci. Total Environ., 755*, Article 143050.

Labib, S. M., Lindley, S., & Huck, J. J. (2020a). Scale effects in remotely sensed greenspace metrics and how to mitigate them for environmental health exposure assessment. *Computers, Environment and Urban Systems, 82*, Article 101501.

Labib, S. M., Lindley, S., & Huck, J. J. (2020b). Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. *Environmental Research, 180*, Article 108869.

Liu, Z., et al. (2023). Green space exposure on depression and anxiety outcomes: A meta-analysis. *Environmental Research, 231*, Article 116303.

Loveland, T. R., & Dwyer, J. L. L. (2012). Building a strong future. *Remote Sensing of Environment, 122*, 22–29.

Lu, Y., Yang, Y., Sun, G., & Gou, Z. (2019). Associations between overhead-view and eye-level urban greenness and cycling behaviors. *Cities, 88*, 10–18.

Markevych, I., et al. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research, 158*, 301–317.

Mathers, C. D., & Loncar, D. (2006). Projections of global mortality and burden of disease from 2002 to 2030. *PLoS Medicine, 3*, e442.

Mayen Huerta, C. (2022). Rethinking the distribution of urban green spaces in Mexico City: Lessons from the COVID-19 outbreak. *Urban Forestry and Urban Greening, 70*, Article 127525.

Mayen Huerta, C., & Utomo, A. (2021). Evaluating the association between urban green spaces and subjective well-being in Mexico city during the COVID-19 pandemic. *Health & Place, 70*, Article 102606.

McCormack, G. R., Rock, M., Toohey, A. M., & Hignell, D. (2010). Characteristics of urban parks associated with park use and physical activity: A review of qualitative research. *Health & Place, 16*, 712–726.

McEachan, R. R. C., et al. (2016). The association between green space and depressive symptoms in pregnant women: Moderating roles of socioeconomic status and physical activity. *Journal of Epidemiology & Community Health, 70*, 253–259.

Montejano Escamilla, J. A., Avila Jiménez, G., & Caudillo Cos, C. A. (2020). Estandarización de las áreas geoestadísticas básicas urbanas para 100 ciudades del Sistema Urbano Nacional. *Real. Datos Espac. Rev. Int. Estad. Geogr., 11*.

Nawrath, M., Guenat, S., Elsey, H., & Dallimer, M. (2021). Exploring uncharted territory: Do urban greenspaces support mental health in low- and middle-income countries? *Environmental Research, 194*, Article 110625.

Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *Int. J. Environ. Res. Public. Health, 18*, Article 11028.

Nieuwenhuijsen, M. J., Khreis, H., Triguero-Mas, M., Gascon, M., & Dadvand, P. (2017). Fifty shades of green. *Epidemiology, 28*, 63–71.

O'Neil-Dunne, J. (2016). *Seattle tree canopy assessment*. University of Vermont. https://www.seattle.gov/trees/docs.

O'Neill, M. S., et al. (2007). Air pollution and inflammation in type 2 diabetes: A mechanism for susceptibility. *Occupational and Environmental Medicine, 64*, 373–379.

Openshaw, S. (1984). Ecological fallacies and the analysis of areal census data. *Environ. Plan. A, 16*, 17–31.

Openshaw, S. & Taylor, P. A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. in Statistical applications in the spatial sciences 127–144 (Pion).

Pina, F., *et al.* Mapping urban parks in Latin America throught the classification of satellite images using collaborative web data.

Quistberg, D. A., et al. (2019). Building a data platform for cross-country urban health studies: The SALURBAL study. *Journal of Urban Health, 96*, 311–337.

Reid, C. E., Kubzansky, L. D., Li, J., Shmool, J. L., & Clougherty, J. E. (2018). It's not easy assessing greenness: A comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York city. *Health & Place, 54*, 92–101.

Rigolon, A., Browning, M., Lee, K., & Shin, S. (2018). Access to urban green space in cities of the global South: A systematic literature review. *Urban Sci, 2*, 67.

Roberts, R. E., & Vernon, S. W. (1983). The center for Epidemiological studies depression scale: Its use in a community sample. *Am. J. Psychiatry*.

Romero-Martínez, M., et al. (2013). Encuesta Nacional de Salud y Nutrición 2012: Diseño y cobertura. *Salud Publica Mex, 55*, S332–S340.

Rugel, E. J., Henderson, S. B., Carpiano, R. M., & Brauer, M. (2017). Beyond the normalized difference vegetation index (NDVI): Developing a natural space index for population-level health research. *Environmental Research, 159*, 474–483.

Salinas-Rodríguez, A., et al. (2013). Validación de un punto de corte para la Escala de Depresión del Centro de Estudios Epidemiológicos, versión abreviada (CESD-7). *Salud Pública México, 55*, 267–274.

Sandoval, V., & Sarmiento, J. P. (2020). A neglected issue: Informal settlements, urban development, and disaster risk reduction in Latin America and the Caribbean. *Disaster Prev. Manag. Int. J., 29*, 731–745.

Schinasi, L. H., Bakhtsiyarava, M., Sanchez, B. N., Kephart, J. L., Ju, Y., Arunachalam, S., Gouveia, N., Caiaffa, W. T., O'Neill, M. S., Dronova, I., & Roux, A. V. D. (2023). Greenness and excess deaths from heat in 323 Latin American cities: Do associations vary according to climate zone or green space configuration? *Environment International, 180*, 108230. https://www.sciencedirect.com/science/article/pii/S0160412023005032.

Sera, F., et al. (2019). How urban characteristics affect vulnerability to heat and cold: A multi-country analysis. *International Journal of Epidemiology, 48*, 1101–1112.

Silverman, B. W. (2017). *Density estimation for statistics and data analysis*. Routledge. https://doi.org/10.1201/9781315140919

Su, J. G., Dadvand, P., Nieuwenhuijsen, M. J., Bartoll, X., & Jerrett, M. (2019). Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. *Environment International, 126*, 162–170.

Tallis, M., Taylor, G., Sinnett, D., & Freer-Smith, P. (2011). Estimating the removal of atmospheric particulate pollution by the urban tree canopy of London, under current and future environments. *Landsc. Urban Plan., 103*, 129–138.

Tan, P. Y., & Samsudin, R. (2017). Effects of spatial scale on assessment of spatial equity of urban park provision. *Landsc. Urban Plan., 158*, 139–154.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landsc. Urban Plan., 158*, 25–38.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*, 127–150.

Tuholske, C., et al. (2021). Global urban population exposure to extreme heat. *Proc. Natl. Acad. Sci., 118*, Article e2024792118.

Ulrich, R. S. (1983). Aesthetic and affective response to natural environment. *Behav. Nat. Environ.*, 85–125.

United Nations Department of Economic and Social Affairs Population & Division. (2018). *World urbanization Prospects*. Highlights.

van Donkelaar, A., et al. (2016). Global estimates of fine particulate matter using a combined Geophysical-statistical method with information from satellites, models, and Monitors. *Environ. Sci. Technol., 50*, 3762–3772.

Votruba, N., Thornicroft, G., & Group, F. S. (2016). Sustainable development goals and mental health: Learnings from the contribution of the FundaMentalSDG global initiative. *Glob. Ment. Health, 3*.

Wang, R., et al. (2021). Dynamic greenspace exposure and residents' mental health in Guangzhou, China: From over-head to eye-level perspective, from quantity to quality. *Landsc. Urban Plan., 215*, Article 104230.

Williams, D. L., Goward, S., & Arvidson, T. (2006). *Landsat. Photogramm. Eng. Remote Sens., 72*, 1171–1178.

Wood, L., Hooper, P., Foster, S., & Bull, F. (2017). Public green spaces and positive mental health – investigating the relationship between access, quantity and types of parks and mental wellbeing. *Health & Place, 48*, 63–71.

Yoo, E.-H., Roberts, J. E., Eum, Y., Li, X., & Konty, K. (2022). Exposure to urban green space may both promote and harm mental health in socially vulnerable neighborhoods: A neighborhood-scale analysis in New York city. *Environmental Research, 204*, Article 112292.

Zhang, Y., Murray, A. T., & Turner, B. L., Ii (2017). Optimizing green space locations to reduce daytime and nighttime urban heat island effects in Phoenix, Arizona. *Landsc. Urban Plan., 165*, 162–171.

Zhang, L., & Tan, P. Y. (2019). Associations between urban green spaces and health are dependent on the analytical scale and how urban green spaces are measured. *Int. J. Environ. Res. Public. Health, 16*, 578.

Zhang, R., Zhang, C.-Q., & Rhodes, R. E. (2021). The pathways linking objectively-measured greenspace exposure and mental health: A systematic review of observational studies. *Environmental Research, 198*, Article 111233.