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Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions

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ABSTRACT

Satellite data is increasingly used to characterize green space for health outcome studies. Literature suggests that green space within 500 m of home is often used to represent neighborhood suitable for walking, air pollution and noise reduction, and natural healing. In this paper, we used satellite data of different spatial resolutions to derive normalized difference vegetation index (NDVI), an indicator of surface greenness, at buffer distances of 50, 100, 250 and 500 m. Data included those of 2 m spatial resolution from WorldView2, 5 m resolution from RapidEye and 30 m resolution from Landsat. We found that, after radiometric calibrations, the RapidEye and WorldView2 sensors had similar NDVI values, while Landsat imagery tended to have greater NDVI; however, these sensors showed similar vegetation distribution: locations high in vegetation cover being high in NDVI, and vice versa. We linked the green space estimates to a health survey, and identified that higher NDVI values were significantly associated with better health outcomes. We further investigated the impacts of buffer size and sensor spatial resolution on identified associations between NDVI and health outcomes. Overall, the identified health outcomes were similar across sensors of different spatial resolutions, but a mean trend was identified in bigger buffer size being associated with greater health outcome.

1. Introduction

Urban green space, including parks, forests, green roofs, streams, and community gardens, provides critical ecosystem services (Wolch et al., 2014). Access to green space has also been associated with various health benefits (Ulmer et al., 2016), such as higher levels of physical activity (Akpinar, 2016; Almanza et al., 2012; Gomez et al., 2010; Gordon-Larsen et al., 2006; Kaczynski et al., 2008; Mytton et al., 2012; Sugiyama et al., 2010; Villeneuve et al., 2018), improved children cognitive skills development (Dadvand et al., 2015a), improved mental health conditions (Dadvand et al., 2016; Gascon et al., 2015; Wood et al., 2017), reduced stress levels (Roe et al., 2017; Thompson et al., 2016), and lower exposure to traffic-related air pollution (Dadvand et al., 2015b). Some studies have, however, found some of the above mentioned associations non-significant (Ali et al., 2017; Cohen-Cline et al., 2015; Picavet et al., 2016; Potestio et al., 2009). Few studies investigated the possible impacts of difference in green space characterization on health outcome estimates. One study using the global positioning system on some 76 participants investigated the Modifiable Area Unit Problem (MAUP) that affected estimated physical activity effects of green space and other built environmental variables (Houston, 2014). That study suggests that both the size (scaling effect) and shape (i.e., the zoning effect) of the spatial units used in an analysis may influence resulting statistical inference. This study found both scaling and zoning effects, with smaller circular buffers generally relating to larger effect sizes when relating green space to objectively

Abbreviations: NDVI, normalized difference vegetation index; TOA, Top of Atmosphere; MAUP, Modifiable Area Unit Problem; USGS, United States Geological Survey; BMI, body mass index; GHQ, General Health Questionnaire; IPAQ, International Physical Activity Questionnaire; SES, socioeconomic status

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measured physical activity. The study, however, did not assess the influence of resolution in the input data for characterizing green space.

To improve green space exposure estimates, researchers have increasingly relied on the remote sensing images taken from satellites (Almanza et al., 2012; Dadvand et al., 2012; Gradinaru et al., 2016; Vatseva et al., 2016). Most of the research using remote sensing satellites has used the normalized difference vegetation index (NDVI) with 30 m resolution from Landsat images or 250 m resolution from the MODIS (Casey et al., 2017; Crouse et al., 2017). To be able to accurately identify green space but at the same time limit potential financial burden, we investigated whether it was necessary to purchase high spatial resolution (e.g., meter or sub-meter) remote sensing data for the identification of health outcomes. Literature suggests that green space within 500 m of home such as those of 50, 100, 250 and 500 m are often used to represent the immediate neighborhood of residence suitable for physical activity like walking (Su et al., 2011; Wolch et al., 2011), and in the presence of green space suitable for reducing noise and air pollution (Dadvand et al., 2015b; Davies et al., 2009). The smaller buffers also may account for immediate green space that could be in view of the home. In an ongoing study, we identified the associations of green space with mental health status, social support and physical activity for the City of Barcelona, Spain using the NDVI data derived from Landsat8 acquisition for buffers of 100, 250 and 500 m of participants' home addresses (Dadvand et al., 2016). In this paper, we extended those green space analyses with three different satellite sensors in respective spatial resolutions of 2, 5 and 30 m, for buffer distances from home address of 50, 100, 250 and 500 m, to take into consideration of potential existence of unmapped trails to and visual effects from green space. We then compared whether these different estimates of green space influence the health outcomes observed in epidemiological studies. We hypothesize that NDVI derived from higher spatial resolution remote sensing data or greater buffer size would lead to larger health outcomes detection from green space exposure.

2. Material and methods

2.1. Remote sensing data analysis

2.1.1. Remote sensing data sources

The City of Barcelona is located on the northeast part of Spain (Fig. 1). It has about 1.6 million people (Figueras et al., 2008). To identify the impacts of spatial resolution on green space characterization, we applied three different resolution remote sensing data for the region (Table 1), all collected in July and early August when vegetation shows greatest greenness: (1) the 2 m resolution WorldView2 imagery (DigitalGlobal, Colorado, USA) collected on August 3rd, 2012, including three visible bands (red, green and blue) and a near infrared band; (2) the 5 m resolution RapidEye imagery (RapidEye AG, Berlin, Germany) collected by satellites on July 23rd, 2012 for three visible (red, green and blue) and two infrared bands; and (3) the 30 m resolution Landsat8 data (USGS, Reston, Virginia, USA) acquired from the United States Geological Survey (USGS) for data collected on July 5th, 2012, including 11 bands. We could not acquire the remote sensing data for the same day due to difference in day of sensor data acquisition and difference in time of acquiring high quality images, e.g., cloud free, for the city. For each satellite imagery retrieval, we assessed green space at buffer sizes of 50, 100, 250 and 500 m around the participants' home addresses.

2.1.2. Processing remote sensing data

When remote sensing data are acquired, they are presented as pixel values or digital numbers. The value recorded for a given pixel includes not only the reflected or emitted radiation from the surface, but also the radiation scattered and emitted by the atmosphere. Given that the data acquired from the three sensors were not captured at the same date and time, radiometric calibrations were applied to remove impacts from atmospheric conditions and other factors that can influence the observed energy on a sensor. Due to the fact that the data were all acquired in summer when vegetation was greenest and they were collected in close proximity in date, we believed that a surface, such as the vigorousness of vegetation, remained unchanged and its corrected reflectance remained the same across the three sensors. However, when the spatial resolution decreases, a pixel on a surface would have more mixed ground information due to increased pixel size. This would result in over- or underestimating the degree of vegetation. At the same time, with increasing buffer size, the over- or underestimation in degree of vegetation would be further exaggerated.

Radiometric calibration and correction on our remote sensing data included the following connected steps: We first converted the original sensor acquired images in digital numbers to radiance based on the rescaling factors provided in the respective sensor metadata files. Based on Earth-Sun distance, solar zenith angel and exoatmospheric irradiance at the time of data acquisition, the radiance was further converted to Top of Atmosphere (TOA) reflectance.

2.1.3. Derivation of vegetation index — NDVI

The NDVI is calculated as follows:

$$NDVI = (NIR - RED)/(NIR + RED) \tag{3}$$

where *RED* and *NIR* stand for the spectral reflectance measurements acquired in the visible red band and near-infrared regions, respectively (Kriegler et al., 1969). Table 1 lists the bandwidths used for deriving NDVI surfaces for the city. NDVI ranges between −1 and 1 with higher numbers indicating more green vegetation. "−1" represents very high reflectance in the visible red band but with little near-infrared scattering such as from snow or cloud cover.

We derived NDVI surfaces for the entire city, maintaining the initial spatial resolutions of the WorldView2, RapidEye and Landsat imagery. Mean NDVI values of circular buffer distances of 50, 100, 250 and 500 m were calculated for all the image pixels in the study region. A regular grid of 10,141 points of 100 m apart was also generated to compare NDVI values from the three sensors across the four buffer sizes and their associated distributions in the study region. The agreements in NDVI values between the three sensors across the four buffer sizes were conducted through paired sample *t*-tests on the regular grid of 10,141 points. We also ranked NDVI values from high to low using the WorldView2 imagery as a reference and identified deviations from the reference line when remote sensing sensor changed.

For a sensitivity analysis, we also generated NDVI surfaces and buffer statistics using the primitive remote sensing data that only had digital numbers [counts]. The purpose of this was to identify whether radiometric calibrations were necessary to create proper vegetation index.

2.2. Health outcome analysis

2.2.1. Study population

The health analysis was based on a cross-sectional study of data obtained from a population-based randomized sample of adults residing in Barcelona. The data was collected in the context of the 2011 Barcelona Health Survey aimed to study the health status, life-styles and use of health services among Barcelona residents. Detailed description of this survey has already been published (Dadvand et al., 2016) and some descriptive statistics are presented in Table 2. Briefly, 4000 people residing across the 10 districts of Barcelona (400 from each district) were randomly selected from the Barcelona municipal register of residents to represent the age and sex structure of that district. An invitation letter was sent to selected subjects, informing them about the objectives of the survey and asking them to participate. The non-responders were substituted by randomly-selected persons of same district, with the same age and sex. For this study, we limited the participants to those with age ≥ 18 years resulting in 3461 adults in the

Fig. 1. The geographic location of Barcelona in Spain, Europe.

Table 1
The remote sensing imagery and bandwidths for creating NDVI indices for Barcelona.

Data source	Acquisition date	Resolution (m)	Red band	Near-infrared band
WordView 2	08/03/2012	2	630–690 nm	770–895 nm
RapidEye	07/23/2012	5	630–685 nm	760–850 nm
Landsat8	07/05/2012	30	640–670 nm	850–880 nm

analytical data set. A participant's main home address in which the interview was conducted was geocoded and the green space metrics described above were assigned to the geocoded location through the ArcGIS interpolation function (ESRI, Redlands, California). We used the 2012 rather than the 2011 NDVI data to match the 2011 health outcome data due to the best available remote sensing data in 2012 on cloud free status in the summer months for all the three sensor acquisitions.

2.2.2. Questionnaire data

The data on the perceived general health, mental health, physical activity, and relevant socio-demographic covariates were obtained through a face-to-face interview survey conducted at the residential place of the study participants. For perceived general health, participants answered a question obtained from the Short-Form 36 (Ware and

Table 2
The descriptive statistics of the participants in demographic characteristics and measured health outcomes.

Variable		Description
Age		
	18–45 years	1571 (45.4%)
	46–65 years	1039 (30.0)
	≥ 65 years	851 (24.6%)
Sex		
	Male	1657 (47.9%)
	Female	1804 (52.1%)
Education		
	No or primary school	666 (19.2%)
	Secondary school	1618 (46.8%)
	University	1148 (33.2%)
	Missing	29 (0.8%)
Subjective general health		
	Excellent/very good/good	2702 (78.2%)
	Fair/bad	755 (21.8%)
Mental health status		
	At risk	480 (14.4%)
	Not at risk	2856 (85.6%)
Physical activity		
	Moderate/high	236 (7.5%)
	Low	2907 (92.5%)

Table 3
The correlation matrix of NDVI indices derived from WorldView2, RapidEye and Landsat NDVI indices at buffer distances of 50, 100, 250 and 500 m through a regular grid of 10,141 points of 100 m apart in the study region.

	WV50	WV100	WV250	WV500	RE50	RE100	RE250	RE500	LS50	LS100	LS250
WorldView (100 m)	0.97										
WorldView (250 m)	0.92	0.97									
WorldView (500 m)	0.89	0.94	0.98								
RapidEye (50 m)	0.99										
RapidEye (100 m)		0.99			0.98						
RapidEye (250 m)			1.00		0.93	0.97					
RapidEye (500 m)				1.00	0.91	0.95	0.99				
Landsat (50 m)	0.97				0.97						
Landsat (100 m)		0.99				0.98			0.98		
Landsat (250 m)			0.99				0.99		0.93	0.97	
Landsat (500 m)				0.99				0.99	0.90	0.94	0.98

Sherbourne, 1992): "In general, would you say that your health is…" with possible responses being excellent/very good/good/fair/bad. The Short-Form 36 has been reported to be a reliable and valid tool to assess perceived general health in the Spanish population (Vilagut et al., 2005). The answers were dichotomized with cut-off at "less than good", following the same methodology used in previous studies (Maas et al., 2006; Triguero-Mas et al., 2015). We considered "less than good" answers as the reference category, therefore a positive association between greenness exposure and this variable could be interpreted as better perceived general health. For mental health, participants answered the twelve questions of the General Health Questionnaire (GHQ-12) (Goldberg, 1978). GHQ-12 has been reported to be a valid and reliable tool for screening non-psychotic mental problems (i.e. psychological distress) in the Spanish population (Sánchez-López and Dresch, 2008). The general score was dichotomized with those having a score ≥ 3 being classified as being at risk of psychological distress (Goldberg, 1978). We considered being at risk of psychological distress as the reference category; therefore, an association between greenness exposure and this variable could indicate lower risk of psychological distress (i.e. better mental health status). For physical activity, participants answered the seven questions of the International Physical Activity Questionnaire (IPAQ-Short version) (Craig et al., 2003). The IPAQ has been reported to have an acceptable validity and reliability for the Spanish population (Roman-Viñas et al., 2010). We developed a binary variable indicating whether the participant could be considered as having moderate or high physical activity levels based on the IPAQ guidelines (i.e. moderate/high vs. low levels of physical activity) (IPAQ Research Committee, 2005). We considered low physical activity level as the reference category; therefore a positive association between greenness exposure and this variable could be interpreted as greater likelihood of achieving moderate to high levels of physical activity.

2.2.3. Statistical analyses

We developed logistic regression models with perceived general health, mental health, and physical activity as outcome (one at a time) and measures of greenness exposure (one at a time) as predictor. The models were further adjusted for potential confounders identified a priori: age (18–45, 46–65, or < 65), sex, and indicators of socio-economic status (SES) at both individual and area levels. Educational attainment (no or primary/secondary/university) was used as the indicator of individual-level SES and tertiles of 2010 household income by neighborhood (Generalitat de Catalunya, 2010) was applied as the indicator of area-level SES.

In extending the previous work (Dadvand et al., 2016), we first modelled the associations of green space metrics with individual health outcomes separately for data acquired from sensors of three spatial resolutions (2, 5 and 30 m) for four buffer sizes (50, 100, 250 and 500 m). The individual health outcomes in mean estimates were then used to conduct trend analysis. Two main trends were analysed: First, we regressed sensor spatial resolution against the modelled mean health estimates through linear regression models. This was done for individual mean health estimates, but also for the three health outcomes combined. For example, when estimating the trends of association of spatial resolution with perceived health, the predictor was "sensor resolution" with values 2, 5 and 30 m and the response was "perceived health" with three corresponding mean estimates on perceived health. The linear regression model had 3-paired values. When the three health outcomes were combined, the predictor "sensor resolution" had 9 values with values 2, 5 and 30 m all occurring 3 times for the three different health outcomes, creating 9-paired values between sensor resolution and modelled mean health estimates. Second, we regressed buffer size against the modelled mean health estimates. The predictor "buffer size" included values of 50, 100, 250 and 500 m. Similarly, the analyses were done for both individual mean health estimates and the three health outcomes combined.

3. Results

3.1. Differences in characterizing green space

The correlation coefficients (R) between the four buffers of a remote sensing imagery on the regular grid of 10,141 points (highlighted areas in Table 3) showed that the degree of agreement in green space was greater when the defined scopes of impact were closer to each other. The degrees of correlation for WorldView2, RapidEye and Landsat8, ranged 0.89–0.98, 0.91–0.99 and 0.90–0.98, respectively, when compared within individual sensors across the four buffer sizes. When compared between two different sensors, we found the correlations were slightly stronger between WorldView2 and RapidEye than between Landsat and these other two sensors. In addition, correlations were slightly stronger with a larger buffer size. Though relative high in correlation coefficients, all the paired two sample *t*-tests showed significant differences in NDVI values derived from two types of sensors.

When comparing NDVI values derived from different sensors (Fig. 2), we found that NDVI values derived from Landsat8 data were on average greatest (mean = 0.27–0.28), while these values decreased for WorldView2 (mean = 0.18) and were closely followed by RapidEye imagery (mean = 0.16). NDVI indices derived from WorldView2 were slightly higher than those derived from RapidEye for the buffer sizes of 50, 100, 250 and 500 m. By comparison, Landsat8 consistently created higher NDVI indices by about 0.1. Even though there were these differences, the NDVI values derived from the three types of sensors showed a similar trend: higher NDVI values in one sensor was associated higher NDVI values in another sensor and vice versa, indicating that NDVI values were high when vegetation cover was high and decreased when degree of vegetation decreased. The spatial patterns largely remained unchanged for NDVI indices derived from the three different sensors.

We also compared the differences in NDVI for two specific neighborhoods of interest: the one at Estadi Olímpic with high in vegetation

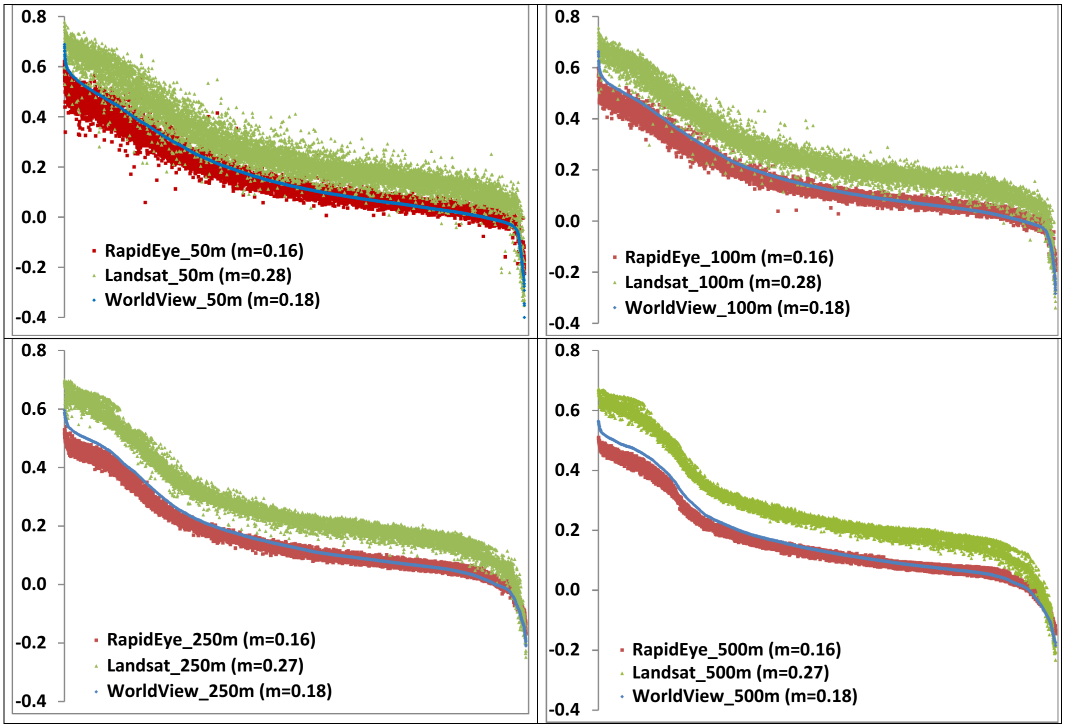

Fig. 2. The distribution of the NDVI values for WorldView2, RapidEye and Landsat data defined by buffer sizes of 50, 100, 250 and 500 m for the City of Barcelona. A regular grid of 10,141 points of 100 m apart was used for the analysis and WorldView2 imagery was used to rank the NDVI values from the highest to the lowest. Numbers in the parentheses are the mean NDVI values derived from a sensor.

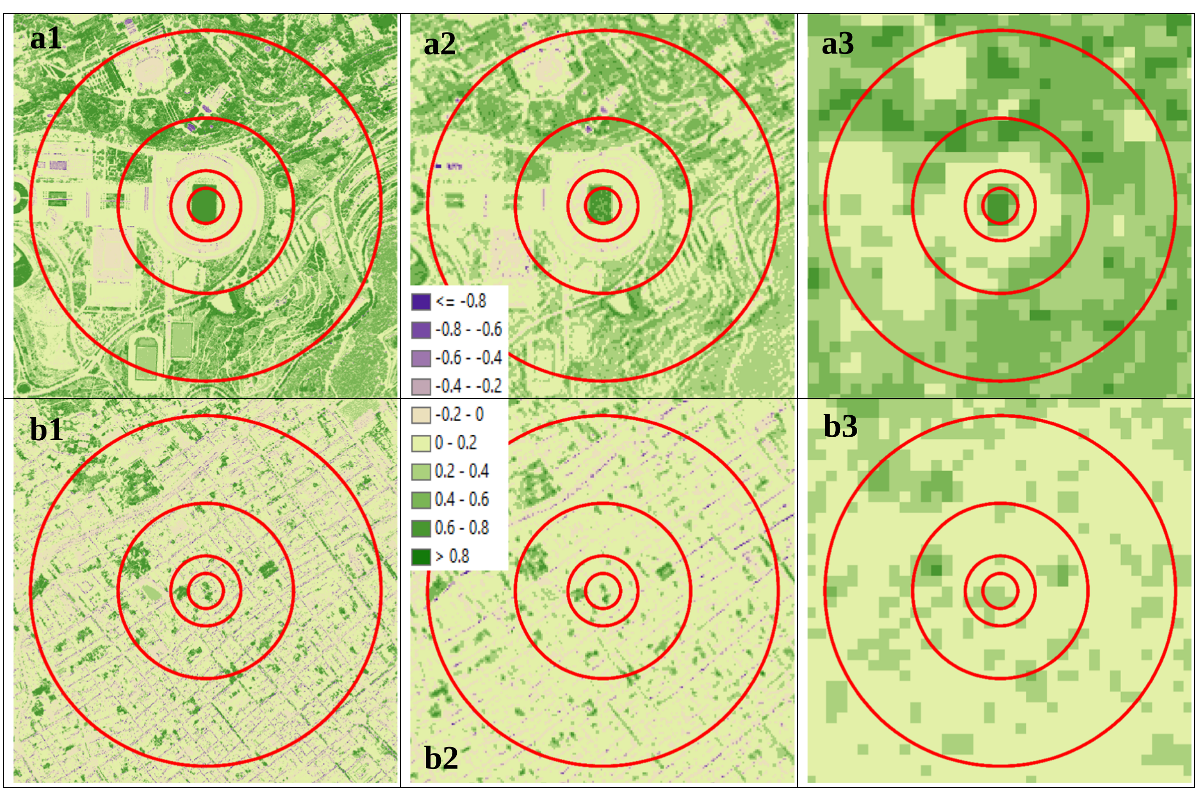

Fig. 3. NDVI surfaces and mean values in buffer sizes of 50, 100, 250 and 500 m (red circles) derived from WorldView2 (a1 for 0.59, 0.21, 0.20 and 0.25; and b1 for 0.10, 0.08, 0.07 and 0.07), RapidEye (a2 for 0.48, 0.17, 0.17 and 0.21;and b2 for 0.12, 0.09, 0.09 and 0.08) and Landsat8 (a3 for 0.60, 0.28, 0.29 and 0.34; and b3 for 0.18, 0.17, 0.18 and 0.17) for points of Estadi Olímpic (a) and Jardins del Mestre Balcells (b) vegetation cover areas in the immediate neighborhoods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

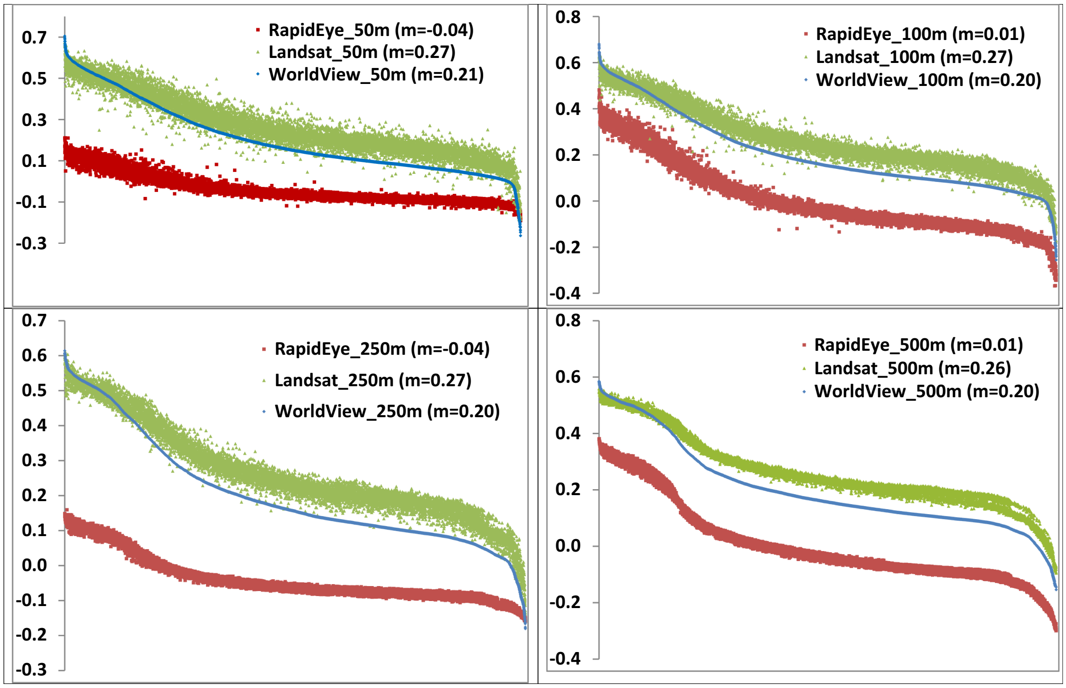

Fig. 4. The distribution of the NDVI values for WorldView2, RapidEye and Landsat data in buffers of 50, 100, 250 and 500 m with the imagery data not being corrected for atmospheric corrections. A regular grid of 10,141 points of 100 m apart was used for the analysis and WorldView2 imagery was used to rank the NDVI values from the highest to the lowest. Numbers in the parentheses are the mean NDVI values derived from a sensor.

cover and the second at Jardins del Mestre Balcells with intermediate vegetation cover (Fig. 3). The high vegetation cover area was centered on a soccer field (a1, a2 and a3 in Fig. 3), and we found that for the buffer defined within 50 m (the smallest circle), the NDVI indices derived from Landsat8 had the greatest value, these values decreased slightly for WorldView2 and then a much bigger reduction by RapidEye. When the bigger buffer sizes were used, some non-vegetated areas were included. The NDVI values decreased but still maintained that green space was greatest for Landsat8. RapidEye imagery, by contrast, maintained a tendency of lower estimates of NDVI values compared to Landsat8. At the area defined by intermediate vegetation cover, we found that both WorldView2 and RapidEye were very similar to each other in estimating NDVI (b1, b2 and b3 in Fig. 3). For Landsat8 data, the estimation of higher NDVI was still seen for all the four buffer sizes.

In addition, we compared the NDVI values derived from the three sensors with buffer sizes of 50, 100, 250 and 500 m using the uncorrected imagery (Fig. 4). For Landsat data, the corrections made slight increases in NDVI values compared to those uncorrected for all the buffer sizes. For the WorldView2 imagery, the corrected imagery had little change to the uncorrected imagery across four buffer sizes. For the RapidEye data, the uncorrected imagery showed significant underestimation of NDVI values than the corrected imagery, with an average difference of 0.15.

3.2. Differences in health outcomes

Overall, our research found that higher vegetation index was associated with better perceived health, better mental health and greater physical activity identified through the three sensors across the four buffer sizes. For trend analysis, we found that some significant linear trend existed in explaining health outcomes with varying buffer sizes ($p = 0.01$). The trend was significant and positive for perceived health ($p = 0.01$) and physical activity ($p < 0.001$) with increasing buffer size, but only marginally insignificant for mental health ($p = 0.09$). When examining individual health outcomes trends in Fig. 5, we found different patterns. Though their 95% confidence intervals overlap, we found that, for perceived health, health associations were relatively larger with the buffer size of 250 m. For mental health, the peak was associated with the buffer size of 100 m. For physical activity, the buffer size of 500 m was seen having relatively larger health effect.

For the satellite resolution (using TOA corrected imagery), we also found that linear trends existed, with higher spatial resolution associated with greater health outcomes; however, these trends were not statistically significant, with p values being 0.58, 0.39, 0.56, and 0.34 for perceived health, mental health, physical activity and the combined health. When limiting comparison within each health outcome to the same buffer size (either 50, 100, 250 or 500 m) (i.e., the association between sensor resolution and a health outcome given a fixed buffer size), we found that the green space characterized by finer spatial resolution had larger health associations. The trends in association were largely not statistically significant, except for physical activity when finer spatial resolution was associated with significant larger health outcomes for both buffer sizes 50 m ($p = 0.05$) and 500 m ($p < 0.001$).

4. Discussion

In this paper, three satellite sensors, including WorldView2, RapidEye and Landsat, with respective imagery of spatial resolution in 2 m, 5 m and 30 m, were used to identify possible difference in characterizing green space in the City of Barcelona. Our research indicates that the vegetation index NDVI derived from three sensors are comparable to each other, with NDVI derived from WorldView2 and RapidEye imagery showing greater similarity and the Landsat imagery having a tendency to predict higher NDVI values compared to the other two sensors. The higher degree of NDVI identified from Landsat was probably (1) due to the use of vegetation as a representation for pixels with mixed vegetation and other land cover information and (2) due to the differences in sensor spectrum design. The latter scenario could be identified from Table 1 that the Landsat's NIR band had relatively higher spectrum wavelength, resulting in greater vegetation reflectance. The difference in the red band wavelength might also

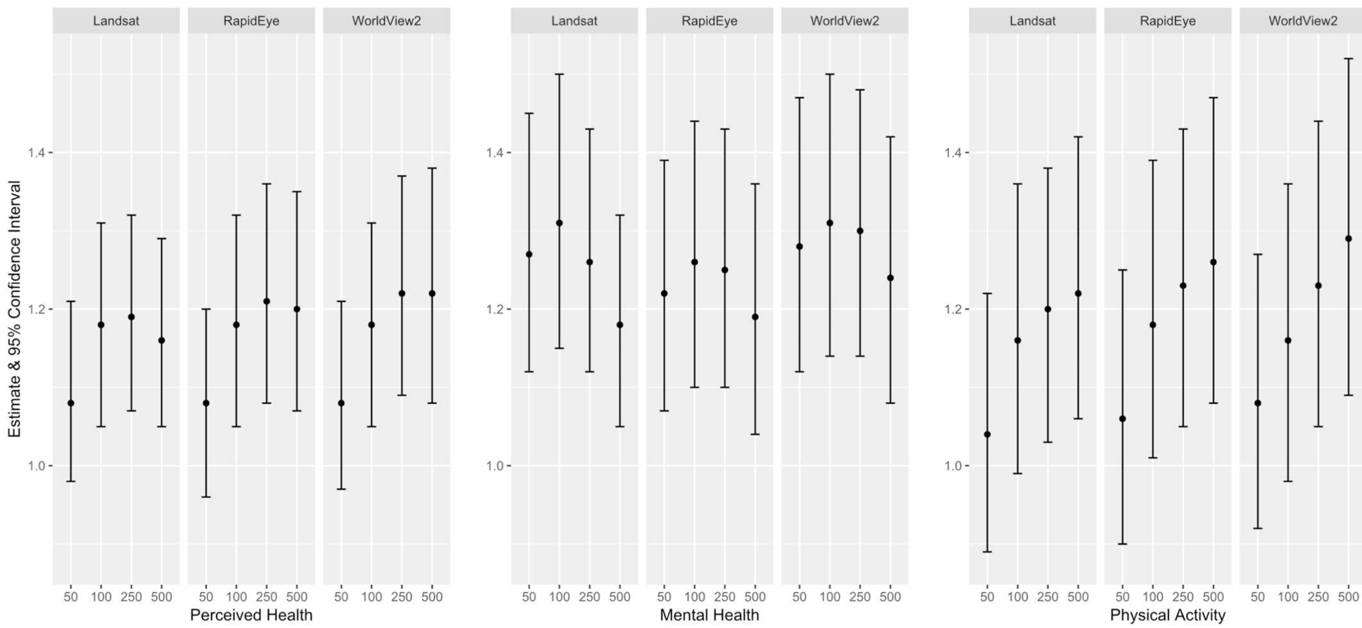

Fig. 5. The modelled health outcomes (adjusted odds ratio & 95% confidence interval) in perceived health, mental health and physical activity using NDVI index identified through buffer sizes of 50, 250, 250 and 500 m for WorldView2, RapidEye and Landsat8 data. The modelled health outcomes were adjusted by age, sex, education and neighborhood level socioeconomic status.

contribute to the NDVI difference and further studies should be conducted to confirm our assumption.

If the imagery data were uncorrected for atmospheric impact, the NDVI values derived from Landsat and WorldView2 imagery showed minor differences compared to the corrected imagery; however, the NDVI values derived from RapidEye showed the necessity of making radiometric calibration before the data could be used. In applications of satellite remote sensing data for land observations, some studies did not apply for radiometric calibrations. This might have minor impacts on results if data from only one sensor at one time period was used, such as the NDVI values derived from WorldView2 and Landsat sensors. If possible, however, the land observation data from satellite sensors should be corrected for impacts from atmosphere and other factors even though the data are acquired from one sensor for one time period. The NDVI values derived from the RapidEye imagery showed that if the imagery was not radiometrically calibrated, the values could be underestimated by 0.15. When data are acquired from multiple themes in multiple time periods or from multiple sensors, radiometric calibrations must be done to adjust for differences created by atmospheric conditions or by sensors themselves.

Our research found that higher vegetation index was largely associated with better perceived health, better mental health and greater physical activity identified through the three sensors across the four buffer sizes. This is similar to our literature search finding that green space was largely associated with better health outcomes; however, some studies showed non-significant associations (Ali et al., 2017; Cohen-Cline et al., 2015; Picavet et al., 2016; Potestio et al., 2009). Those non-significant associations could be due to the difference in green space characterization. It is typical in built environment studies that researchers define the neighborhood as a distance from a residence < 500 m. Given the small distance in defining a neighborhood, we still found that difference in buffer size had an impact on identified strength of associations with health outcomes and that mental health, perceived health and physical activity had different buffer sizes in charactering respective strength of association with health outcome. In identifying the associations of green cover with increased physical activity, reduced air pollution and noise, or natural healing from stress reduction in the immediate neighborhood, we suggest that the first option is to identify activity space of an individual through GPS-enabled tracking system that will help us resolve the MAUP issue. If GPS data are not available, the next option is to explore multiple buffer sizes of impact to identify whether the associations between green space and health are sensitive to the size of the buffer used to specify the potential relationship. Our study showed that perceived health had stronger association with relatively smaller buffer size in trend analysis, possibly due to the visual impact of green space seen from home on health. The physical activity instead, 500 m showed the greatest impact, possibly indicating that people might travel further than perceived health participants to participate in neighborhood activities. These results contrast with Houston (2014) who found larger effects on physical activity from smaller buffers. Our results may be different because people in Barcelona take > 47% of their trips by foot (Ajuntament de Barcelona, 2016) and possibly have slightly larger non-motorized activity space than in Los Angeles where among the five major counties walking trips range from 8.09 to 14.67% of the total trips taken (Joh et al., 2015).

Our study also found that the green space characterized using different spatial resolution satellite data detected similar associations. Though Landsat8 data tended to overestimate vegetation index, it did not significantly improve the identified associations. Given the higher costs associated with acquiring (including purchasing) finer spatial resolution data, an alternative option is to obtain a relatively coarser spatial resolution remote sensing data, especially when an analysis area is too large to be cost bearable for a project. However, higher spatial resolution imagery like those from WorldView2 allows the identification of very small green areas such as those in backyard and front yard. If a task is to identify objects or green space at that spatial resolution or to be linked to GPS-enabled activity space, we would suggest using those fine spatial resolution data for analysis. Though relatively coarser spatial resolution in Landsat8 data, they still have a spatial resolution of 30 m, which is considered very high spatial resolution compared to most satellite data which are > 1 or 10 km in spatial resolution. We do not suggest using a remote sensing data that is too coarse with substantial mixed pixel information so that the underlying phenomenon is greatly distorted or cannot be correctly identified.

We used images from the three sensors for year 2012, rather than for year 2011 when the survey was conducted. This was due to the availability of the best images for the entire city of Barcelona: we focused on date closeness from the three sensors for best available images in summer when vegetation showed greatest greenness. All the remote sensing data were collected in July or early August in 2012, which made it possible for us to get similar surface reflectance across the three sensors after radiometric calibration. We do not expect significant changes in vegetation greenness in Barcelona between the two neighboring years in summer when vegetation is greenest. The identified impact would remain largely the same if the year 2011 remote sensing data were available.

Our study relied on cross-sectional data, and we could not estimate temporal relationships between the NDVI exposure and health outcomes. In addition, we could not identify whether self-selection had any impact on the identified health outcomes. Further the identified health outcomes were obtained from a survey, which could have bias issues (Dal Grande et al., 2016; Regber et al., 2013). The health outcomes across the 4000 participants were not identified by physicians, although the self-assessed and mental health outcomes have been well validated in other studies. We also recognize that without objective ascertainment of physical activity, we cannot with definitive certainty ascribe health or behavioral changes to actual use or visual contact with the green space. In this analysis, we used home address as single location of green space exposure; however, we understand that exposure could occur in the community, at work, at home, at school and elsewhere. Significant limitations exist in this study and the majority of the current studies with the ability to identify personal activity space and exposure (Guarnieri and Balmes, 2014). Future work is needed to assess time-activity based exposure to green space rather than home-location based exposure to reduce exposure misclassification. The availability of Google Street View (GSV) as a street-level urban greenery assessment tool (Li et al., 2015) could help us assess time-activity based green exposure. Activity space-based exposure models could help us understand the optimal buffer distances in activity space of various groups of participants and whether the resolution of remote sensing sensors might have impact on identified health outcomes.

5. Conclusion

Though the advantage of using satellite data for green space characterization, cautions should be taken in selecting a reasonable buffer size of impact. We suggest investigating underlying mechanics for a health outcome in order to identify an optimal distance of impact. Our study also suggests that sensor spatial resolution did not significantly improve or reduce a health outcome estimate. Given financial strains and other limits, data from a coarser spatial resolution sensor might be a feasible alternative to the data derived from finer spatial resolution sensors for green space characterization. However, more highly resolved satellite data will reduce the problem of mixed pixels (i.e., misclassification of green space exposure due to pixels with nearly equal areas that are green versus those that are not). Reducing the mixed pixel problem should therefore reduce one potential component of measurement error that could bias epidemiological inference.

We also suggest that in order to best characterize green space including its accessibility and quality, satellite data should be combined with other evaluations of quality and accessibility. In this way, researchers will be able to assess the degree of vegetation, its accessibility, and quality so the potential health effects of exposure to green space can be more accurately identified. Such characterization may also help to illuminate the likely pathways from green space to various health outcomes, such as stress reduction, reduction of noise and air pollution, or physical activity.

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