Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China

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ABSTRACT

Background: Residential green and blue spaces may be therapeutic for the mental health. However, solid evidence on the linkage between exposure to green and blue spaces and mental health among the elderly in non-Western countries is scarce and limited to exposure metrics based on remote sensing images (i.e., land cover and vegetation indices). Such overhead-view measures may fail to capture how people perceive the environment on the site.
Objective: This study aimed to compare streetscape metrics derived from street view images with satellite-derived ones for the assessment of green and blue space; and to examine associations between exposure to green and blue spaces as well as geriatric depression in Beijing, China.
Methods: Questionnaire data on 1190 participants aged 60 or above were analyzed cross-sectionally. Depressive symptoms were assessed through the shortened Geriatric Depression Scale (GDS-15). Streetscape green and blue spaces were extracted from Tencent Street View data by a fully convolutional neural network. Indicators derived from street view images were compared with a satellite-based normalized difference vegetation index (NDVI), a normalized difference water index (NDWI), and those derived from GlobeLand30 land cover data on a neighborhood level. Multilevel regressions with neighborhood-level random effects were fitted to assess correlations between GDS-15 scores and these green and blue spaces exposure metrics.
Results: The average cumulative GDS-15 score was 3.4 (i.e., no depressive symptoms). Metrics of green and blue space derived from street view images were not correlated with satellite-based ones. While NDVI was highly correlated with GlobeLand30 green space, NDWI was moderately correlated with GlobeLand30 blue space. Multilevel regressions showed that both street view green and blue spaces were inversely associated with GDS-15 scores and achieved the highest model goodness-of-fit. No significant associations were found with NDVI, NDWI, and GlobeLand30 green and blue space. Our results passed robustness tests.
Conclusion: Our findings provide support that street view green and blue spaces are protective against depression for the elderly in China, yet longitudinal confirmation to infer causality is necessary. Street view and satellite-derived green and blue space measures represent different aspects of natural environments. Both street view data and deep learning are valuable tools for automated environmental exposure assessments for health-related studies.

1. Introduction

Awareness is mounting that neighborhood outdoor environments are vital for people's health (Helbich, 2018; Nieuwenhuijsen et al., 2017). Exposure to natural environments including green spaces (e.g., grass, trees) and blue spaces (e.g., rivers, lakes) seems to have an array of mental health benefits (Hartig et al., 2014; Silva et al., 2018), as a meta-review suggests (van den Bosch and Sang, 2017).

Some studies observed a positive relationship between mental health and green (Beyer et al., 2014; Sarkar et al., 2018; Triguero-Mas et al., 2015; Zock et al., 2018) or blue space (De Bell et al., 2017; Nutsford et al., 2016), while others reported no associations (Alcock

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et al., 2015; Boers et al., 2018). Yet, health impacts of blue space are less clear (Dadvand et al., 2016; Dempsey et al., 2018; Foley and Kistemann, 2015; Gascon et al., 2017; Triguero-Mas et al., 2015). Most research is concerned with Europe and North America, while the Asian context remains under-represented (Markevych et al., 2017). Further, the existing body of knowledge usually deals with the working age population (Gascon et al., 2018) or youth (Dzhambov et al., 2018); only a few address mental health outcomes among elderly people (Dempsey et al., 2018; Kabisch et al., 2017). This conflicts with contemporary debates about aging societies (e.g., in China 41% of the population will be aged > 60 in 2050), where it is crucial to ensure mental health later in life (United Nations, 2017).

The operationalization of green and blue space in epidemiological studies is not trivial, as multiple ways are conceivable (Cusack et al., 2017; Larkin and Hystad, 2018; Reid et al., 2018; Rhew et al., 2011; Villeneuve et al., 2018). Remote sensing, the gold-standard to generate such indicators (Markevych et al., 2017; Mitchell et al., 2011), either uses derivates of vegetation or water indices (McFeeters, 1996; Tucker, 1979) or classifies images into land use and land cover categories (e.g., forests, waterbodies) as surrogate measures (Helbich et al., 2018; Zock et al., 2018). Substantial methodological drawbacks arise due to the spatially moderate resolution of the images (e.g., 30 m of Landsat 8), the minimum mapping size constraining the smallest detectable objects (Van Dillen et al., 2012), etc. More importantly, downward-facing satellites conceptually represent a bird's eye perspective, but do not necessarily reflect the ground-level perspective people have on green and blue space (Dong et al., 2018; Lu et al., 2018). As a consequence, distinct deviations are possible and smaller and/or vertical areas of perceived green and blue spaces (e.g., street trees, lawns, green walls), which are particularly essential in cities, remain unrecognized.

A common way to assess small green and blue spaces in streetscapes is to carry out in situ audits (Gidlow et al., 2018). De Vries et al. (2013), for example, audited a sample of four streets per neighborhood. This manual approach is questionable due to its limited sample size, which is inefficient in large-scale field observations, and may be biased due to observers' subjective ratings. Although such bias can be reduced through rater training (Van Dillen et al., 2012) and well thought out rating scales (Gidlow et al., 2018), comprehensive on-site visits are labor-intensive and time-consuming.

An infrequently used alternative is street view services on the web (e.g., Google, Tencent) which allow researchers to virtually navigate through urban spaces composed of geo-tagged street-level images (Rundle et al., 2011). While these services coupled with desktop-based audit tools are a valuable source of place-based information about neighborhoods (Rzotkiewicz et al., 2018), the manual analyses of many pictures and larger areas is tedious.

To overcome these constraints, objective and automated assessments of street view data are favored (Doersch et al., 2012; Gebru et al., 2017; Gong et al., 2018; Middel et al., 2019). State-of-the-art machine learning supports an automatic, comprehensive evaluation of high-resolution street view images, while simultaneously being effective and accurate (Dong et al., 2018; Li et al., 2018; Weichenthal et al., 2019). Seiferling et al. (2017), for instance, utilized street view data for Boston and New York (US) to determine tree crowns in public space. However, the utilization of street view data for exposure assessments to study the mental health impacts of green and blue space is novel, and comparisons with traditional remote sensing-based assessments are lacking.

Therefore, the aim of this study was to examine the fitness for use of street view green and blue space measures, and to analyze associations between depressive symptoms and streetscape natural environments (i.e., green and blue space) among elderly people in Beijing, China. The following were our research questions:

1. Do differently operationalized green and blue space metrics (i.e., street view vs. remotely sensed) lead to diverging results?
2. Are both green and blue spaces protective against depressive symptoms among the elderly in Beijing?

Two hypotheses were generated, namely that street view green and blue spaces are weakly correlated with remote sensing-based measures, and that exposure to street view green and blue spaces is negatively associated with depressive symptoms among the elderly.

This study contributes to the literature in proposing objective and automated street view exposure assessments based on a large number of street view images and deep learning algorithms (LeCun et al., 2015; Long et al., 2015). It explores the elderly in Beijing – an understudied but vulnerable population group in a fast growing Asian metropolis (Markevych et al., 2017). The prevalence of mental diseases is, at 32%, considerable high there (China Health and Retirement Longitudinal Study, 2015).

2. Materials and methods

2.1. Research design and study population

This cross-sectional population-based study used the mental health survey conducted by Renmin University in China between March and August 2011. The study population comprised elderly people residing in the Haidian district in Beijing, China. This inner-city district in the northwestern part of Beijing has a total population of 3.59 million (2016) and covers an area of 431 km². The prevalence of mental disorders in Haidian is higher than in other districts and many elderly people live there (China Health and Retirement Longitudinal Study, 2015): In 2011, approximately 386,000 people aged over 60 years lived there; by 2015, this figure had increased to 470,000 (+22%). These features made the district of Haidian a fertile research area.

The participant recruitment procedure was based on a two-stage stratified sampling design. In the first phase, 48 residential neighborhoods (*juweihui*) in the 13 districts (*jiedao*) were randomly selected by means of stratified sampling from Haidian District (*qu*). Then, in phase two, 30 persons in each sampled neighborhood were approached at their residential address using a stratified sampling method. This procedure led to a random sample of 1250 participants, each of whom met the inclusion criteria of aged > 60 and living in the district for > 10 years. The survey addressed a wide range of questions dealing with participants' mental health, demographics, socioeconomic situation, etc. All participants gave their consent to the survey. The linkage to environmental data was based on the most detailed available neighborhood level (i.e., administrative units) within which people live. The average neighborhood size was small (2 km²; SD ± 1.5), ranging from 0.4 to 4.2 km². After cleaning the data (e.g., removing incomplete surveys), a total of 1190 people remained in the dataset.

2.2. Mental health data

Information on the mental health of the elderly was collected through questionnaires. The assessment was carried out with the self-rated Geriatric Depression Scale (GDS-15) (Sheikh and Yesavage, 1986). As the long version (originally covering 30 items) is rather time-consuming to fill in and may lead to fatigue, we used the shortened 15-item GDS-15 to screen depressive symptoms over the previous week (Sheikh and Yesavage, 1986; Smarr and Keefer, 2011). The GDS-15 was found to be an accurate screening instrument (de Craen et al., 2003), recommended to recognize late-life depression (Mitchell et al., 2010). The included items comprise, for example, characteristics of depression such as sadness and crying, as well as cognitive aspects like thoughts of helplessness, hopelessness, worthlessness, etc. The GDS-15 score ranges from 0 to 15, where 0 refers to no depressive symptoms and 15 refers to severe depressive symptoms. The internal consistency across the items was, at 0.862, excellent as assessed by Cronbach's alpha.

2.3. Residential green and blue space data

2.3.1. Street view data

We assessed green and blue space per neighborhood based on a series of street view images collected 2012. The images were extracted from Tencent Map,[2] the Chinese equivalent of Google Maps. It is the most comprehensive service with the largest image coverage providing street view photos taken from various positions (Long and Liu, 2017).

Based on OpenStreetMap (Arsanjani, 2015), we constructed point transects along the road network. The sampling points were 100 m apart; a compromise between detail and computation time. Given these locations, the closest pictures in the horizontal direction were queried through an HTTP URL and crawled through the application programming interface. To include the entire streetscape at each sampling point, we took images taken in the four main cardinal directions (i.e., 0, 90, 180, and 270 degrees) (Lu et al., 2018). The size of each image was 480 × 320 pixels with a vertical angle of 0 degrees. In total, 134,778 street view images were obtained. We considered, on average, 2807 images (standard deviation (SD) ± 1053) per neighborhood.

2.3.2. Remote sensing data

To compare street view with remotely sensed green and blue space, the GlobeLand30 repository,[3] maintained by the National Geomatics Center of China, was assessed. The repository is a global land cover archive obtained from Landsat scenes (Chen et al., 2015). The data have a spatial resolution of 30 m. Since quality assessments of multiple sites and against multiple products yield a high thematic accuracy (> 80%), the data were suitable for our purpose (Brovelli et al., 2015). To match with the other data, we used the most recent data, namely for 2010. To abstract environmental exposures, the 10 land cover classes were reclassified. For green space, cultivated land (i.e., land used for agriculture, gardens, etc.), forest (i.e., land covered with trees, with > 30% vegetation cover), and grassland (i.e., land covered by natural grass with > 10% cover) were aggregated. For blue space, we used the land cover category water bodies (rivers, lakes, etc.). The proportion of green and blue space per neighborhood was determined (in %).

Alternatively, the levels of green and blue space were also mapped through two indices quantifying the surface reflectance, namely the normalized difference vegetation index (NDVI) (Tucker, 1979) and the normalized difference water index (NDWI) (McFeeters, 1996). Both measures are computed based on the different wavelengths of the light absorbed by green plant canopies and water features. Before determining the average NDVI per neighborhood, we omitted pixels with a negative NDVI, as recommended elsewhere (Markevych et al., 2017; Rugel et al., 2017). With a range of between − 1 and + 1, more positive NDVI values indicate denser vegetation. To assess the quantity of water surfaces per neighborhood, we averaged the NDWI. Higher NDWI values indicate a pronounced availability of water features. We employed Landsat 8 satellite images for June 2010 with a spatial resolution of 30 m, obtained from the United States Geological Survey data repository,[4] as data source for both indices.

2.4. Control variables

Guided by literature reviews (Kraaij et al., 2002), multiple covariate data on an individual level were obtained through the survey. We included a person's gender to adjust for varying depression prevalence between men and women. Age (in years) was adjusted for increasing depression risk over the life time (Kraaij et al., 2002). A respondent's educational background was considered as a categorical variable comprising three classes, that is, primary school or below, high school,

and college and above. In the Chinese context, ethnic minority groups and a local hukou are important (Yang et al., 2018); lacking the latter was found a risk factor for mental disorders (Wang et al., 2018). Both variables were included as dummy variables. We also considered a person's household composition, as single, divorced, or widowed people are high-risk groups (Wang et al., 2018). Functional ability was assessed by the Activities of Daily Living scale (Pluijm et al., 2005). The total score was reclassified into a binary variable. When subjects had problems with at least one of the activities, "restricted" was assigned. Given that physical illness affects mental health (Moussavi et al., 2007), we controlled for whether respondents had one or more chronic diseases (high blood disease, diabetes, etc.). Finally, we considered air pollution suggested to be related to depression (Buoli et al., 2018). Nitrogen dioxide (NO_2) concentrations (in μg/m^3) for the year 2011 were extracted from a globally available land use model with a spatial resolution of 100 m (Larkin et al., 2017).

2.5. Deep learning for image segmentation

A machine learning approach was implemented to extract street view green and blue space from the downloaded images. To circumvent the limitations of pixel-wise classifications using an image's additive colors (e.g., natural and manmade green objects are not discriminable) (Larkin and Hystad, 2018), we applied a semantic segmentation technique that is capable of accurately identifying green and blue space from street view image data (Li et al., 2015).

As deep learning performed well for pattern recognition tasks (LeCun et al., 2015; Rawat and Wang, 2017), we used a fully convolutional neural network for semantic segmentation (i.e., the FCN-8s) (Long et al., 2015) to segment the street view images into common ground objects (e.g., river, tree). Fig. 1 illustrates the network structure.

In essence, to learn different levels of abstraction of the data, the FCN-8s is composed of numerous processing layers linking the input layer (street view images) and the output layer (semantically segmented images). Given an input street view image, convolutional layers extract features and pooling layers compress the data to learn high-level feature maps, while reducing the spatial dimension of the feature maps (Krizhevsky et al., 2012). By comparing the model output and manually marking the segmentation images, FCN-8s uses cross entropy to adjust the parameters of each layer, and obtains a high-accuracy semantic segmentation network through multiple rounds of training. For a technical description of the deep learning, see LeCun et al. (2015), Long et al. (2015), and Rawat and Wang (2017).

Fig. 2 summarizes the workflow. To train the network, we used a collection of annotated images from the ADE20K scene parsing and segmentation database[5] (Zhou et al., 2016, 2017). ADE20K consists of a large number of annotated object categories (e.g., tree, car). After obtaining the image segmentations by feeding the street view images into the trained network, the proportion of green space (e.g., trees, grass, plants, palm trees) and blue space (e.g., rivers, lakes, fountains, waterfalls, swimming pools) was determined.

Streetscape green space per sampling point represents the ratio of the number of green space pixels per image summed over the four cardinal directions to the total number of pixels per image summed over the four cardinal directions (Dong et al., 2018). Streetscape blue space was computed similarly. Finally, the averages per neighborhood were determined (Li and Ghosh, 2018) and attached to the survey data.

2.6. Statistical analyses

After data cleaning, chi^2 and *F*-tests were used to assess differences between the retained survey respondents and the removed ones. Data were summarized through descriptive statistics. Bivariate relations
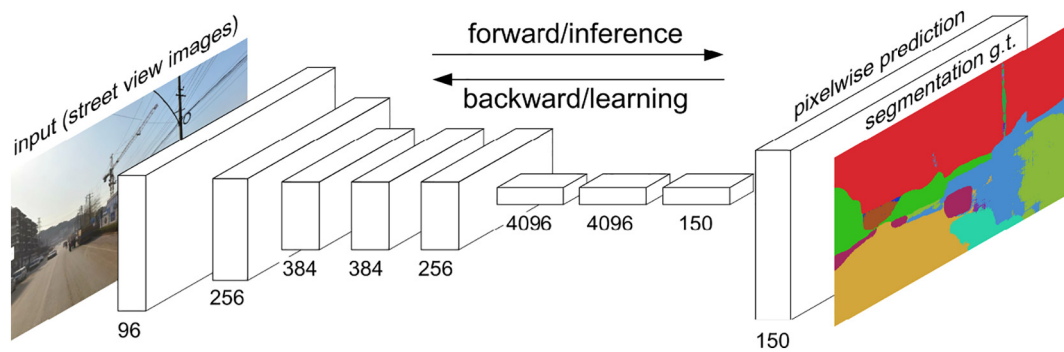

Fig. 1. Architecture of the fully convolutional network (adopted from Long et al., 2015). The attached numbers refer to a layer's convolution kernel size.
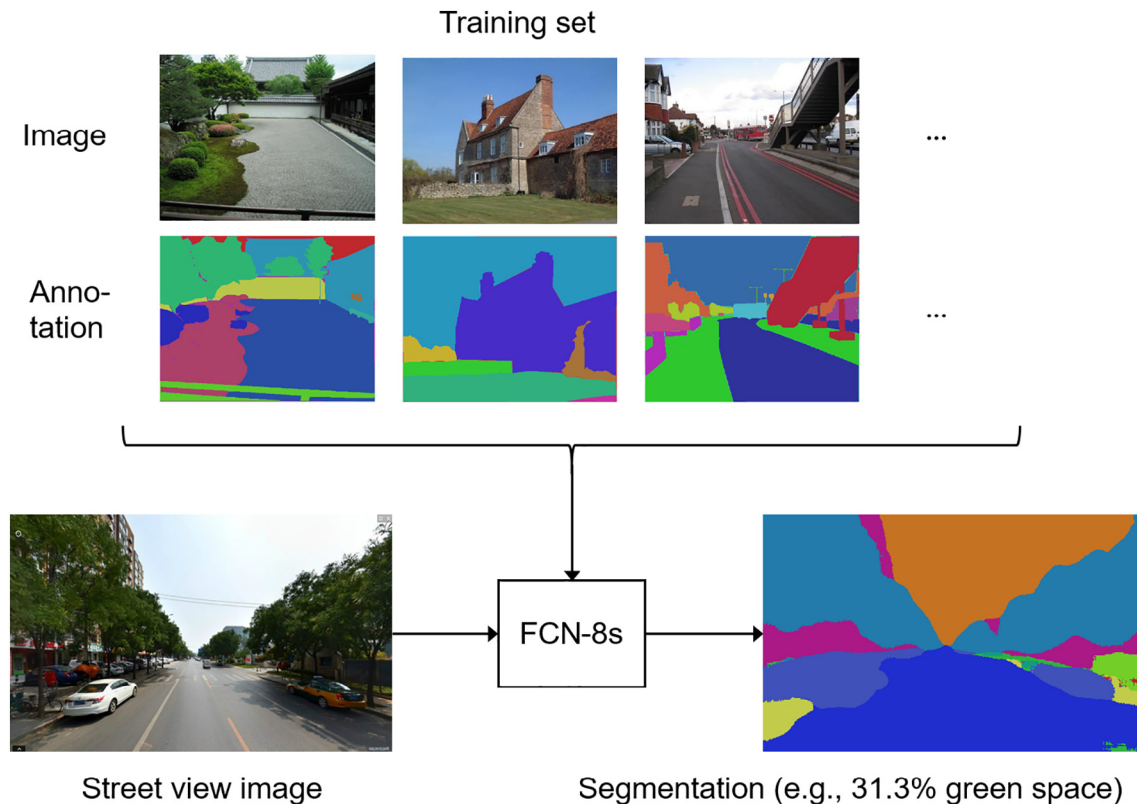

Fig. 2. Street view image segmentation through the fully convolutional neural network.

across the exposure metrics were assessed with non-parametric Spearman correlations. Variance inflation factors were used to investigate multicollinearity among the variables. Values > 3 are deemed as problematic.

Due to the hierarchical nature of the data, we fitted multilevel linear models (Raudenbush and Bryk, 2002) with the GDS-15 score per person as outcome. Random intercepts were employed to adjust for the fact that people cluster in neighborhoods. As relations between green and blue spaces and depression showed non-linearity (Helbich et al., 2018), and to ease interpretation (Rugel et al., 2017), we considered their quartiles (Cusack et al., 2017).

Different models with different adjustment levels were fitted. Besides a null model (i.e., a model without any variables to investigate intra-class correlations), we fitted a baseline model containing only the socioeconomic, demographic, and physical health covariates (Model 1). To examine whether street view green and blue space would improve the goodness-of-fit, Models 2 and 3 extended Model 1 by iteratively adding street view exposures. Model 4 was fully adjusted, including green and blue space together. Models 5 and 6 replaced the street view

measures with the NDVI and NDWI separately while Model 7 considered both NDVI and NDWI. Finally, Models 8 to 10 incorporated either GlobeLand30 green and blue space independently or in combination.

Model performance was assessed by the Akaike information criterion (AIC). A smaller AIC score represents a better goodness-of-fit. An AIC difference of 2 indicates a substantial difference between the models (Burnham and Anderson, 2003). We considered p-values < 0.050 to be statistically significant. Statistics were computed in STATA 15.1.

2.7. Sensitivity and robustness tests

As a self-selection bias between neighborhood environments and residents' health outcomes may exist, propensity score matching (Dehejia and Wahba, 2002) was used in combination with the fully adjusted models (Models 4, 7, and 10). Three matching methods were implemented: k-nearest neighbor matching, radius matching, and kernel matching. The average treatment effect on the treated (ATT) was

estimated to represent the effect of exposure to green/blue space, which was calculated as the difference between the treated group (i.e., people who were significantly influenced by green/blue space) and the untreated group (i.e., people who were not significantly influenced by green/blue space). To ensure ATT robustness, we defined residents in different green/blue space quartiles as the treated group.

For the best fitting model, the following additional sensitivity tests were performed. Since people aged > 80 may have a different perception of natural environments (Gascon et al., 2018), we excluded them from the sample and re-ran the fully adjusted model (Model 4a). We also checked whether excluding respondents who suffered from other diseases (e.g., cataracts, glaucoma, Alzheimer, neuropathy) affected the correlations (Model 4b). We repeated our analyses with a binary classified GDS-15 score using a multilevel logit regression (Model 4c). Respondents with a GDS-15 score above 8 were considered as being depressed (Lam et al., 2004).

3. Results

3.1. Characteristics of the study population

The removal of survey respondents with missing information ($N = 60$) resulted in no differences compared to the retained sample ($N = 1190$). Chi^2 and F-tests for all variables were insignificant (Table A1, supplementary materials).

Table 1 summarizes the characteristics of the study population. The average GDS-15 score of the 1190 respondents was 3.4, with an SD of ± 2.7. Table A2 provides descriptives stratified between people with depressive symptoms (GDS-15 ≥ 8) and those without depressive symptoms (GDS-15 < 8). Overall, the mean age was 70.7 years and 59.7% were female. About 31.2% of the respondents attended at least primary school, 43.9% had a high school degree, and 24.9% had a college degree or a higher qualification. Only 3.6% belonged to a minority group, while a large proportion had a local hukou (94.0%). About a half (46.0%) were not functionally restricted, and 20.1% had no chronic disease. Descriptive statistics per quartiles of green and blue space are given in Tables A2–A8.

3.2. Street view green and blue space

The FCN-8s model achieved an accuracy of 0.814 on the training data and 0.768 on the test data. An example of an image segmentation result via the trained FCN-8s is shown in Fig. 3. For example, the model accurately separates built-up areas (e.g., streets, buildings), grassland, trees, etc.

Fig. 4 maps parts of the green and blue space exposure metrics. Fig. 5 shows scatterplots between the green and blue space measures. The Spearman coefficients of street view green space versus GlobeLand30 green space and the NDVI showed associations of 0.056 ($p = 0.704$) and 0.225 ($p = 0.124$); for GlobeLand30 blue space it was −0.177 ($p = 0.228$) and −0.674 ($p < 0.001$) for NDWI. With 0.817 NDVI was highly correlated with GlobeLand30 green space; so was NDWI and GlobeLand30 blue space (0.408). Both correlations were statistically significant ($p < 0.001$; $p = 0.004$).

3.3. Multilevel regression models

The neighborhood-level intra-class correlation of the null model was 0.12. This indicates that GDS-15 scores are moderately clustered within the neighborhood, which justifies the validity of the multilevel approach. Adding variables of either street view green space (Model 2) or blue space (Model 3) to Model 1 leads to a decrease in AIC scores and thus an improvement in model goodness-of-fit. The fully adjusted model (Model 4), with both street view green and blue space, has the lowest AIC score. The refitted models with the NDVI and the NDWI (Models 5–7, Table A9) and variables derived from GlobeLand30

Table 1
Descriptive statistics.

	Proportion	Min.	Mean (SD)	Max.
GDS-15 score		0.0	3.4 (2.7)	15.0
Street view green space (%): 1st quartile		6.8	11.0 (2.5)	13.6
2nd quartile		13.8	15.6 (1.0)	17.1
3rd quartile		17.3	178 (0.4)	18.6
4th quartile		19.1	21.5 (1.8)	24.4
Street view blue space (%): 1st quartile		0.0	0.1 (0.0)	0.2
2nd quartile		0.3	0.3 (0.2)	0.4
3rd quartile		0.4	0.5 (0.8)	0.7
4th quartile		0.7	1.0 (0.2)	1.5
GlobeLand30 green space (%): 1st quartile		0.0	1.2 (1.1)	2.9
2nd quartile		3.1	4.5 (1.2)	6.2
3rd quartile		6.4	18.4 (8.1)	33.9
4th quartile		34.2	62.1 (18.4)	87.6
GlobeLand30 blue space (%): 1st quartile		0.0	0.0 (0.0)	0.1
2nd quartile		0.3	0.6 (0.2)	1.0
3rd quartile		1.2	1.6 (0.3)	2.1
4th quartile		2.2	3.5 (0.9)	4.5
NDVI[a] 1st quartile		2.3	3.8 (0.1)	4.8
2nd quartile		4.9	5.2 (0.0)	5.7
3rd quartile		5.7	7.0 (0.1)	8.0
4th quartile		9.3	13.3 (0.1)	19.4
NDWI[a]: 1st quartile		3.8	4.7 (0.1)	5.6
2nd quartile		5.7	6.0 (0.0)	6.3
3rd quartile		6.3	6.8 (0.0)	7.2
4th quartile		7.3	8.9 (0.1)	12.4
NO$_2$ (in µg/m^3)		19.0	30.4 (4.8)	36.2
Age (years)		60.0	70.7 (7.0)	95.0
Gender (%): male	40.3			
Female	59.7			
Education (%): primary school or below	31.2			
High school	43.9			
College and above	24.9			
Ethnicity (%): Han Chinese	96.3			
Minority	3.7			
Marital status (%): Single, divorced, or widowed	22.3			
Married, living with spouse	76.7			
Married, not living with spouse	1.0			
Party membership (%): Yes	44.0			
No	56.0			
Hukou status (%): local hukou	94.0			
Non-local hukou	6.0			
Functional ability (%): restricted	54.0			
Not restricted	46.0			
Physical health status (%): with chronic disease	79.9			
No chronic disease	20.1			

[a] NDVI and NDWI values multiplied by 100.

remote sensing data (Models 8–10, Table A11) performed worse than those with variables derived from street view data as indicated by notable AIC differences.

We observed a statistically significant and negative association between street view green and blue space and GDS-15 ($p < 0.010$) (Table 2, Model 4). People exposed to more green and blue space (i.e., 2nd, 3rd, or 4th quartile) had significantly lower GDS-15 scores than people residing in neighborhoods with a low coverage of green and blue space (i.e., 1st quartile). The green and blue space coefficients were most pronounced in the third quartile. In contrast, neither green nor blue space was significantly correlated with GDS-15 when rerunning the models with NDVI, NDWI, and GlobeLand30 metrics (Table A9 and A11).

Adding variables of exposure to green and blue space did not alter the significance levels of the covariates (Table 2, Model 4), although the magnitude of the coefficients changed slightly. Some of the covariates were statistically significant. Age was negatively correlated with GDS-15 ($p < 0.010$). Both having a physical disease and being restricted in functional ability increased the risk of depressive symptoms
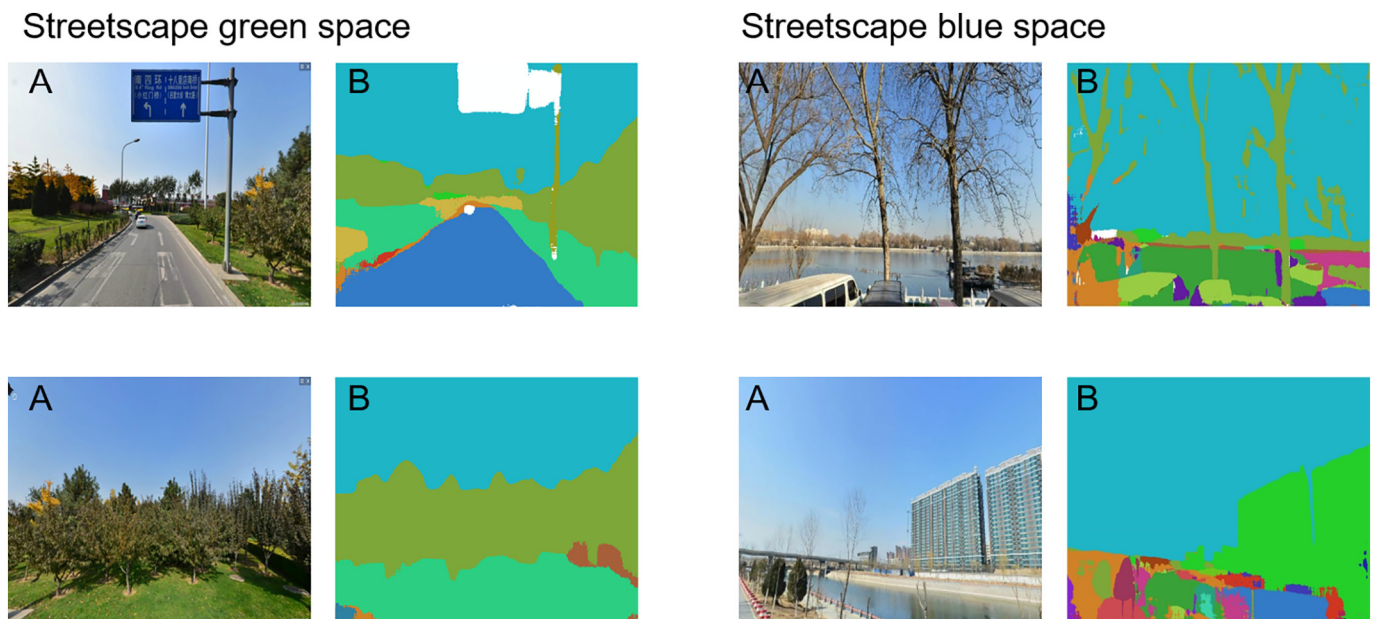
Streetscape green space

Streetscape blue space

Fig. 3. Street view scene segmentation results of the trained FCN-8s: street view image before (A) and after the segmentation (B).

($p < 0.010$). We found no evidence that gender, education, ethnicity, hukou status, and NO_2 were significantly related to GDS-15.

Results (Model 4) from propensity score-matching confirm negative associations between exposure to green and blue space and GDS-15 scores (Table 3). The absolute values of ATT became larger when treatment groups were smaller. Different matching methods resulted in only slight differences in the ATT values, which confirmed a robust inverse relationship between green and blue space exposure and geriatric depression. Propensity score-matching results for Model 7 and 10 did not alter our conclusions of insignificant associations (Tables A10 and A12).

Table 4 summarizes the results of other robustness tests on the correlation between GDS-15 and green and blue space exposure. Despite some differences in magnitude, the significance of the green and blue space associations remained constant.

4. Discussion

This study was among the first to examine the linkage between mental disorders (i.e., depression symptoms) and exposure to natural environments at the street-level among elderly people in China. While remote sensing-based metrics of green and blue space are widespread in epidemiological studies (Boers et al., 2018; Dzhambov et al., 2018; Groenewegen et al., 2018; Nutsford et al., 2016; Tomita et al., 2017), we took an alternative avenue to assess green and blue space, relying on machine learning and street view data.

4.1. Interpretation of the findings in the context of available evidence

Our results showed weak and insignificant correlations between street view and remote sensing-based green and blue space exposures. Although they did not rely on machine learning, Larkin and Hystad (2018) reported similar low correlations (i.e., −0.02 to 0.5) between green space extracted from street view images and satellite-based measures including the NDVI. We found no evidence of positive correlations for street view blue space with alternative measures; reference studies are, however, lacking. As with prior studies (Cusack et al., 2017; Mitchell et al., 2011), which reported moderate to strong correlations derived from different remote sensing data sources (e.g., Landsat, Corine), ours were also considerably high, namely 0.817 for green space (NDVI vs. GlobeLand30) and 0.408 for blue space (NDWI vs.

GlobeLand30).

These findings strengthen our initial hypothesis that both operationalizations quantify different aspects of natural environments, namely that street view images represent more closely how environments are perceived and experienced by people on the ground compared to overhead-view assessments based on remotely sensed imagery. This provides empirical support to Lu et al. (2018), who indicated marked differences across both approaches to measure environmental exposures. Further, Dempsey et al. (2018) found that the visual perception of coastal blue space reduces the prevalence of depression in Irish older adults. Supported by these findings and others (De Bell et al., 2017; Garrett et al., 2018), we argue that street-level exposure assessments could better reflect actual exposures to green and blue space, as small-sized and/or vertical natural elements (e.g. trees along a street, green walls), which may also be beneficial to resident' health (de Vries et al., 2013; Mitchell and Popham, 2008; Van Dillen et al., 2012), are normally not identified based on remote sensing data. Therefore, underpinning Weichenthal et al. (2019), our results suggest that street view imagery along with machine learning are powerful tools for environmental exposure assessments in urban landscapes. As web services such as Tencent Map and Google Street View provide georeferenced and publicly available street view image databases with broad spatial coverage, the potential to develop novel place-based environmental exposure measures to explore environment–health relations is significant.

Our hypothesis that both green and blue spaces are protective against geriatric depression, as already proven for adults (Beyer et al., 2014; Gascon et al., 2018; Helbich et al., 2018; Triguero-Mas et al., 2015; Zock et al., 2018), was partly confirmed depending on how the exposure assessment was conducted. Less complete is the knowledge base for older people (Dempsey et al., 2018; Kabisch et al., 2017; Maas et al., 2006) but utilizing street view data, we found negative associations between the street view green and blue spaces and depressive symptoms. Multiple stratified models revealed similar and consistent results. However, we found little evidence for such inverse associations when metrics of green and blue space were derived from NDVI, NDWI, and GlobeLand30 remote sensing data. Such discrepancies corroborate with Villeneuve et al. (2018), who compared a neighborhood NDVI with street view green space, and found that the latter but not the former was correlated with people's mental health. It is plausible that the inconsistency between the overhead and the street view green and
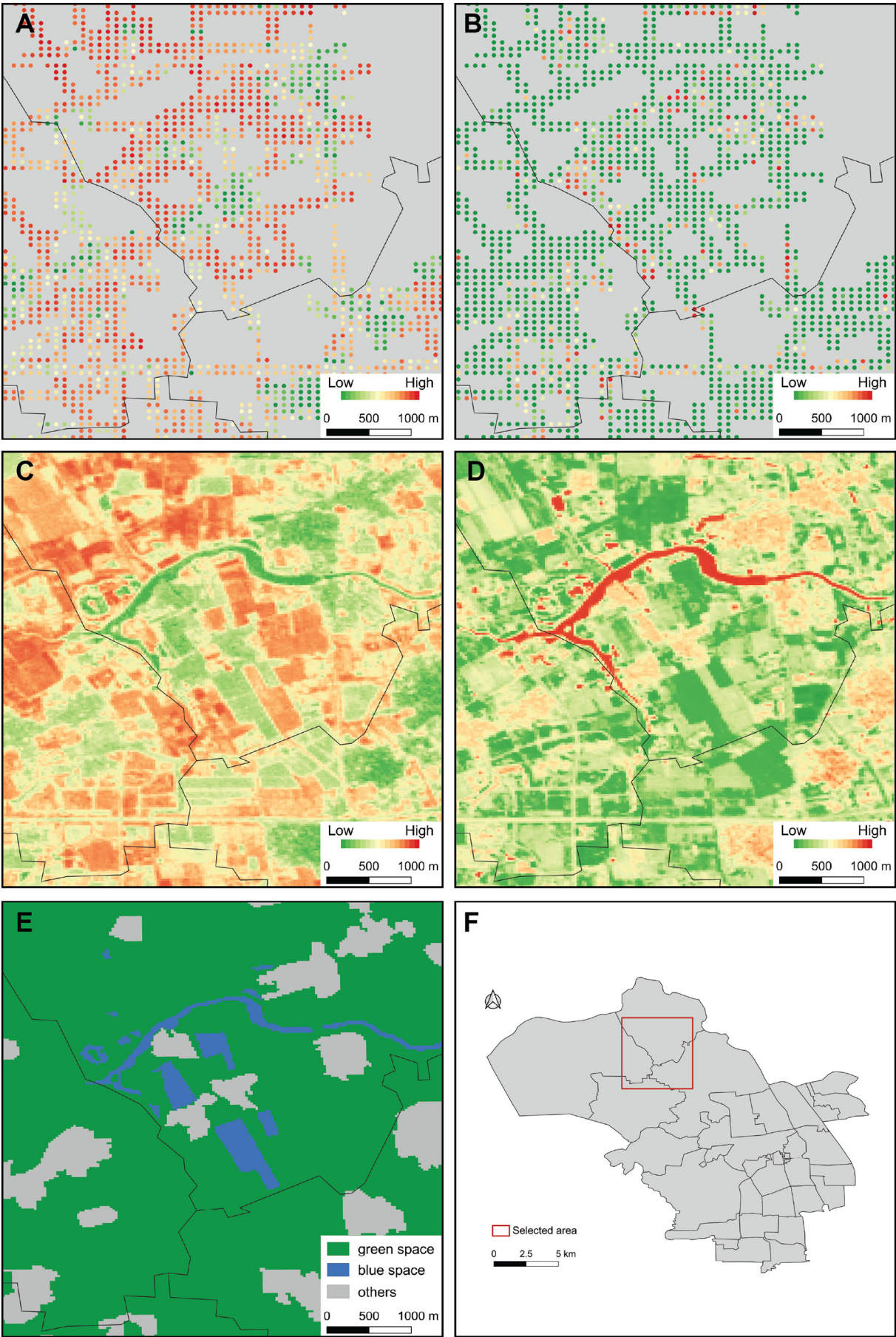
(caption on next page)

Fig. 4. Comparisons of green and blue space exposure metrics: (A) street view green space, (B) street view blue space, (C) NDVI, (D) NDWI, (E) GlobeLand30, (F) study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

blue metrics translate further into model estimation, which may explain the inconsistent findings (Gascon et al., 2017; van den Bosch and Sang, 2017).

Several biopsychosocial pathways linking exposure to green and blue spaces to mental health are the subject of debate (Gascon et al., 2018; Hartig et al., 2014; Lachowycz and Jones, 2013; Silva et al., 2018; Völker and Kistemann, 2011). Among these mechanisms are, noise reduction, attention restoration, and stress recovery (Markevych et al., 2017). While eye-level green space may be more relevant for doing physical activity, remotely sensed green space may be more important to mitigate air pollution. For example, both seen and unseen trees may effectively filter air pollutants or be related to reduced traffic intensity. Since street view exposure assessments have only recently emerged, additional studies are needed to refine the underlying pathway.

Our findings about the salutogenic effects of green space align, in general, with cross-sectional and longitudinal evidence obtained for the Netherlands (Helbich et al., 2018), South Africa (Tomita et al., 2017), the UK (Sarkar et al., 2018), the United States (Beyer et al., 2014), etc. We are only aware of a few street view studies in the mental health context (de Vries et al., 2013; Van Dillen et al., 2012). In line with our results, Van Dillen et al. (2012), for example, found for the Netherlands that streetscape green space identified through site visits significantly correlates with better mental health. Street view greenery in Hong Kong was also found to promote walking (Lu et al., 2018), which is, in turn, protective against depression (Roe and Aspinall, 2011). Less comprehensive is the scientific evidence on blue space (Dempsey et al., 2018; Gascon et al., 2017). Among adults, Nutsford et al. (2016) found that pronounced exposure to blue space diminishes psychological distress.

4.2. Strengths and limitations

Numerous strengths need to be emphasized. First, whereas the majority of studies on the associations between street view exposure to green and blue space and depression have focused on Western countries (van den Bosch and Sang, 2017), we focused on a densely populated Chinese city. Whether our promising results obtained for Beijing may be generalized to other cities, requires verification. Second, we made a new attempt to validate street view data coupled with deep learning to extract metrics of green and blue space for exposure assessments, as opposed to using remote sensing data. Both approaches yield objective measures, preventing a rating bias that may be at play in other studies (Dadvand et al., 2018). Third, the application of street view data to assess green and blue space, rather than to audit neighborhood environments (Rzotkiewicz et al., 2018), is innovative, capturing how people perceive the environment on the site. Our deep learning approach enables us to identify green and blue space more efficiently and more accurately compared to pixel-wise classifications (Larkin and Hystad, 2018). Fourth, numerous robustness tests corroborate the protective effects of street view green and blue space on mental health.

Our study was limited in several ways, however. First, street view and remote sensing data covered different points in time. Specifically, street view data are limited in their spectral information and cannot capture season changes. Nevertheless, the indicators of both sources remain comparable, because green and blue spaces in Beijing change only slowly over time. While street view data represent public green space well, inaccessible locations (e.g., domestic gardens) are disregarded. It remains unclear how these issues affected our results. Second, deficits of the NDVI (e.g., oversaturation where the vegetation density is high) remain and other vegetation indices may be better suited, but impeded comparisons with others (Rugel et al., 2017).
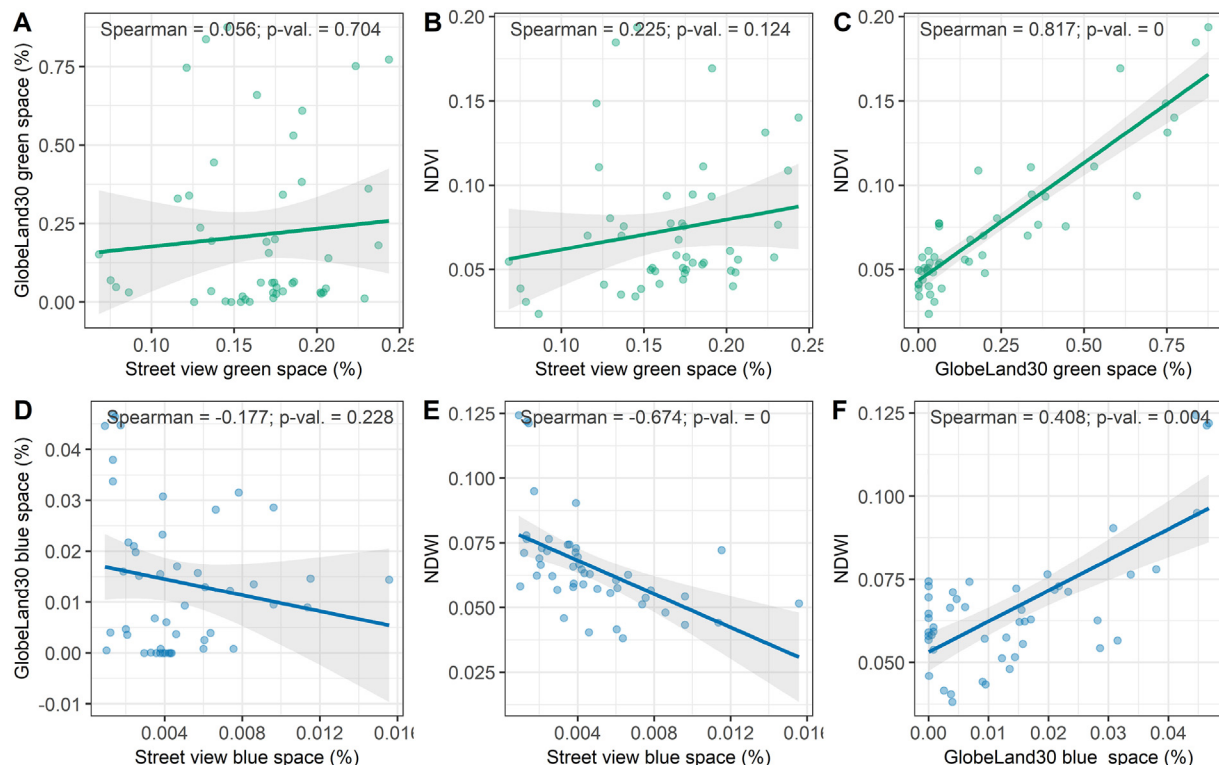

Fig. 5. Scatterplots and Spearman correlations across green and blue space metrics. Grey shaded areas represent the 95% confidence interval along robust regression lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Multilevel regression model results with street view green and blue space.

	Model 1	Model 2	Model 3	Model 4
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Gender (ref.: female)	0.095 (0.167)	0.091 (0.167)	0.074 (0.167)	0.063 (0.166)
Age	−0.043*** (0.013)	−0.041*** (0.013)	−0.044*** (0.013)	−0.042*** (0.013)
Education (ref.: primary school)				
High school	0.091 (0.199)	0.114 (0.200)	0.087 (0.200)	0.106(0.199)
College and above	−0.066(0.244)	−0.036 (0.243)	−0.045 (0.243)	−0.017 (0.241)
Minority (ref.: Han Chinese)	0.101 (0.400)	0.107 (0.398)	0.077 (0.399)	0.066 (0.397)
Marital status (ref.: single)				
Married, living with spouse	−0.324 (0.200)	−0.315 (0.200)	−0.329 (0.200)	−0.318 (0.200)
Married, not living with spouse	0.467 (0.760)	0.453 (0.759)	0.415 (0.759)	0.390 (0.757)
Party member (ref.: no)	−0.538*** (0.168)	−0.509*** (0.168)	−0.539*** (0.167)	−0.507*** (0.167)
Local hukou (ref.: non)	0.302 (0.322)	0.364 (0.320)	0.262 (0.320)	0.321 (0.318)
Physical health status (ref.: no chro. disease)	0.938*** (0.199)	0.936*** (0.199)	0.920*** (0.199)	0.910*** (0.198)
Functional ability (ref.: not restricted)	0.742*** (0.166)	0.735*** (0.166)	0.747*** (0.166)	0.740*** (0.166)
NO_2	0.017 (0.034)	0.024 (0.030)	0.024 (0.037)	0.020 (0.038)
Street view green space (ref.: 1st quartile)				
2nd quartile		−1.320*** (0.383)		−1.097*** (0.340)
3rd quartile		−1.478*** (0.390)		−1.215*** (0.342)
4th quartile		−1.286*** (0.382)		−0.951** (0.382)
Street view blue space (ref.: 1st quartile)				
2nd quartile			−1.276*** (0.393)	−1.202*** (0.350)
3rd quartile			−1.471*** (0.422)	−1.263*** (0.390)
4th quartile			−1.211*** (0.452)	−1.059*** (0.455)
Constant	5.650*** (1.442)	6.147*** (1.370)	8.070*** (1.625)	7.738*** (1.513)
Variance (neighborhood-level constant)	0.926***	0.618***	0.637***	0.410***
Variance (residuals)	6.159***	6.162***	6.156***	6.160***
AIC	5644.642	5636.656	5636.719	5629.217

Significance levels: "*" $p < 0.100$, "**" $p < 0.050$, "***" $p < 0.010$. SE = standard error.

Third, the FCN-8s is an efficient and frequently used deep learning approach (Middel et al., 2019), but future studies are advised to test alternative deep learning architectures as they may perform even better (Zhao et al., 2017). Fourth, data protection issues prevented the application of buffers centered on respondents' homes to represent residential neighborhoods (Boers et al., 2018). On average, however, the neighborhood areas were small, corresponding to an 800-meter buffer radius. We disregarded exposures along people's daily mobility (Helbich, 2018). That is defendable, since the elderly's day-to-day activity space are well approximated by neighborhoods (Arnberger et al., 2017). Fifth, although the GDS-15 is well-tested (Mitchell et al., 2010; Smarr and Keefer, 2011), depression severity was self-reported, which may have biased the regression estimates. Like others, we cannot rule out that confounders were omitted (e.g., noise, air pollution). Finally, given the cross-sectional research design, shortcomings, including the limited capability to establish causality, are inevitable.

5. Conclusion

This study provides a better understanding of the extent to which exposures to street view green and blue space are related to geriatric depression in Beijing, China. Instead of in situ field observations or vegetation indices based on remote sensing, we utilized street view data and deep learning to extract metrics of green and blue space.

Correlation analysis showed that neither street view green nor blue space were related with those derived from remote sensing data (i.e., NDVI, NDWI, GlobeLand30 land cover). Our findings imply that green/blue space from downward-facing satellites may not fully capture what people perceive on the ground. Our multilevel regressions showed that exposure to street view green and blue space is inversely associated with depressive symptoms among the elderly. No evidence was found that sensing-based measures of green and blue space are correlated with depressive symptoms.

Our findings highlight how important it is that environmental exposure assessments accurately reflect people's perceptions. Although some challenges still need to be overcome, street view data in combination with deep learning provide a valuable tool for automated environmental assessments of physical streetscapes, applicable to large epidemiological studies. If replicated by future studies, our finding that streetscape natural environments counter depression will make an important contribution to the promotion of healthy urban environments that support healthy aging in the long run. Urban policies should ensure the preservation of small-scale natural environments to mitigate the impact of rapid urbanization.

Table 3
Results of the propensity score-matching with Model 4.

	k-Nearest neighbor matching	Radius matching	Kernel matching
Treatment group (street view green space)			
a) ≥2nd quartile	−1.441*** (0.231)	−1.343*** (0.232)	−1.351*** (0.223)
b) ≥3rd quartile	−0.445** (0.211)	−0.612*** (0.162)	−0.632*** (0.162)
c) ≥4th quartile	−0.367* (0.215)	−0.501*** (0.263)	−0.485*** (0.162)
Treatment group (street view blue space)			
a) ≥2nd quartile	−1.272*** (0.281)	−1.261*** (0.312)	−1.279*** (0.242)
b) ≥3rd quartile	−0.623*** (0.211)	−0.435** (0.215)	−0.517*** (0.174)
c) ≥4th quartile	−0.551** (0.211)	−0.392* (0.232)	−0.356** (0.173))

Models adjusted for all individual-level covariates. a) ≥2nd quartile: 1st quartile = referenced group, 2nd-4th quartile = treated group; b) ≥3rd quartile: 1st-2nd quartile = referenced group, 3rd-4th quartile = treated group; c) ≥4th quartile: 1st-3rd quartile = referenced group, 4th quartile = treated group; Significance levels: "*" $p < 0.100$, "**" $p < 0.050$, "***" $p < 0.010$.

Table 4
Other robustness tests.

	Model 4a	Model 4b	Model 4c
	Coef. (SE)	Coef. (SE)	OR (95% CI)
Street view green space (ref.: 1st quartile)			
2nd quartile	−1.182*** (0.334)	−1.074*** (0.373)	0.267*** (0.124–0.577)
3rd quartile	−1.224*** (0.336)	−1.234*** (0.377)	0.228*** (0.109–0.478)
4th quartile	−1.023*** (0.374)	−0.859** (0.421)	0.285** (0.115–0.705)
Street view blue space (ref.: 1st quartile)			
2nd quartile	−1.333*** (0.345)	−1.275*** (0.385)	0.365** (0.173–0.769)
3rd quartile	−1.343*** (0.381)	−1.474*** (0.430)	0.288*** (0.118–0.707)
4th quartile	−1.066** (0.444)	−1.236** (0.506)	0.403** (0.143–0.435)
Number of observations	1049	1014	1190

Significance levels: "*" $p < 0.100$, "**" $p < 0.050$, "***" $p < 0.010$. Models adjusted for individual-level covariates. Model 4a excluded people aged > 80, Model 4b excluded people who had other diseases. Model 4c considered GDS-15 as binary. SE = standard error, OR = odds ratio, CI = confidence interval.

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Author contributions

MH and RW developed the research idea. YL, JZ, and PL collected and organized the street view data. YY developed the deep learning algorithm. RW carried out the statistical analysis. MH wrote the manuscript with contributions from RW. MH, RW, and YL revised the manuscript. All authors approved the final manuscript.

Declaration of interest

None.

Conflict of interest

The authors have no conflict of interest to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2019.02.013.

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