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Research Paper

Can't see the wood for the trees? An assessment of street view- and satellite-derived greenness measures in relation to mental health

Marco Helbich [a,*], Ronald Poppe [b], Daniel Oberski [c], Maarten Zeylmans van Emmichoven [d], Raoul Schram [e]

[a] *Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, the Netherlands*
[b] *Information and Computing Sciences, Faculty of Science, Utrecht University, the Netherlands*
[c] *Methodology and Statistics, Faculty of Social and Behavioural Sciences, Utrecht University, the Netherlands*
[d] *Physical Geography, Faculty of Geosciences, Utrecht University, the Netherlands*
[e] *Data Engineering, Information and Technology Services, Utrecht University, the Netherlands*

HIGHLIGHTS

- Greenness from remotely-sensed and street view images were moderately associated.
- Measures of greenness may capture different aspects about greenery.
- Differences across metrics did not translate into mental health–greenness associations.
- No evidence found that depression and anxiety were associated with residential greenness.
- Insignificant associations were not sensitive to the assessed scale and geographic context definitions.

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ABSTRACT

Greenness in the urban living environment is inconsistently associated with mental health. Satellite-derived measures of greenness may inadequately characterize how people encounter greenness visually on site, but systematic comparisons are lacking. We aimed 1) to compare associations between remotely sensed and street view (SV) greenness, and 2) to examine whether these greenness metrics are differently associated with mental health outcomes. We used cross-sectional depressive and anxiety symptoms data on adults in Amsterdam, the Netherlands. We employed a convolutional neural network to segment greenness in SV panoramas. Greenness was measured top-down by normalized difference vegetation indices (NDVI) from 1 m resolution orthophotos (OP) and 30 m resolution Landsat-8 (LS) imagery per postal code, and 100 and 300 m concentric and street-network buffers at the home address. Correlation analyses assessed associations across greenness measures. Covariate-adjusted regressions (e.g., noise, air pollution, deprivation) were conducted to assess associations between each greenness metric and mental health outcomes. Correlations between greenness metrics were significantly positive and moderately high. SV greenness was less sensitive across scales and residential contexts than OP and LS greenness. There was no statistically significant evidence that people with less urban residential greenness had higher depression or anxiety scores than those exposed to higher levels. Nor did different greenness measures, scales, or residential context definitions alter our null associations. This suggests that even though SV and remotely sensed measures capture different aspects of greenness, these differences across exposure metrics did not translate into an association with mental health outcomes.

* Corresponding author.
E-mail addresses: m.helbich@uu.nl (M. Helbich), r.w.poppe@uu.nl (R. Poppe), d.l.oberski@uu.nl (D. Oberski), m.j.zeylmansvanemmichoven@uu.nl (M. Zeylmans van Emmichoven), r.d.schram@uu.nl (R. Schram).

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1. Introduction

Urban greenness (e.g., parks, gardens, trees) is a vital environmental resource that benefits human health (Frumkin et al., 2017) and provides critical ecosystem services (Bratman et al., 2019). A growing body of research indicates that people respond physically and mentally to the presence of greenness (Hartig, Mitchell, De Vries, & Frumkin, 2014; Roberts, Van Lissa, Hagedoorn, Kellar, & Helbich, 2019; Twohig-Bennett & Jones, 2018). Some studies revealed that exposure to greenness has therapeutic qualities; for example, it alleviates stress (Hazer, Formica, Dieterlen, & Morley, 2018), improves the mood (Tyrväinen et al., 2014), and limits depression risk (Helbich et al., 2019). However, there are also inconsistencies across studies, demonstrating a lack of mental health-supportive associations of greenness (de Vries et al., 2016; Pelgrims et al., 2021; Picavet et al., 2016).

To some extent, this divergent evidence on mental health–greenness associations can be attributed to the ways in which greenness was mapped (Ekkel & de Vries, 2017; Labib, Lindley, & Huck, 2020). Objectively captured greenness is usually retrieved from earth observation data (Sogno, Traidl-Hoffmann, & Kuenzer, 2020). The advantages of satellite and aerial imagery include cost- effectiveness, standardized data processing, large coverage, and the availability of sensors with different spatial and spectral resolutions for different seasons (Shahtahmassebi et al., 2020). Results are, however, heterogeneous in terms of the assessed health outcome (Gascon et al., 2018; Mears, Brindley, Jorgensen, & Maheswaran, 2020; Zhang, Tan, & Richards, 2021), the operationalization of greenness (Helbich et al., 2019; Klompmaker et al., 2018; Sadeh, Brauer, Dankner, Fulman, & Chudnovsky, 2020), data sources (Mitchell, Astell-Burt, & Richardson, 2011; Reid, Kubzansky, Li, Shmool, & Clougherty, 2018), and scale of exposure assessments (Su, Dadvand, Nieuwenhuijsen, Bartoll, & Jerrett, 2019), which impedes study comparability.

The normalized difference vegetation index (NDVI), which captures chlorophyll content in vegetation canopies, is well established. Though aligning closely with expert ratings (Rhew, Vander Stoep, Kearney, Smith, & Dunbar, 2011), a barrier is the numerous decisions involved in NDVI-based exposure assessments. A traditional way to determine the health-influencing geographic context is to assign people to the administrative neighborhoods in which they live. This procedure is criticized, however, due to conceptual flaws (e.g., similar greenness conditions are assigned to everyone per unit) (Helbich, 2018) and methodological flaws attributed to the modifiable areal unit problem (Openshaw, 1981) and spatial context uncertainties (Kwan, 2018).

Methods to improve greenness exposure estimates evolved with the application of geographic information systems (GIS), which typically involve buffers centered on specific receptor points, such as people's home addresses (Labib et al., 2020; Nordbø, Nordh, Raanaas, & Aamodt, 2018). However, there is no gold standard for the buffer size, nor consensus about the buffer shape most indicative of health effects (Browning & Lee, 2017; Ekkel & de Vries, 2017; Mears et al., 2020; Su et al., 2019). Because the predominantly used circular buffers ignore obstructions, natural barriers, etc., street network buffers that represent the traversable environment are promoted (James et al., 2014). Most critically, many of these choices, each likely affecting the exposure assessment, are usually made *ad hoc*, potentially distorting the exposure–response relationship of interest (Burns et al., 2014; Helbich, 2018).

Regardless of the buffer size and shape, both satellite and aerial imagery represent a top-down view on greenness that may not offer a good representation of street-level vegetation (Dong, Zhang, & Zhao, 2018) and people's perception on site (Helbich et al., 2019; Larkin & Hystad, 2018). Urban environments are complex with horizontally obscured greenness, vertical greenness on facades, and individual trees covering people's visual viewshed that cannot be detected from downward-facing measurements (Helbich et al., 2019). Others, therefore, advocate a human-centric view on greenness (Middel, Lukasczyk, Zakrzewski, Arnold, & Maciejewski, 2019), resonating with results from experimental environmental psychology that suggest that health-supportive stimuli are triggered by viewing greenness (Brown, Barton, & Gladwell, 2013; Grassini et al., 2019; Tang et al., 2017). Some have argued that perceiving even small patches of greenness (e.g., green facades) (Elsadek, Liu, & Lian, 2019) contributes to mental health by supporting restorative capacities (e.g., attention restoration, stress recovery) (Hartig et al., 2014).

In-situ audits to collect streetscape data are impracticable for a large number of neighborhoods because, for example, they are time-consuming, costly, and labor-intensive (Jiang et al., 2017). New opportunities to assess the appearance of places in urban environments emerged through geo-referenced street view (SV) images (Rzotkiewicz, Pearson, Dougherty, Shortridge, & Wilson, 2018). A meta-analysis found that SV images are a reliable and effective resource for neighborhood assessments, although small transient objects may remain unrecognized compared to in-person street audits, which require observer training (Nesse & Airt, 2020). Owing to progress in computer vision (Kang, Zhang, Gao, Lin, & Liu, 2020), deep learning (LeCun, Bengio, & Hinton, 2015) permits an automated, accurate, and objective assessment of massive amounts of SV data resembling what people see on site (Gebru et al., 2017; Middel et al., 2019). At the moment, however, deep learning-based SV measures are rarely used in the literature. While the application of SV-based greenness exposures gained some momentum, the few available studies deal with Asian cities (Dong et al., 2018; Liu et al., 2019; Wang et al., 2019; Yao et al., 2021), while Europe is underrepresented. Even weaker is the European evidence regarding the relationship between SV greenness and mental health.

No study we are aware of has systematically examined to what extent greenness metrics from SV and remote sensing data correlate across geographic scales and residential context definitions. This knowledge gap risks the use of inappropriate greenness exposure assessments. Responding to this research need, our aims were 1) to examine associations between remote sensing-derived measures of greenness and SV greenness across geographic scales and contexts (i.e., postal code areas, circular and network buffers), and 2) to evaluate associations between greenness measures and people's depressive and anxiety symptoms. Given the conceptual differences, we hypothesized that SV greenness correlates weakly to moderately with remotely sensed NDVI. Further, we hypothesized that exposure to more greenness is inversely associated with depression and anxiety symptoms. Variation in the magnitude of the associations across metrics could be interpreted as complementing pathways.

2. Materials and methods

2.1. Study area and participants

We made use of cross-sectional survey data collected across the Netherlands between September and December 2018 for the purposes of the NEEDS project (Helbich, 2019a). To be eligible for recruitment, participants had to be a) registered in the population register, b) aged 18–65 years, c) not living in institutions or care homes, and d) not sampled by Statistics Netherlands in the previous year. Based on multi-stage sampling, respondents were randomly selected (25.6% response rate). We employed a self-administered online survey. A total of 11,524 people completed the survey, of which 441 were from Amsterdam.

With 870,000 inhabitants, it is the most populated city in the country. Amsterdam therefore provided an ideal setting for this analysis because, despite ongoing densification, the city aims to enhance its livability through greening strategies (Muller, 2020). Moreover, the city of Amsterdam provided open SV data.

2.2. Instruments to measure mental health outcomes

Instruments measuring self-reported symptoms of mental health were administered through the survey. We considered the following two mental health outcomes:

First, severity of depressive symptoms was measured with the Patient Health Questionnaire (PHQ–9) (Kroenke & Spitzer, 2002). This screener contains nine multiple-choice questions on people's mood over the previous two weeks. Each item can be scored between 0 ("not at all") and 3 ("nearly every day"). One can obtain a total score of between 0 and 27. Higher scores indicate more pronounced depressive symptoms. Cronbach's alpha was 0.897.

Second, severity of anxiety symptoms over the previous two weeks was assessed with the 7-item Generalized Anxiety Disorder (GAD–7) scale (Spitzer, Kroenke, Williams, & Löwe, 2006). Response options are scored from 0 ("not at all") to 3 ("nearly every day"). The GAD–7 ranges between 0 and 21, with higher scores indicating pronounced symptom severity. Cronbach's alpha was 0.909.

2.3. Assessment of residential greenness

2.3.1. Deep learning for image segmentation

We obtained geo-tagged SV images with city-wide coverage from Amsterdam's data portal. Image sampling points were defined every 16 m along the streets. Rather than using images for each cardinal direction, we queried cubic panoramas (including metadata), which provide a more comprehensive description of the scenery. Each panorama comprised six cubic images with a dimension of 512 × 512 pixels. Top and bottom cubic images were discarded as they were not part of the initial model training.

For each panorama, the remaining four cubic images were semantically segmented with a convolutional neural network (CNN) hierarchically employing convolution and pooling operations. Based on a large number of learned parameters, CNNs can identify textural and shape patterns across scale, position, and illumination variations (LeCun et al., 2015). We assigned a class label to each pixel of the input images, resulting in the semantic labeling of regions per cubic image.

Specifically, we employed the Xception-71 CNN (Chollet, 2017) (for the network architecture, see Fig. S1 in the supplementary materials), which had been pre-trained on the large-scale Cityscapes dataset of annotated urban street scenes that differentiate roads, humans, vehicles, or constructions (Cordts et al., 2016). We focused on the vegetation label representing trees, hedges, vertical green, etc. In a benchmark (Kamann & Rother, 2020), the Xception-71 performed favorably against related CNN architectures for semantic segmentation. Then, we determined the weighted average of the number of vegetation pixels per panorama. Weighting was necessary to account for the distortion of the pixels, which depends on their relative position within the image (i.e., pixels on the edges cover a larger area than those at the center). We interpolated the point-wise SV greenness values to get area-wide greenness at non-sampled locations by fitting an exponential function to the semi-variogram using locations within the tile and the eight adjacent tiles followed by local ordinary kriging (Webster & Oliver, 2007).

2.3.2. Aerial and remote sensing imagery

Greenness was additionally measured with the multispectral NDVI, which reflects that chlorophyll absorbs the red light and the mesophyll leaf structure scatters the near-infrared (Pettorelli et al., 2005). The index is defined as the near-infrared radiation minus visible radiation divided by near-infrared radiation plus visible radiation. Values range from -1.0 to $+1.0$; more positive values indicate greener vegetative cover, while negative ones represent non-biomass (e.g., water). Values around zero represent rocks and bare soil.

We relied on two datasets for the NDVI. The first was based on high-resolution color infrared aerial orthophotos (OP) for 2018 obtained from the Dutch National Georegister (Fig. 1, left panel). Images were mosaicked with a 25 cm resolution for spring/summer months, corrected for the relief displacements at ground level, and color-balanced to receive a continuous image. We resampled the composite to 1 m by bilinear interpolation to reduce file size and computation time; individual tree canopy remained apparent.

The second dataset was from Landsat-8 (LS) (NASA/U.S. Geological Survey), obtained from and processed with Google Earth Engine (Fig. 1, right panel). We included all Tier 1 satellite imagery scenes for 2018 to map NDVI at a 30 m resolution. Due to seasonal vegetation cycles, we only included orthorectified and atmospherically corrected scenes collected during vegetation-rich months (i.e., May–September). Scenes with $>$ 40% cloud cover and pixels with a cloudiness score of $>$ 25 were removed.

2.3.3. Exposure assessment at the home location

Questionnaire mailing addresses were geocoded through linking register data with the land registry. No missing addresses occurred. We abstracted for each participant the mean SV and NDVI greenness in the surrounding of their residential address. The home location is among the places people spend large amounts of their time (Nordbø et al., 2018). Because negative pixel values distort the mean NDVI toward zero, we

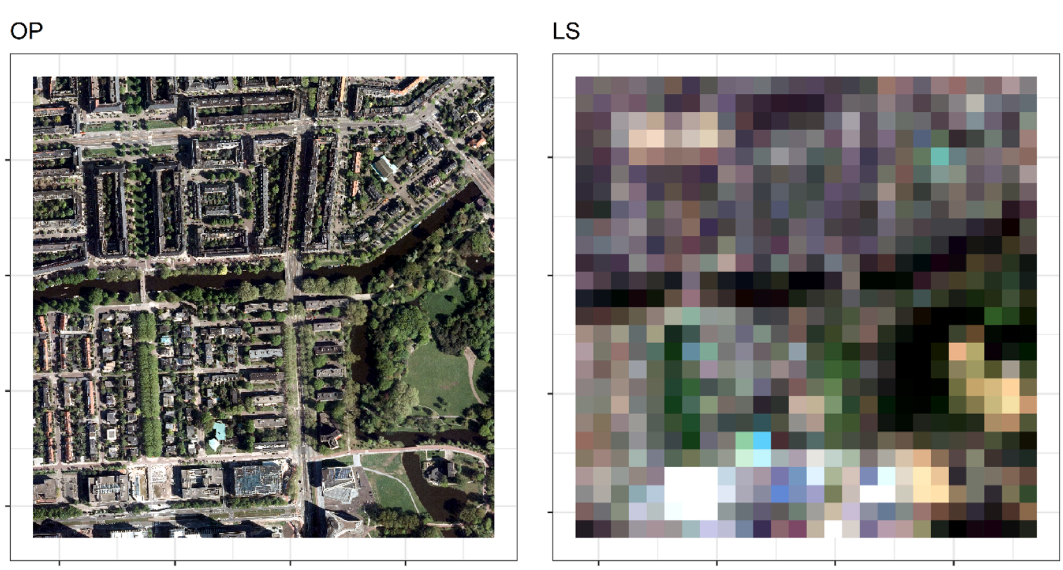

Fig. 1. Aerial orthophoto (OP) and Landsat-8 (LS) remote sensing imagery used for the exposure assessment for the eastern part of Beatrix Park, Amsterdam (52°21′N, 4°53′E). The left image refers to the OP with a 25 cm resolution and the right image refers to the LS scene with a 30 m resolution.

omitted those pixels. To reduce geographic context uncertainties, we measured greenness per 5-digit postal code area (median area = 0.059 km^2, standard deviation [SD] ± 0.555), and within 100 and 300 m buffer radii (Labib et al., 2020; Nordbø et al., 2018). Buffers of smaller size were found to be more strongly associated with health outcomes (Su et al., 2019). Beyond 300 m, the use of greenness declines (Ekkel & de Vries, 2017), which is congruent with recommendations that public greenness should be reachable within 300 m (World Health Organization, 2017). We generated circular and road network buffers per address using road data from the 1:10,000 topographical map (2018). Fig. 2 shows the residential context definitions.

2.4. Statistical analysis

Summary statistics of the central tendencies were calculated per greenness measure. We calculated Pearson correlations (ρ) among the *z*-scored greenness metrics for different buffer types and radii with *p*-values adjusted for multiple hypotheses testing (Holm, 1979).

To test associations between the mental health outcomes (i.e., PHQ–9 and GAD–7) and the greenness measures together with 95% confidence intervals (CIs), we estimated generalized additive models (GAM) with a Gaussian outcome distribution (Wood, 2017). To retain comparability with earlier studies, the *z*-scored greenness measures were reclassified into quartiles. Analyses were done in R, version 3.5.

Two models with incremental adjustments were fitted per outcome: Model 1 only included a greenness measure. Model 2 was adjusted for individual-level covariates, namely sex (male, female), age (years), marital status (married, separated/divorced, widowed, unmarried), labor market involvement (employed, unemployed, non-working, other), education level (low [up to lower secondary education], medium [up to upper secondary education], high [university education]), and household income in quintiles from register data for January 1, 2016. As area-level covariates per postal code and 100/300 m buffer, we included annual average concentrations of ultra-fine particles ($PM_{2.5}$, μm/m^3) (Schmitz et al., 2019), estimated average traffic-related noise over a 24-h period classified into six day–evening–night noise dB classes (Rijksinstituut voor Volksgezondheid en Milieu, 2019), and a register-based deprivation measure for 2016 based on summed *z*-scores of unemployment rate, reversely coded standardized median household income, and the share of households with a standardized income below the poverty line.

3. Results

3.1. SV image segmentation

In total, we processed 209,507 panoramas distributed across a 7.3 × 7.3 km area. Images were taken between May 2016 and July 2019, with annual peaks during summer months (Supplementary Fig. S2). Fig. 3 shows a segmented SV image illustrating that, in general, our CNN accutrately distinguished between vegetation and other objects (e.g., cars, buildings, the sky). The proportion of segmented vegetation in Fig. 3 was 23.7%. In a benchmark on related SV data, the Jaccard index for the vegetation class was 94%, indicating good accuracy (Kamann & Rother, 2020).

3.2. Comparison of the greenness metrics

Fig. 4 shows interpolated SV greenness together with OP and LS-based greenness in the surroundings of Beatrix Park. The SV and LS measures show an overall similar pattern as the high-resolution OP capturing individual tree crowns. Both SV and LS smooth over small-scale landscape elements such as canals. For SV greenness, the smoothing is a consequence of the kriging procedure, the lower resolution, and the viewing distance. In the case of canals, some smoothing can be expected, because a person can see the vegetation on the other side of the canal. Pearson correlations for the rasters were: ρ_{SV-OP}=0.486, ρ_{SV-LS}=0.703, and ρ_{OL-LS} = 0.421 (all $p < 0.001$).

To assess dissimilarities between the SV and OP/LS greenness maps, Fig. 5 displays pixel-by-pixel differences obtained by subtracting the *z*-scored OP/LS values from the SV *z*-scores. SV-OP/LS differences were apparent within Beatrix Park. Here, SV greenness is perceived as markedly greener than is captured by airborne sensors.

3.3. Bivariate correlations across exposure assessments

Based on respondents' exact living addresses (Supplementary Fig. S3), we determined their average greenness exposures using 100 and 300 m circular and network buffers. Respondents were nested in 349 postal code areas (79.5% had a unique postal code, while each of 17 postal codes had 3 respondents [4.9%]). Boxplots (Supplementary Fig. S4) showed some differences in greenness across the geographic contexts. The 100 m buffers had the most pronounced mean variations

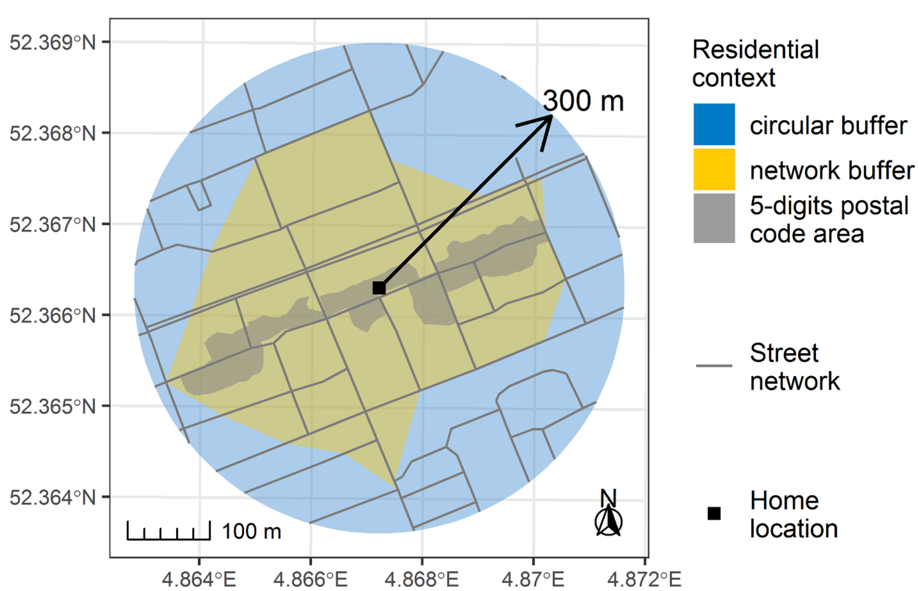

Fig. 2. Different geographic context definitions including the 5-digit postal code area, a circular buffer of 300 m, and a street network buffer of 300 m centered on a home location in Amsterdam.

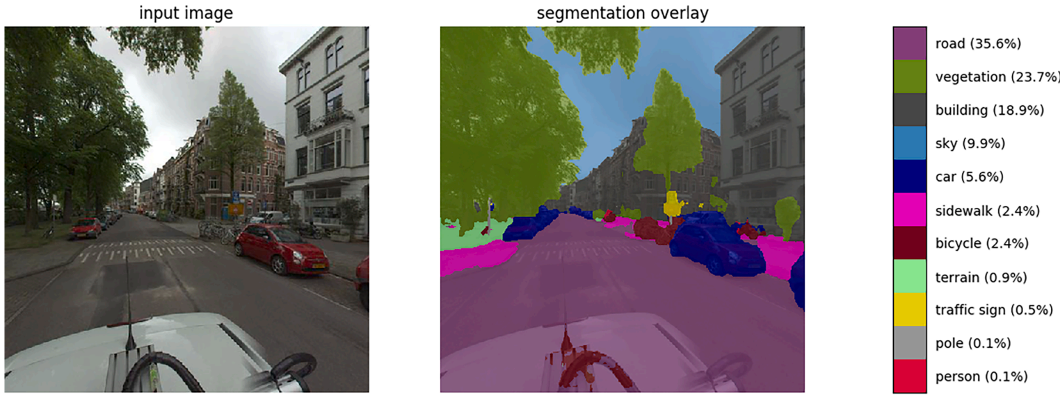

Fig. 3. Input SV images (left) and the image overlayed with the resulting segmentation (right).

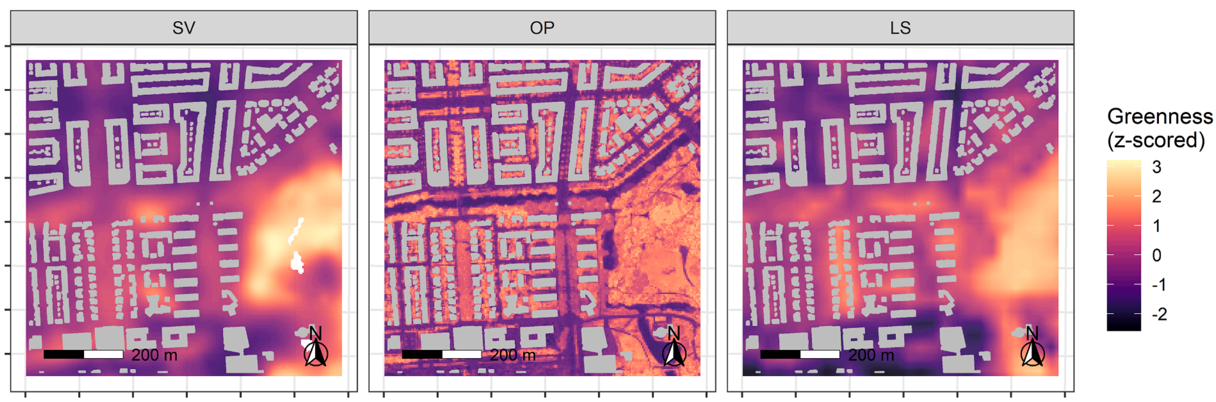

Fig. 4. Greenness metrics for the eastern part of Beatrix Park, Amsterdam. For comparative purposes and to eliminate different baseline units, the street view (SV), orthophoto (OP), and Landsat-8 (LS) greenery rasters were *z*-scored. More positive values refer to higher levels of greenness. Gray areas represent building shapes obtained from the land registry.

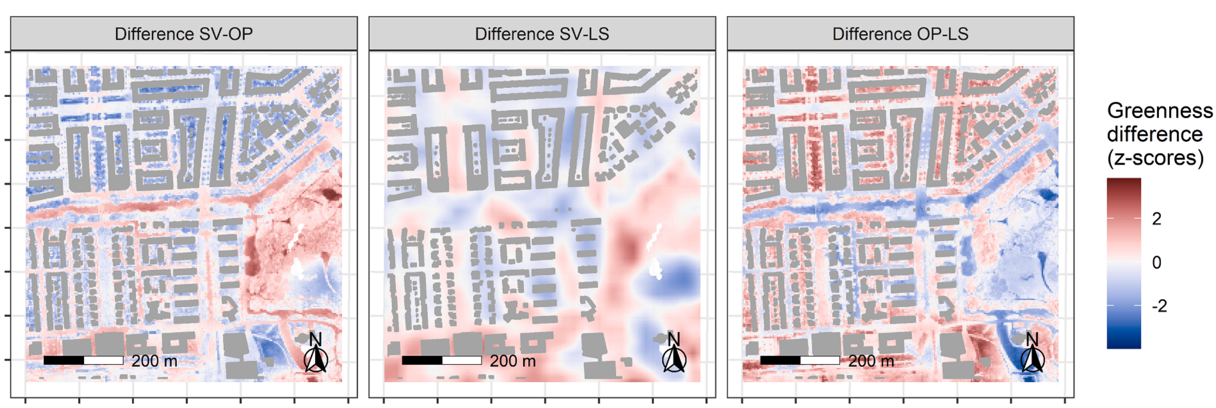

Fig. 5. Pixel-wise comparison of the greenness maps for the eastern part of Beatrix Park, Amsterdam. The *z*-scores of OP/LS (and LS) were subtracted from the SV scores (OP scores). Red colors indicate higher SV *z*-scores than OP/LS *z*-scorers, as well as higher OP *z*-scores than LS *z*-scores, while blue colors indicate lower *z*-scores. For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.

while the mean NDVI scores were rather similar for the postal codes.

Correlations between greenness assessments are summarized in Fig. 6. While all correlations were positive and moderately high (all $p < 0.001$ after considering multiple hypothesis testing), some patterns were noticeable. With correlations between 0.58 and 0.89, it seems that SV greenness is less sensitive to variations in spatial context definitions. Less strongly correlated across context definitions were OP-based greenness measures: Correlations ranged from 0.28 to 0.71. SV greenness was more strongly correlated with LS than with OP-based assessments. Correlations for similar buffer sizes showed that the 300 m buffers were more strongly associated with each other than the 100 m buffers. The 100 m buffers with OP data were less strongly correlated with the 300 m buffers than the SV and LS measures.

3.4. *Associations between mental health outcomes and the greenness metrics*

On average, the respondents' PHQ–9 score was 5.526 (SD ± 4.995) and their GAD–7 score was 4.883 (SD ± 4.596). The respondents' mean age was 41 years (SD ± 14); 54% were female, 25% were employed or

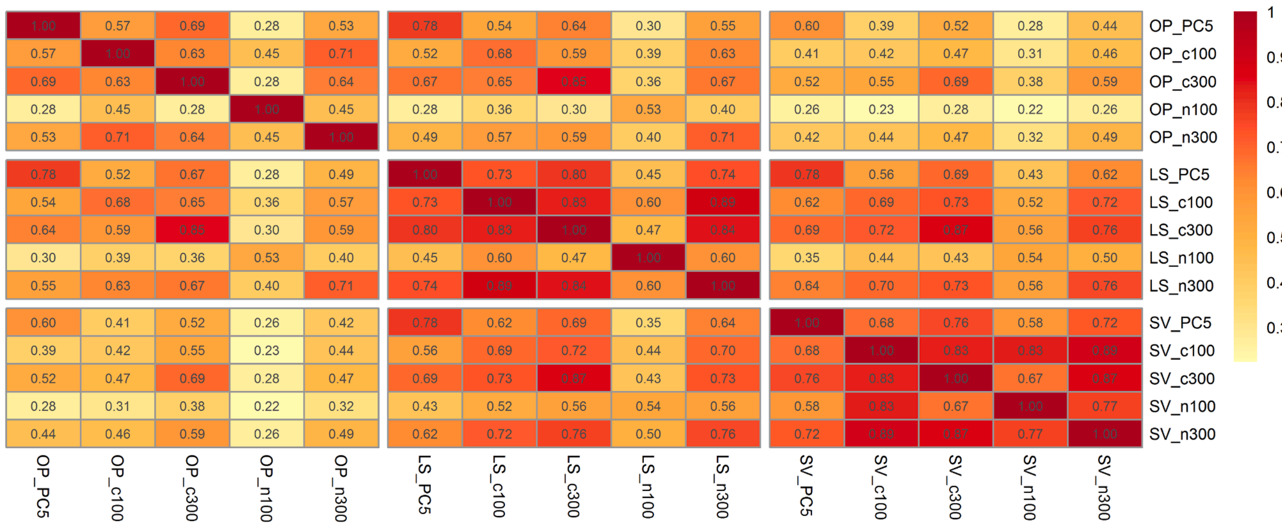

Fig. 6. Correlation matrix of greenness measures. Correlations are organized per data source (OP, LS, SV) followed by different context definitions. Note, "c" refers to concentric and "n" to network buffers, while "100" and "300" refer to the applied buffer size (in m). "PC5" refers to 5-digit postal code areas.

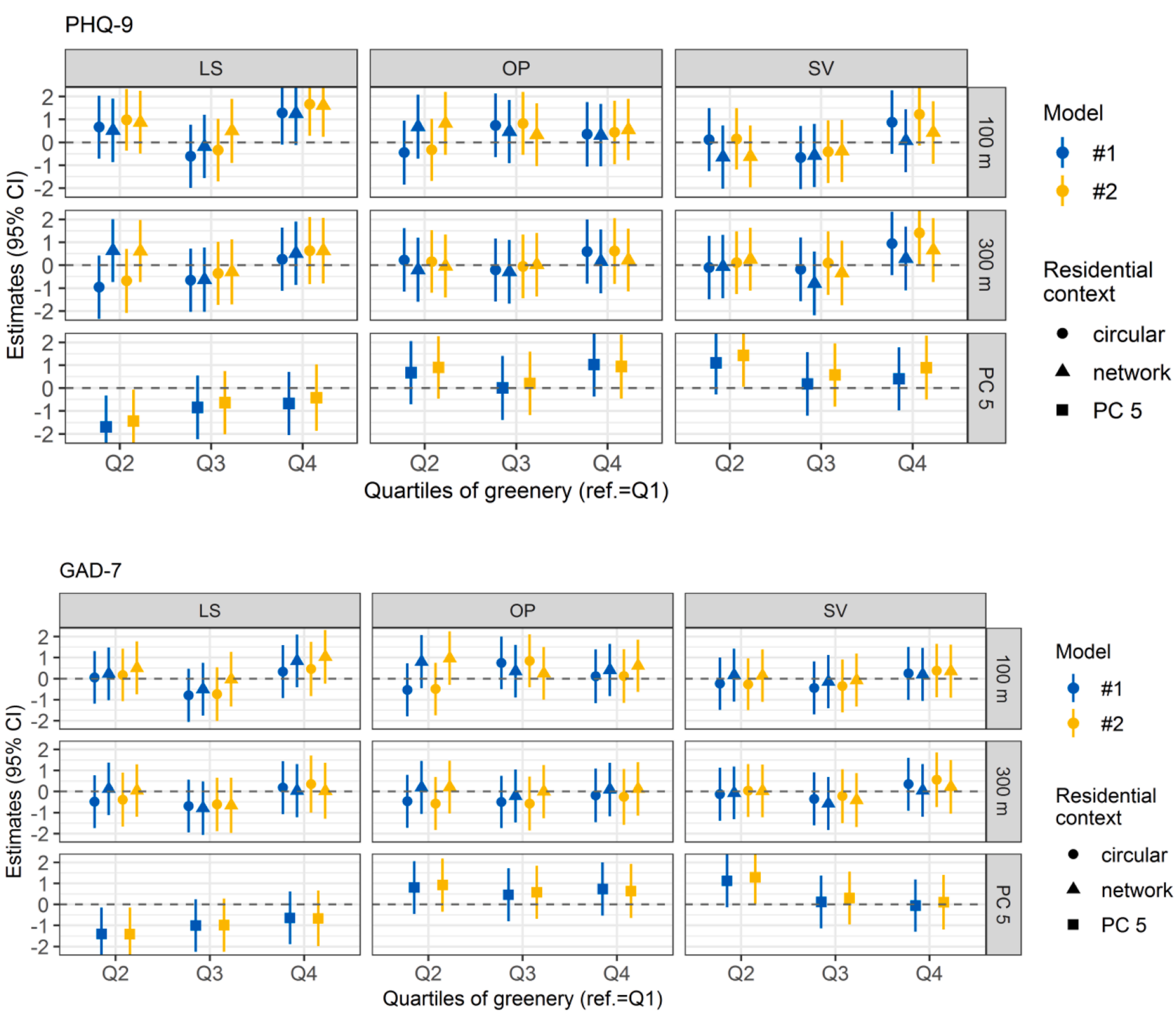

Fig. 7. Associations between greenness quartiles at the residential place and PHQ–9 scores (top) and GAD–9 scores (bottom) across different operationalizations together with 95% confidence intervals (CI). The reference category was the 1st quartile (Q). Model 1 was unadjusted. Model 2 was adjusted for sex, age, employment, household income, marital status, education, $PM_{2.5}$, noise, and deprivation.

non-working, and 29% were married. Further descriptives are given in Table S1.

Variance inflation factors did not indicate any problems with multicollinearity. The models' adjusted R^2 were between 6% and 8% of the PHQ–9 scores after full adjustments were made; the adjusted R^2s for GAD–7 were around 4%. There was no indication that the goodness-of-fits varied systematically across buffer sizes or geographic context definitions.

Estimated associations between PHQ–9 and GAD–7 and greenness are summarized in Fig. 7. Full numeric results are given in Tables S2 and S3. The magnitudes of the associations between greenness and the PHQ–9 and GAD–7 scores were attenuated after person-level and area-level adjustments (Model 1 vs. Model 2). We found no evidence that people exposed to higher levels of SV greenness in the 2nd to 4th quartiles had significantly lower PHQ–9 and GAD–7 scores than those living in areas with the lowest levels of SV greenness (1st quartile). Estimates did not reach significance when re-fitting the models with NDVI based on OP or LS rather than SV greenness. Associations remained insignificant when employing the 300 m instead of the 100 m buffers or the postal code areas.

4. Discussion

There is no consensus about the operationalization of exposure to greenness in health studies nor about how to define the health-influencing geographical context to which people are exposed. Our study advanced the state of the art by systematically evaluating streetscape greenness with traditional top-down NDVI across input data, scales, and context definitions and assessing their associations with mental health outcomes.

4.1. Streetscape and remotely sensed greenness

Our visual comparison between high resolution OP and LS-based greenness revealed that the latter, though frequently used (Yang, Lu, Yang, Yang, & Gou, 2021), has a too coarse spatial resolution to map greenness in urban environmnets accurately. We observed, in line with our first hypothesis, that greenness perceived on site mapped through SV images was only moderately correlated with both top-down remote sensing-based greenness metrics. Expanding on earlier findings (Gu et al., 2019; Helbich et al., 2019; Larkin & Hystad, 2018), our results suggest that eye-level greenness represents different aspects of the urban landscapes. Others proposed that this is particularly the case when greenness at eye-level is moderate to high (Jiang et al., 2017). Our results conflict with those for Beijing, China, where SV–remote sensing-based greenness associations were insignificant (though positive, like ours) for a few larger administrative areas (Helbich et al., 2019). Such a discrepancy in greenness correlations is possibly susceptible to uncertainties arise through differences in the incorporated size and shape of the geographical context. Bolstered by higher correlations among SV-based greenness across scales and residential contexts, our findings also suggest that SV measures were less sensitive than NDVI measures.

Attempts to compare greenness exposures across numerous GIS-based residential contexts are rare and less comprehensive than ours (Larkin & Hystad, 2018; Su et al., 2019; Wang et al., 2019; Ye et al., 2019). We found that larger buffers (300 m) tended to be more strongly correlated than smaller ones (100 m), independent of the input data and context definition. Our findings are contrary to results from Singapore, where associations diminished as circular buffers increased from 20 to 100 m (Ye et al., 2019). A reasonable explanation for such differences is that our larger buffers of 100 and 300 m averaged out local differences in greenness scores, which resulted in stronger correlations.

We replicated previous findings that variations in the spatial resolution of the NDVI measure (LS vs. OP) influence exposure metrics (Browning & Lee, 2017; Reid et al., 2018; Su et al., 2019). Differences in correlations between moderate-resolution LS and high-resolution OP data were expected due to the sensor-specific technical limitations (e.g., resolution, minimum mapping unit) of the former resulting in more land cover types within a pixel. By comparing NDVI scores based on World-View2 (2 m), RapidEye (5 m), and Landsat-8 (30 m) for Barcelona, Spain, Su et al. (2019) substantiate our results by showing that Landsat likely overestimates greenness levels. Yet, Landsat seems to be the gold standard, although scattered and isolated tree canopies remain unrecognized due to a minimum mapping size (Helbich et al., 2019; Jiang et al., 2017). While SV and OP are capable of differentiating isolated small-scale greenness, their application could be complicated by computational constraints, particularly for nationwide analyses. Further, objects (e.g., trees) farther away from an observer are represented by a reduced number of pixels in SV images. Taken together, these differences across assessments could translate into inconsistencies in effect size (or even sign reversals) when examining greenness–mental health associations.

4.2. Associations between greenness and depressive and anxiety symptoms

Contrary to expectations, our regression analyses revealed null associations between exposure to residential greenness and mental health. Neither streetscape nor remotely sensed greenness showed a statistically significant correlation with depression and anxiety symptoms. Further, the estimated associations between greenness and both mental health outcomes remained consistently insignificant when scales and health-influencing spatial contexts were modified.

Not in line with theory, we did not find evidence that experiencing greenness promotes the restoration of attention (Kaplan, 1995) and stress recovery by evoking positive feelings (Ulrich et al., 1991), which leads to mental health benefits. Moreover, contrary to earlier suggestions (Wang et al., 2019), our results did not indicate that SV and remote sensing-based greenness have different underlying pathways affecting people's mental health. We speculate, first, that urban environments are sensorily more demanding than greenness, as suggested through a controlled psychological experiment (Grassini et al., 2019). It could be that the stress-relieving capacities of urban green are outweighed by other risk factors of the urban living environment (Gong, Palmer, Gallacher, Marsden, & Fone, 2016). Second, the null findings are possibly a consequence of our rather small sample not having enough statistical power for small associations. Elsewhere it was concluded that the health-supportive effects of greenness are not large (den Berg, Maas, Verheij, & Groenewegen, 2010). Third, given that we focused on the immediate residential area, as guided by previous studies (Gascon et al., 2018), it is plausible that our sample was imbalanced concerning people having pleasing greenness of sufficient size close-by encouraging them to be physically active and interact socially with others (Hartig et al., 2014). Though contrasting with results from New York City (USA) that trees outside parks are also supportive of mental health (Reid, Clougherty, Shmool, & Kubzansky, 2017), this explanation corroborates a UK study that reported that larger areas of greenness seem to be more healthful than smaller patches (Mitchell et al., 2011), echoing others where only associations with larger buffer sizes beyond 1 km were significant (Maas et al., 2009).

Evidence that mental health benefits are related to exposure to greenness is not uniform. While no previous European study had addressed eye-level greenness, our findings contrast with those of a study among the elderly in Beijing (Helbich et al., 2019) and one on adults in Guangzhou (China) (Liu et al., 2019). Residential surrounding NDVI was also not significantly associated with depression or anxiety in Barcelona, Spain (Gascon et al., 2018), and among adolescents in Cincinnati, USA (Hartley et al., 2021). As in ours, a study in Brussels (Belgium) found null associations between greenness measures (e.g., NDVI, tree density) and depressive and anxiety disorders based on multi-exposure models (Pelgrims et al., 2021). Netherlands-specific findings were contradictory as well. For example, a nationwide study reported the anticipated protective association between self-reported mood and anxiety disorders and greenness at a postal code level (de Vries et al., 2016). However, this association was likely overestimated due to a lack of co-occurring exposures (e.g., air pollution and noise). A health record linkage study found that postal code natural greenness was insignificantly related to diagnosed depression and anxiety, while agricultural greenness remained inversely associated with anxiety, even after adjusting for numerous environmental correlates (Zock et al., 2018). Finally, in a pooled multi-cohort study, continuous depression scores were insignificantly related to greenness (Generaal et al., 2019); null associations were also reported in a longitudinal study in city of Eindhoven (Noordzij, Beenackers, Groeniger, & Van Lenthe, 2020).

4.3. Strengths and limitations

We made the first attempt to systematically compare different greenness metrics per address. A strength of our study was that individual-level survey data was extracted from a nationally representative survey, while greenness was extracted from SV images and very-high-resolution orthophotos. This is an advance compared to previous studies, which were often restricted to earth observation data that was frequently of limited resolution (Gascon et al., 2018; Reid et al., 2018). We also took advantage of having each respondent's exact home address to assign exposures, rather than only employing the administrative unit in which they lived (de Vries et al., 2016; Zock et al., 2018). Our individualized approach resulted in more accurate exposure assessments. Relatedly, instead of using a single buffer type to assess health-influencing environmental context, as done elsewhere (Su et al., 2019), we made efforts to rigorously test different operationalization (i.e., postal codes, concentric and network buffers of varying sizes). Thus, our analyses are better safeguarded against geographic context misrepresentations. Our exposure assessment expanded on advances in computer vision and deep learning to derive objective measures of greenness that correspond well with people's on-site perceptions. A high volume of SV images in combination with an efficient segmentation algorithm allowed us to determine greenness efficiently and accurately. There is no longer need for pixel-wise assessments based on an image's additive colors (Larkin & Hystad, 2018) or even in situ data collection through labor-intensive and time-consuming neighborhood audits (Rzotkiewicz et al., 2018).

Although we broke new ground, there were limitations to this study. The NDVI as a marker of greenness has methodological deficits (e.g., oversaturation where the biomass is high) (Pettorelli et al., 2005). The index fails to capture varying qualities (Jarvis, Gergel, Koehoorn, & van den Bosch, 2020) and to acknowledge that different greenness types are not equally supportive of mental health (Zhang et al., 2021; Zock et al., 2018). Whether other greenness metrics are better suited remains an open question (Rugel, Henderson, Carpiano, & Brauer, 2017; Sadeh et al., 2020). Exposure assessments using SV images necessarily lead to incomprehensive greenness measures. Inaccessible and private greenness (e.g., in backyards) are unrecognized, as images are taken from public streets. It is also possible that different settings in processing the SV images (e.g., spacing between images, the direction) has influenced our SV greenness metric. There is no guarantee that SV images are collected during the growing season and extensive time series are not available. The latter is also problematic for cross-sections, because temporally poorly aligned data may obscure green space–health associations (Helbich, 2019b). We cannot rule out the possibility that other deep learning architectures perform better, but possible differences in greenness may average out across buffers. More critical are uncertainties arising through home-based exposure assessments. While the residential neighborhood is an anchor in people's lives, an assumption usually made (Liu et al., 2019; Su et al., 2019), people habitually spend a part of their day elsewhere (e.g., at work) (Roberts & Helbich, 2021). Without movement data, the extent to which this assumption affected our results is difficult to establish. Limited by the availability of SV data, we relied on Amsterdam but focused on heterogeneous neighborhoods in terms of their socio-demographic and environmental conditions. Whether our findings are transferable to other European cities is unknown. Our survey data are susceptible to self-reported measurement response errors and may not be representative for the Dutch population. Although we took steps to adjust for multiple exposures, we cannot exclude that other exposures may have affected the association. Finally, although people self-select themselves into specific neighborhoods, we cannot infer causality.

5. Conclusions

We rigorously assessed streetscape and remotely sensed greenness across multiple data sources and geographical contexts. For our Amsterdam data, our analyses emphasized moderate correlations between eye-level and satellite-derived greenness. The results suggest that a downward view captures different aspects of greenness than a street level view, and that SV-based greenness is less sensitive to differences in the residential context definition. While these correlational findings are relevant for health studies at large, there was no evidence that these differences in greenness measures translate into mental health–exposure assessments. Regressing depressive and anxiety symptoms on each greenness metric, no significant exposure–response associations appeared. We observed no differences in the association across postal code units, buffer types, or buffer sizes. Without further research, it remains premature to prioritize one greenness metric over another.

6. Ethics

Ethical approval for the study was obtained from the Ethics Committee at Utrecht University (FETC17–060). Survey data were enriched with registers. In line with Dutch privacy legislation, register data are non-publicly accessible for scientific research in the secure environment of Statistics Netherlands. Data records were fully anonymized.

CRediT authorship contribution statement

Author order after the first author was randomly chosen in R: `set.seed (26012019); sample (c("Raoul", "Maarten", "Daniel", "Ronald"))`. **Marco Helbich:** Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft, Project administration, Funding acquisition. **Ronald Poppe:** Conceptualization, Methodology, Writing - review & editing. **Daniel Oberski:** Conceptualization, Methodology, Writing - review & editing. **Maarten zeylmans emmichoven:** Formal analysis, Writing - review & editing. **Raoul Schram:** Data curation, Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability statement and code

Street view data were obtained through http://data.amsterdam.nl. Our workflow to compute greenness based on street view images was implemented in Python 3.6+ and is available through GitHub (https://github.com/UtrechtUniversity/streetview-greenery). The TensorFlow DeepLab Model Zoo is also accessible via GitHub (https://github.com/tensorflow/models/blob/master/research/deeplab/g3doc/model_zoo.md). Orthophotos are available through the Dutch National Georegister (https://www.nationaalgeoregister.nl/geonetwork/srv/dut/catalog.search#/home). The health data are part of the NEEDS project and are non-publicly available due to privacy restrictions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104181.

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