

Characterizing green and gray space exposure for epidemiological studies: moving from 2D to 3D indicators

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ABSTRACT

The presence of green spaces has been associated with improved physical health and better mental health and wellbeing. In contrast, the presence of gray features including build-up areas might have a negative impact on the health and wellbeing of citizens. To date, the available evidence on the health effects of green and gray spaces have mainly relied on 2-dimensional (2D) indicators of these spaces such as land use maps or, more recently, satellite derived indices (e.g., green space indices such as

normalized difference vegetation index (NDVI) or gray space indices such as imperviousness). Although they are acceptable proxies of these exposures, 2D indicators could have inaccuracies when characterizing diverse set of vegetation types in combination with different types of gray spaces, which is typical of urban environments. To overcome this gap, we developed a set of three-dimensional (3D) indicators derived mainly from airborne LiDAR (Light Detection and Ranging) acquired in 2008 and 2010 over the metropolitan area of Rome (Italy). In particular, we extracted volume of green features such as shrubs and trees (Green volume [m³/ha]), volume of buildings (Gray volume[m³/ha]), a novel index called Normalized Difference Green-Gray Volume index (NDGG) as well as indicators of the tree count. We compared the 3D indicators with two widely used 2D indicators for characterizing green and gray spaces (i.e., NDVI and imperviousness) in different buffers around 79140 address points in the city. For the green indicators, we found that the Pearson correlations between NDVI and Green Volume were 0.47 (50m buffer) and 0.33 (300m buffer) while the correlations between NDVI and number of trees were 0.56 (50m buffer) and 0.58 (300m buffer). For gray indicators, the correlations between imperviousness and gray volume were 0.62 (50m buffer) and 0.79 (300m buffer). For NDGG, the correlations were higher with both NDVI (0.76 and 0.83 for 50m and 300m buffers) and imperviousness (-0.75 and -0.83 for 50m and 300m buffers). Our results showed that the use of 3D indicators can have potential benefits, especially regarding green features which can be highly heterogeneous in complex urban landscapes such as the city of Rome.

Keywords: LiDAR; Urban Forestry; Green Spaces; Green Volume; Gray Volume; Human Health; 3D Indicators; Remote Sensing

1. Introduction

An accumulating body of evidence has associated green and/or gray features with a wide range of physical and mental health outcomes. Being surrounded by green spaces has been suggested to reduce the risk of non-communicable diseases such as cardiovascular conditions, mortality and mental health problems, among others (James et al., 2015; Rojas-Rueda et al., 2019; Spano et al., 2020). On the other hand, spatial distribution of gray features (e.g. building density, percentage of imperviousness, or road network connectivity), have been found to be associated with mortality risk (Fecht et al., 2016), cardiovascular diseases (Dzhambov et al., 2022; Sanchez et al., 2018), and social vulnerability (Sabrin et al., 2020).

To date, a wide range of methods have been used to estimate the exposure to green and gray spaces, mainly relied on two-dimensional (2D) indicators derived from either land cover/use maps or, more recently, remote sensing indices such as NDVI (Normalized Difference Vegetation Index) or imperviousness obtained from satellite such as Landsat or Sentinel-2. Although 2D indicators are considered as a good proxy of urban structures (Gascon et al., 2016), they can result in considerable exposure misclassification when considering the heterogenous structure of an urban environment. For example, comparing the presence of greenness through NDVI can be challenging as the indicator is a function of latitude, slope, climate conditions and species composition (Beck et al., 2006; Kumari et al., 2020; Yang et al., 2021). Furthermore, 2D indicators are not able to assess three-dimensional (3D) characteristics, such as volume, height, or biomass, which have been suggested to provide a large variety of ecosystem services and, at the same time, possibly be relevant to human health (Jiang et al., 2016; Marziliano et al., 2013; Sanesi et al., 2009). For example, a greater stand volume mitigate the heat island effect and reduce air pollution (Tan et al., 2016). In terms of health benefits, density of biomass has been found associated with substantial reduction in self-reported stress and with increased social capital (Holtan et al., 2014; Jiang et al., 2016). Moreover, evidence have been found on the association between tri-dimensional structure of

green areas and its relationship with the presence of gray features. For example, Kuo and Sullivan (2001) found association between levels of aggression and mental fatigue with the presence of surrounding greenness and/or buildings, while Kuo (2001) found greater effectiveness in managing major life issues and less mental fatigue in residents surrounded by green features in opposition with those surrounded by buildings without nearby trees and grass.

The increased availability of Light Detection and Ranging (LiDAR) data has provided the opportunity to introduce 3D indicators, alongside 2D indicators. Several studies analyzed the relationship among 3D characteristics, such as vegetation and building volumes, and environmental factors such as temperature or air pollution. For example, Gage and Cooper (2017) analyzed the influence of horizontal and vertical landscape structure on the variation of land surface temperature of a suburb in Colorado (USA) stressing the need of the vertical dimension in assessing urban climate conditions. In terms of air pollution, tree crowns derived from LiDAR have been also been found to be correlated with altered PM₁₀ concentrations in the city of Antwerp (Belgium) (Hofman et al., 2016). On the contrary, in epidemiological studies, the associations between 2D/3D indicators and health outcomes or on how these indicators are related to each other, has remained vastly unexplored.

Quantification of green through the use of LiDAR-derived 3D indicators, such as green volume or number of trees, can provide urban planners and policy makers with a more tangible and practical understanding of the quantity of vegetation required to obtain the desired beneficial health effects (Mattijssen et al., 2017; Sanesi et al., 2007; Tomao et al., 2017; van der Jagt et al., 2019). Similarly, the gray volume and the balance between green and gray volumes can provide policymakers and urban planners with practical clues on how to implement the interventions and/or design the city in order to maximize the health benefits of the urban environment (Badiu et al., 2019).

The overarching goal of this short communication was to present a methodological framework to calculate a set of 3D indicators of green and gray urban characteristics derived mainly from LiDAR data. Towards the aim, we developed (1) three 3D indicators describing green and gray features

volume and their balance (i.e., (a) Green volume, (b) Gray volume and (c) Normalized difference Green Gray Volume - NDGG); and (2) a proxy of the number of trees through the extraction of LiDAR Treetops. As a real-life case study, these indicators were abstracted in buffers of 50 and 300 meters around the addresses of the residents in a well-established population-based cohort in the city of Rome. We then compared the 3D indicators with two widely used 2D indicators for characterizing green and gray spaces (i.e., NDVI and Imperviousness).

2. Material and methods

2.1. Study area

The study was conducted in the municipality of Rome (41°53'36"N 12°28'58"E). The municipality extends for about 1290 km² and has a population of about 2.7 million inhabitants (ISTAT, National Institute of Statistics, 2021). The population density varies substantially over each administrative subdivision going from ~800 residents per km² of the “Municipio XV”, located on the north-west of the municipality, to over 9000 persons per km² of the “Municipio I”, located in the city center. The area has a Mediterranean climate and includes multiple land use classes such as continuous and discontinuous urban, agriculture and forest areas (Fig. 1a) (Barbati et al., 2013; Salvati et al., 2008).

2.2. Study population

We used data from the Rome Longitudinal Study, an administrative cohort of 1,263,712 participants aged 35+ years residing in Rome at the Census date of Oct. 20th, 2001 (Cesaroni et al., 2013). For each participant, information was available on the residential address at baseline. These addresses were then intersected with the LIDAR-based retrievals (available only for a portion of the Rome territory), resulting in the inclusion of 79,140 (out of ~ 200,000) addresses corresponding to sub-cohort of 414,964 citizens. Sociodemographic profile of the sub-cohort sample is shown in Table 1.

2.3. *Green volume, Gray volume and Normalized Difference Green-Gray Volume (NDGG)*

LiDAR data was provided by the “*Ministero dell’Ambiente e della Tutela del Territorio e del Mare*”. It was acquired using the ALTM Gemini and ALTM 3100EA sensors produced by Optech company. The intersection between the available LiDAR data and cohort study area covered approximately 550 km², corresponding to less than half of Rome municipality (Fig.1). The matched LiDAR data was mainly acquired in 2008 and 2010 and had a resolution of three points per m².

The processing and the analysis of the LiDAR data was carried out by LAStools, R, and Arcmap (ArcGIS, 2017; Isenburg, 2014; R Core Team, 2020). The points were classified into ground, vegetation and building using a batch procedure involving a set of LAStools (i.e. lasground_new, lasheight and lasclassify) (Isenburg, 2014). The resulting classification was visually checked and corrected using freely available high-resolution data (i.e. OpenStreetMap) (Haklay and Weber, 2008). The classified LiDAR ground points were then used to create a Digital Terrain Model (DTM), with a spatial resolution of 1 meter, using the Inverse Distance Weighting algorithm in ArcGIS (ArcGIS, 2017). From vegetation points, a 1-meter resolution Canopy Height Model (CHM) was created using the p2r algorithm included in the lidR R package and further corrected using a neighborhood averaging operation with a 3x3 matrix to eliminate pit and spikes (Roussel et al., 2020). CHM was then used to calculate green volume by multiply the pixel area by the corresponding CHM height (Handayani et al., 2018). Lastly, a Building Height Model (BHM) was extracted from the Urban Atlas’ Building Height 2012 layer, a 10m resolution raster derived from Cartosat-1 satellite containing building heights of European Capitals (European Environment Agency, 2012). Similarly to the calculation used for green volume, the gray volume was calculated by multiply the pixel area by the corresponding BHM height (Handayani et al., 2018).

Green and gray volume were used to calculate the Normalized Difference Green-Gray Volume (NDGG), a dimensionless indicator meant to describe, straightforwardly, the volume of vegetation

and buildings and their relationship in each point in space, for a given buffer. It is based on the widely known Normalized Difference Vegetation Index, which is calculated as:

$$NDVI_{px} = (NIR_{px} - RED_{px}) / (NIR_{px} + RED_{px}) \quad [1]$$

where NIR_{px} and RED_{px} are the spectral reflectance values, for a given pixel, in the near-infrared band and in the red (visible) bands, respectively. Similarly, the NDGG here presented is calculated as:

$$NDGG_{px} = (Green\ volume_{buf} - Gray\ volume_{buf}) / (Green\ volume_{buf} + Gray\ volume_{buf}) \quad [2]$$

Where $Green\ volume_{buf}$ [m^3/ha] is the volume of green features (e.g., shrubs, trees) for a given buffer, and $Gray\ volume_{buf}$ [m^3/ha] is the volume of buildings for a given buffer (e.g., 50m or 300m). It expresses the ratio between vegetation and buildings volume and can vary from -1, where the totality of volume is composed by gray features to 1 where the totality of volume is composed by green features, passing from 0 where green and gray volumes are equally present.

For each participant of the sub-cohort included in the study, we averaged the green volume, gray volume and NDGG across buffers of 50 m and 300 m around the residential addresses

2.4. Treetops extraction

Each individual tree was identified applying a tree detection algorithm on the CHM. To do so, we used the local maxima filter algorithm (lmf) developed by Popescu and Wynne (2004) and implemented in the lidR R package (Roussel et al., 2020). The algorithm discriminates trees on the basis of the assumption that higher values of height, in a moving window of variable size (function of height), corresponds to the apex of a tree. For our analysis, we sized the variable moving window

following the equation developed by Popescu and Wynne (2004) for deciduous and mixed forest. In particular we used the following equation:

$$W_SIZE_i = CHM_i^2 * 0.00895 + 3.09632 \quad [3]$$

where W_SIZE is the moving window size and CHM is the height value in a particular pixel. All the treetops with a height less than two meters were then excluded from the dataset (Giannico et al., 2016; Næsset, 1997). For each residential address of the cohort participant, the number of treetops per hectare was calculated over a buffer of 50 and 300 meters.

2.5. 2D indicators

Two-dimensional indicators were calculated from a variety of sources. For the calculation of imperviousness, we used the 2009 imperviousness density layer provided by the Copernicus program (European Environment Agency, 2009). The imperviousness density layer is a 20m spatial resolution layer representing the percentage of impermeable soil cover for a given pixel. It is calculated based on high-resolution satellite images (IRS-P6/Resourcesat-2 LISS-III, SPOT 5 and Landsat 8). NDVI map was obtained over the city of Rome using the Google Earth Engine platform (Gorelick et al., 2017). In particular, we used 16 Landsat 5 surface reflectance images at 30 m × 30 m resolution, acquired between the 1st of March and the 30th of September of 2010, i.e., the greenest months of the year in Rome. The images, already corrected radiometrically and atmospherically, were masked from the presence of clouds, cloud shadow and snow using the provided pixel quality assessment band (Elia et al., 2020; Giannico et al., 2021). The collection of images was reduced to one image by computing the median of all the values at each pixel across the image collection individually for each band. The resulting image was used to calculate NDVI (equation [1]). Furthermore, we mapped the land use classes of our study areas using the Corine Land Cover 2012, a vector land cover map with a Minimum Mapping Unit (MMU) of 25 hectares (ha), provided by the Copernicus European program

(European Environment Agency, 2012b). In line with our approach for calculating 3D indicators, for each residential address, the mean imperviousness and mean NDVI were calculated across buffers of 50 m and 300 m.

2.6. Correlation analysis

To understand the correlation between the 2D and 3D green and gray indicators, we calculated the Pearson's correlation coefficient among 2D (NDVI and imperviousness) and 3D (i.e., green volume, gray volume, number of treetops and NDGG) indicators calculated at 50 meters and 300 meters buffer around each address of the sub-cohort.

3. Results

The green and gray space indicators were extracted for a total of 79,140 residential addresses, of which 19,420 were distributed over continuous urban fabric (urban structures > 80%); 51,950 over discontinuous urban fabric (urban structure between 30% and 80%); and 7,770 over other types of areas (Fig. 1 and 2).

Green 3D indicators (i.e., green volume and treetops) were positively correlated to each other although the correlation was low for both buffers (i.e., 0.27 and 0.35 for 50m and 300m respectively) (Table 2). When correlated with NDGG, both green volume and treetops had higher correlations at 50m buffer (0.61 and 0.62 respectively). However, when a larger buffer was considered (i.e., 300m), the correlation between green volume and NDGG was lower (0.45) while remained over 0.60 between treetops and NDGG. A strong negative correlation was instead found between the gray 3D indicator (gray volume) and the NDGG for both the buffers considered (-0.80 at 50m and -0.87 at 300m buffer). Looking at the correlations between green indicators (3D vs 2D), we found that NDVI was positively correlated with green volume (0.47 at 50m and 0.33 at 300m buffer) and treetops (0.56 at 50m and 0.58 at 300m buffer) although the correlations were low (Table 2). On the other hand, the correlations

between gray 3D and 2D indicators (i.e., gray volume and imperviousness) were slightly higher especially for the larger buffer size (0.62 at 50m and 0.79 at 300m buffer). Finally, we found a strong correlation between the NDGG and NDVI (0.76 at 50m and 0.83 at 300m buffer), and between NDGG and Imperviousness (-0.75 at 50m and -0.83 at 300m buffer).

When comparing green and gray 3D indicators, we found a weak negative correlation between green and gray volume at 300m (-0.04) and 50m buffer (-0.20) (Table 2). In contrast, the negative correlation between treetops and gray volume was slightly higher for the two buffer sizes (-0.54 at 50m and 300m buffer). On the other hand, the correlations between green and gray 2D indicators, showed a very strong inverse correlation between NDVI and imperviousness at 50m buffer (-0.88) and even stronger at 300m buffer (-0.94).

4. Discussion

In this short communication, we presented a methodological framework to extract a set of 3D indicators of green and gray urban features. We compared these novel indicators with two widely adopted 2D indicators (i.e., NDVI and imperviousness) demonstrating the potential benefits of using 3D indicators.

Green volume and number of treetops were positively correlated with NDVI although the correlation coefficients were small for both 50 m and 300 m buffers. Urban green features have a complex structure that varies as a function of a number of characteristics (e.g. stand volume or vertical forest stratification) (Giannico et al., 2016). These characteristics are difficult to retrieve from a 2D layer, such as NDVI, which cannot take into account vegetation's 3D proprieties (Casalegno et al., 2017). Other studies compared 3D volume indicators with NDVI obtained slightly different results. Davis *et al.* (2016) estimated green and gray volume using LiDAR data to assess the role of 3D features in changes of the urban air temperature in Chicago (IL, USA). They reported a correlation of 0.54 and 0.66 between NDVI and green volumes for 100 m and 250 m buffers, respectively, which were higher

compared to our observed correlations of 0.47 and 0.33 for respectively 50 m and 300 m buffers. This difference is probably due to the differences in the landscape heterogeneity and vegetation types of the study areas. In comparison to the area of Chicago, the area covered in this study had a large portion of agriculture and semi-natural forests areas, which could, at least in part, explain the differences between NDVI and green volume (Fig. 1b). Moreover, the agricultural fields in our study area included olive trees and vineyards, which could strongly impact the NDVI values (Barbati et al., 2013).

Among our green and gray 3D indicators, NDGG was found to have the strongest correlations with 2D indicators. This stronger correlation is probably because, similarly to NDVI, NDGG is calculated taking into consideration both green and gray features. However, while the calculation of NDVI for a given buffer is, depending on the resolution, very likely to be influenced by background (e.g., soil or non-vegetated surfaces) (Giannico et al., 2018; Marzban et al., 2018; Todd and Hoffer, n.d.; Weng et al., 2004), NDGG is not affected by backgrounds and thus has the potential to provide cleaner indication of the ratios between volumetric green and gray features. Few other studies have also developed indicators to express relationship between green and gray areas. For example, Laforteza and Giannico (2019) developed a remote sensing based indicator called Normalized Difference Green-Building Volume (NDGB) using LiDAR and very high resolution multispectral data (i.e. WorldView-2 images) through complex focal functions. The indicator was found to be a good predictor of individuals' perceptions of green space benefits. Differently from NDGG, the indicator developed by Laforteza and Giannico (2019) requires very high resolution data which is not always available for urban areas and, therefore, its application can be limited. On the contrary, the calculation of the NDGG, requiring only LiDAR data, can be more widely adopted.

When we analyzed the relationship between 2D and 3D indicators, we found gray volume and imperviousness to be the most correlated and the coefficients were higher when the calculation were done at 300 meters buffers. Although no previous studies has directly investigated the relationship

between these gray indicators, previous studies analyzed the influence of different urban structure types on imperviousness and gray volume discovering similar trends (Berger et al., 2017; Heiden et al., 2012). For example, Heiden et al., (2012), found that imperviousness and the density of buildings was positively correlated. In our analysis, the higher correlation of imperviousness with gray volume in comparison of NDVI with green volume was probably due to the high level of vegetation structure diversity that characterize our area of study.

The results presented in this short communication have some limitations which are important to underline. The input data used in our analysis come from different sources, years, and resolution (i.e., LiDAR data was acquired in 2008 and 2010, NDVI in 2010, imperviousness in 2009, and building height in 2012). Although, we do not expect many changes at city level in a 4-year period, it is important to take this discrepancy into account, when interpreting the results. It is also important to note that a large portion of trees belong to private areas and thus difficult to assess through field data.

Despite evidence is accumulating on the potential beneficial effects underlying the interaction between green exposure and human health, a current challenge of the research topic is represented by the differentiation of the effects of natural and built elements on specific human health and well-being outcomes. Greater variability in the characterization of greenness is expecting to produce an increased accuracy in differentiating its effects on physical and mental health, thus, offering insights for more complex urban planning that meets the needs of different groups of individuals. In light of the complexity on the differentiation of green and gray space, we believe that future studies might take greater account a community dimension of health. For instance, socialization represents a crucial intervening variable in the relationship between greenness and mental health (Carrus et al., 2015; de Vries et al., 2013). It would be useful to disentangle the mediating role of social and community aspects (e.g., cohesion, interaction, use of space) in the relationship between the composite information provided by the proposed 3D indicators and physical and mental health outcomes.

5. Conclusion

The introduction of 3D green and gray indicators in the context of epidemiological studies of the health effects of gray and green spaces is still little explored. In this short communication, we presented a methodological framework to assess the 3D characteristics of the landscape through the use of LiDAR data, which is, nowadays, a *de-facto* standard for 3D measurements and already available at no cost in many areas. Our results showed, unsurprisingly, that 3D indicators could tell a different story than 2D indicators especially when the exposure to greenspace is sought. Future epidemiological studies of the health effects of green and gray spaces are recommended to accompany the widely used 2D indicators with 3D indicators to obtain a holistic characterization of the horizontal and vertical green/gray structures in complex urban areas.

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References

- ArcGIS, 2017. . Environmental Systems Research Institute, ESRI, Redlands, CA (USA).
- Badiu, D.L., Onose, D.A., Niță, M.R., Laforteza, R., 2019. From “red” to green? A look into the evolution of green spaces in a post-socialist city. *Landscape and Urban Planning* 187, 156–164. <https://doi.org/10.1016/j.landurbplan.2018.07.015>
- Barbati, A., Corona, P., Salvati, L., Gasparella, L., 2013. Natural forest expansion into suburban countryside: Gained ground for a green infrastructure? *Urban Forestry & Urban Greening* 12, 36–43. <https://doi.org/10.1016/j.ufug.2012.11.002>
- Beck, P.S.A., Atzberger, C., Høgda, K.A., Johansen, B., Skidmore, A.K., 2006. Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sensing of Environment* 100, 321–334. <https://doi.org/10.1016/j.rse.2005.10.021>
- Berger, C., Rosentreter, J., Voltersen, M., Baumgart, C., Schmullius, C., Hese, S., 2017. Spatio-temporal analysis of the relationship between 2D/3D urban site characteristics and land surface temperature. *Remote Sensing of Environment* 193, 225–243. <https://doi.org/10.1016/j.rse.2017.02.020>
- Carrus, G., Scopelliti, M., Laforteza, R., Colangelo, G., Ferrini, F., Salbitano, F., Agrimi, M., Portoghesi, L., Semenzato, P., Sanesi, G., 2015. Go greener, feel better? The positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. *Landscape and Urban Planning* 134, 221–228. <https://doi.org/10.1016/j.landurbplan.2014.10.022>
- Casalegno, S., Anderson, K., Hancock, S., Gaston, K.J., 2017. Improving models of urban greenspace: from vegetation surface cover to volumetric survey, using waveform laser scanning. *Methods in Ecology and Evolution* 8, 1443–1452. <https://doi.org/10.1111/2041-210X.12794>
- Cesaroni, G., Badaloni, C., Gariazzo, C., Stafoggia, M., Sozzi, R., Davoli, M., Forastiere, F., 2013. Long-Term Exposure to Urban Air Pollution and Mortality in a Cohort of More than a Million Adults in Rome. *Environmental Health Perspectives* 121, 324–331. <https://doi.org/10.1289/ehp.1205862>
- Davis, A.Y., Jung, J., Pijanowski, B.C., Minor, E.S., 2016. Combined vegetation volume and “greenness” affect urban air temperature. *Applied Geography* 71, 106–114. <https://doi.org/10.1016/j.apgeog.2016.04.010>
- de Vries, S., van Dillen, S.M.E., Groenewegen, P.P., Spreeuwenberg, P., 2013. Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. *Social Science & Medicine* 94, 26–33. <https://doi.org/10.1016/j.socscimed.2013.06.030>
- Dzhambov, A.M., Lercher, P., Markevych, I., Browning, M.H.E.M., Rüdiger, J., 2022. Natural and built environments and blood pressure of Alpine schoolchildren. *Environmental Research* 204, 111925. <https://doi.org/10.1016/j.envres.2021.111925>
- Elia, M., Giannico, V., Spano, G., Laforteza, R., Sanesi, G., 2020. Likelihood and frequency of recurrent fire ignitions in highly urbanised Mediterranean landscapes. *Int. J. Wildland Fire*. <https://doi.org/10.1071/WF19070>
- European Environment Agency, (EEA), 2012a. Building Height 2012 [WWW Document]. URL <https://land.copernicus.eu/local/urban-atlas/building-height-2012> (accessed 4.19.21).
- European Environment Agency, (EEA), 2012b. Corine Land Cover 2012 [WWW Document]. URL <https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012> (accessed 4.19.21).
- European Environment Agency, (EEA), 2009. Imperviousness Density 2009 [WWW Document]. URL <https://land.copernicus.eu/pan-european/high-resolution-layers/imperviousness/status-maps/2009> (accessed 4.19.21).
- Fecht, D., Fortunato, L., Morley, D., Hansell, A.L., Gulliver, J., 2016. Associations between urban metrics and mortality rates in England. *Environ Health* 15, S34. <https://doi.org/10.1186/s12940-016-0106-3>

- Gage, E.A., Cooper, D.J., 2017. Relationships between landscape pattern metrics, vertical structure and surface urban Heat Island formation in a Colorado suburb. *Urban Ecosyst* 20, 1229–1238. <https://doi.org/10.1007/s11252-017-0675-0>
- Gascon, M., Cirach, M., Martínez, D., Dadvand, P., Valentín, A., Plasència, A., Nieuwenhuijsen, M.J., 2016. Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry & Urban Greening* 19, 88–94. <https://doi.org/10.1016/j.ufug.2016.07.001>
- Giannico, V., Chen, J., Shao, C., Ouyang, Z., John, R., Laforteza, R., 2018. Contributions of landscape heterogeneity within the footprint of eddy-covariance towers to flux measurements. *Agricultural and Forest Meteorology* 260–261, 144–153. <https://doi.org/10.1016/j.agrformet.2018.06.004>
- Giannico, V., Laforteza, R., John, R., Sanesi, G., Pesola, L., Chen, J., 2016. Estimating stand volume and above-ground biomass of urban forests using LiDAR. *Remote Sensing* 8, 339. <https://doi.org/10.3390/rs8040339>
- Giannico, V., Spano, G., Elia, M., D’Este, M., Sanesi, G., Laforteza, R., 2021. Green spaces, quality of life, and citizen perception in European cities. *Environmental Research* 196, 110922. <https://doi.org/10.1016/j.envres.2021.110922>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. <https://doi.org/10.1016/j.rse.2017.06.031>
- Haklay, M., Weber, P., 2008. OpenStreetMap: User-Generated Street Maps. *IEEE Pervasive Comput.* 7, 12–18. <https://doi.org/10.1109/MPRV.2008.80>
- Handayani, H., Murayama, Y., Ranagalage, M., Liu, F., Dissanayake, D., 2018. Geospatial Analysis of Horizontal and Vertical Urban Expansion Using Multi-Spatial Resolution Data: A Case Study of Surabaya, Indonesia. *Remote Sensing* 10, 1599. <https://doi.org/10.3390/rs10101599>
- Heiden, U., Heldens, W., Roessner, S., Segl, K., Esch, T., Mueller, A., 2012. Urban structure type characterization using hyperspectral remote sensing and height information. *Landscape and Urban Planning* 105, 361–375. <https://doi.org/10.1016/j.landurbplan.2012.01.001>
- Hofman, J., Bartholomeus, H., Janssen, S., Calders, K., Wuyts, K., Van Wittenberghe, S., Samson, R., 2016. Influence of tree crown characteristics on the local PM 10 distribution inside an urban street canyon in Antwerp (Belgium): A model and experimental approach. *Urban Forestry & Urban Greening* 20, 265–276. <https://doi.org/10.1016/j.ufug.2016.09.013>
- Holtan, M.T., Dieterlen, S.L., Sullivan, W.C., 2014. Social Life Under Cover: Tree Canopy and Social Capital in Baltimore, Maryland. *Environment and Behavior* 47, 502–525. <https://doi.org/10.1177/0013916513518064>
- Isenburg, M., 2014. LAStools, “Efficient LiDAR Processing Software.”
- ISTAT, National Institute of Statistics, 2021. Bilancio demografico anno 2021 (dati provvisori) [WWW Document]. URL <http://demo.istat.it/bilmens/query.php?anno=2021&lingua=ita&Rip=S3&Reg=R12&Pro=P058&Com=91&submit=Tavola> (accessed 4.19.21).
- James, P., Banay, R.F., Hart, J.E., Laden, F., 2015. A Review of the Health Benefits of Greenness. *Curr Epidemiol Rep* 2, 131–142. <https://doi.org/10.1007/s40471-015-0043-7>
- Jiang, B., Li, D., Larsen, L., Sullivan, W.C., 2016. A Dose-Response Curve Describing the Relationship Between Urban Tree Cover Density and Self-Reported Stress Recovery. *Environment and Behavior* 48, 607–629. <https://doi.org/10.1177/0013916514552321>
- Kumari, N., Saco, P.M., Rodriguez, J.F., Johnstone, S.A., Srivastava, A., Chun, K.P., Yetemen, O., 2020. The Grass Is Not Always Greener on the Other Side: Seasonal Reversal of Vegetation Greenness in Aspect-Driven Semiarid Ecosystems. *Geophys. Res. Lett.* 47. <https://doi.org/10.1029/2020GL088918>
- Kuo, F.E., 2001. Coping with Poverty: Impacts of Environment and Attention in the Inner City. *Environment and Behavior* 33, 5–34. <https://doi.org/10.1177/00139160121972846>

- Kuo, F.E., Sullivan, W.C., 2001. Aggression and Violence in the Inner City: Effects of Environment via Mental Fatigue. *Environment and Behavior* 33, 543–571. <https://doi.org/10.1177/00139160121973124>
- Laforteza, R., Giannico, V., 2019. Combining high-resolution images and LiDAR data to model ecosystem services perception in compact urban systems. *Ecological Indicators*, From urban sprawl to compact green cities – indicators for multi-scale and multi-dimensional analysis 96, 87–98. <https://doi.org/10.1016/j.ecolind.2017.05.014>
- Marzban, F., Sodoudi, S., Preusker, R., 2018. The influence of land-cover type on the relationship between NDVI–LST and LST- T_{air} . *International Journal of Remote Sensing* 39, 1377–1398. <https://doi.org/10.1080/01431161.2017.1402386>
- Marziliano, P.A., Laforteza, R., Colangelo, G., Davies, C., Sanesi, G., Giannico, V., 2013. Structural diversity and height growth models in urban forest plantations: A case-study in northern Italy. *Urban Forestry & Urban Greening* 12, 246–254. <https://doi.org/10.1016/j.ufug.2013.01.006>
- Mattijssen, T.J.M., van der Jagt, A.P.N., Buijs, A.E., Elands, B.H.M., Erlwein, S., Laforteza, R., 2017. The long-term prospects of citizens managing urban green space: From place making to place-keeping? *Urban Forestry & Urban Greening* 26, 78–84. <https://doi.org/10.1016/j.ufug.2017.05.015>
- Næsset, E., 1997. Determination of mean tree height of forest stands using airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing* 52, 49–56. [https://doi.org/10.1016/S0924-2716\(97\)83000-6](https://doi.org/10.1016/S0924-2716(97)83000-6)
- Popescu, S.C., Wynne, R.H., 2004. Seeing the Trees in the Forest. *Photogrammetric Engineering & Remote Sensing* 70, 589–604. <https://doi.org/10.14358/PERS.70.5.589>
- R Core Team, 2020. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
- Rojas-Rueda, D., Nieuwenhuijsen, M.J., Gascon, M., Perez-Leon, D., Mudu, P., 2019. Green spaces and mortality: a systematic review and meta-analysis of cohort studies. *The Lancet Planetary Health* 3, e469–e477. [https://doi.org/10.1016/S2542-5196\(19\)30215-3](https://doi.org/10.1016/S2542-5196(19)30215-3)
- Roussel, J.-R., Auty, D., Coops, N.C., Tompalski, P., Goodbody, T.R.H., Meador, A.S., Bourdon, J.-F., Boissieu, F. de, Achim, A., 2020. lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sensing of Environment* 251, 112061. <https://doi.org/10.1016/j.rse.2020.112061>
- Sabrin, S., Karimi, M., Fahad, M.G.R., Nazari, R., 2020. Quantifying environmental and social vulnerability: Role of urban Heat Island and air quality, a case study of Camden, NJ. *Urban Climate* 34, 100699. <https://doi.org/10.1016/j.uclim.2020.100699>
- Salvati, L., Petitta, M., Ceccarelli, T., Perini, L., Di Battista, F., Scarascia, M.E.V., 2008. Italy’s renewable water resources as estimated on the basis of the monthly water balance. *Irrig. and Drain.* 57, 507–515. <https://doi.org/10.1002/ird.380>
- Sanchez, M., Mila, C., Ambros, A., Ranzani, O., Kinra, S., Dadvand, P., Tonne, C., 2018. Residential Built-Up Area in Relation to Markers of Cardiovascular Health in Peri-Urban South India. *ISEE Conference Abstracts*. <https://doi.org/10.1289/isesisee.2018.P02.2260>
- Sanesi, G., Laforteza, R., Marziliano, P.A., Ragazzi, A., Mariani, L., 2007. Assessing the current status of urban forest resources in the context of Parco Nord, Milan, Italy. *Landscape Ecol Eng* 3, 187–198. <https://doi.org/10.1007/s11355-007-0031-2>
- Sanesi, G., Padoa Schioppa, E., Lorusso, L., Bottoni, L., Laforteza, R., 2009. Avian Ecological Diversity as an Indicator of Urban Forest Functionality. Results from Two Case Studies in Northern and Southern Italy. *ARBORICULTURE & URBAN FORESTRY* 35, 80–86.
- Spano, G., Giannico, V., Elia, M., Bosco, A., Laforteza, R., Sanesi, G., 2020. Human Health–Environment Interaction Science: An emerging research paradigm. *Science of The Total Environment* 704, 135358. <https://doi.org/10.1016/j.scitotenv.2019.135358>
- Tan, Z., Lau, K.K.-L., Ng, E., 2016. Urban tree design approaches for mitigating daytime urban heat island effects in a high-density urban environment. *Energy and Buildings*, SI:

- Countermeasures to Urban Heat Island 114, 265–274.
<https://doi.org/10.1016/j.enbuild.2015.06.031>
- Todd, S.W., Hoffer, R.M., n.d. Responses of Spectral Indices to Variations in Vegetation Cover and Soil Background 7.
- Tomao, A., Quatrini, V., Corona, P., Ferrara, A., Laforteza, R., Salvati, L., 2017. Resilient landscapes in Mediterranean urban areas: Understanding factors influencing forest trends. *Environmental Research* 156, 1–9. <https://doi.org/10.1016/j.envres.2017.03.006>
- van der Jagt, A.P.N., Smith, M., Ambrose-Oji, B., Konijnendijk, C.C., Giannico, V., Haase, D., Laforteza, R., Nastran, M., Pintar, M., Železnikar, Š., Cvejić, R., 2019. Co-creating urban green infrastructure connecting people and nature: A guiding framework and approach. *Journal of Environmental Management* 233, 757–767. <https://doi.org/10.1016/j.jenvman.2018.09.083>
- Weng, Q., Lu, D., Schubring, J., 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment* 89, 467–483. <https://doi.org/10.1016/j.rse.2003.11.005>
- Yang, L., Guan, Q., Lin, J., Tian, J., Tan, Z., Li, H., 2021. Evolution of NDVI secular trends and responses to climate change: A perspective from nonlinearity and nonstationarity characteristics. *Remote Sensing of Environment* 254, 112247. <https://doi.org/10.1016/j.rse.2020.112247>

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Table 1. Sociodemographic Profile of the sub-cohort sample of the Rome Longitudinal Study derived from the intersection with LiDAR data.

Variable	Stratum	Sub-cohort	
		n	%
Age (mean, SD)	-	55.1	15.5
Sex	<i>females</i>	187,649	45.2
	<i>males</i>	227,315	54.8
Place of birth	<i>rome</i>	220,068	53.0
	<i>out of Rome</i>	194,896	47.0
Marital status	<i>married</i>	270,442	65.2
	<i>single</i>	65,812	15.9
	<i>divorced</i>	31,469	7.6
	<i>widow</i>	47,241	11.4
Education level	<i>University</i>	77,213	18.6
	<i>High-school</i>	141,684	34.1
	<i>Junior school</i>	104,855	25.3
	<i>≤ Primary</i>	91,212	22.0
Occupation	<i>Employed</i>	192,925	46.5
	<i>Homemaker</i>	84,982	20.5
	<i>Unemployed</i>	19,692	4.7
	<i>Retired</i>	117,365	28.3
SEP (quintiles)	<i>1</i>	89,496	21.6
	<i>2</i>	98,823	23.8
	<i>3</i>	85,014	20.5
	<i>4</i>	71,567	17.2
	<i>5</i>	70,064	16.9
Income (deciles)	<i>1</i>	1,688	0.4
	<i>2</i>	35,841	8.6
	<i>3</i>	31,848	7.7
	<i>4</i>	27,744	6.7
	<i>5</i>	30,478	7.3
	<i>6</i>	62,372	15.0
	<i>7</i>	75,889	18.3
	<i>8</i>	98,952	23.8
	<i>9</i>	35,103	8.5
	<i>10</i>	15,049	3.6

Table 2. Matrix of Pearson correlation coefficients between 2D and 3D green and gray Indicators.

Green volume = Volume of green features (e.g., shrubs, trees) within buffers of 50 m and 300 m; Gray volume = Volume of gray features (e.g.,

	Green	Gray	Gray	Treetops	Treetops	NDGG	NDGG	NDVI	NDVI	Imperviousness	Imperviousness
	volume (300m)	volume (50m)	volume (300m)	(50m)	(300m)	(50m)	(300m)	(50m)	(300m)	(50m)	(300m)
Green volume (50m)	0.58	-0.20	-0.10	0.27	0.25	0.61	0.34	0.47	0.26	-0.49	-0.21
Green volume (300m)		0.01	-0.04	0.06	0.35	0.24	0.45	0.23	0.33	-0.18	-0.24
Gray volume (50m)			0.76	-0.54	-0.45	-0.80	-0.66	-0.66	-0.55	0.62	0.56
Gray volume (300m)				-0.51	-0.54	-0.63	-0.87	-0.65	-0.76	0.58	0.79
Treetops (50m)					0.61	0.62	0.50	0.56	0.44	-0.49	-0.41
Treetops (300m)						0.49	0.64	0.50	0.58	-0.39	-0.44
NDGG (50m)							0.69	0.76	0.57	-0.75	-0.57
NDGG (300m)								0.69	0.83	-0.62	-0.83
NDVI (50m)									0.77	-0.88	-0.74
NDVI (300m)										-0.67	-0.94
Imperviousness (50m)											0.70

buildings) within buffers of 50 m and 300 m; treetops = number of treetops per hectare within a buffers of 50m and 300m; NDGG = Normalized

Difference Green-Gray Volume within buffers of 50 m and 300 m; NDVI = Normalized Difference Vegetation Index within buffers of 50 m and 300

m;

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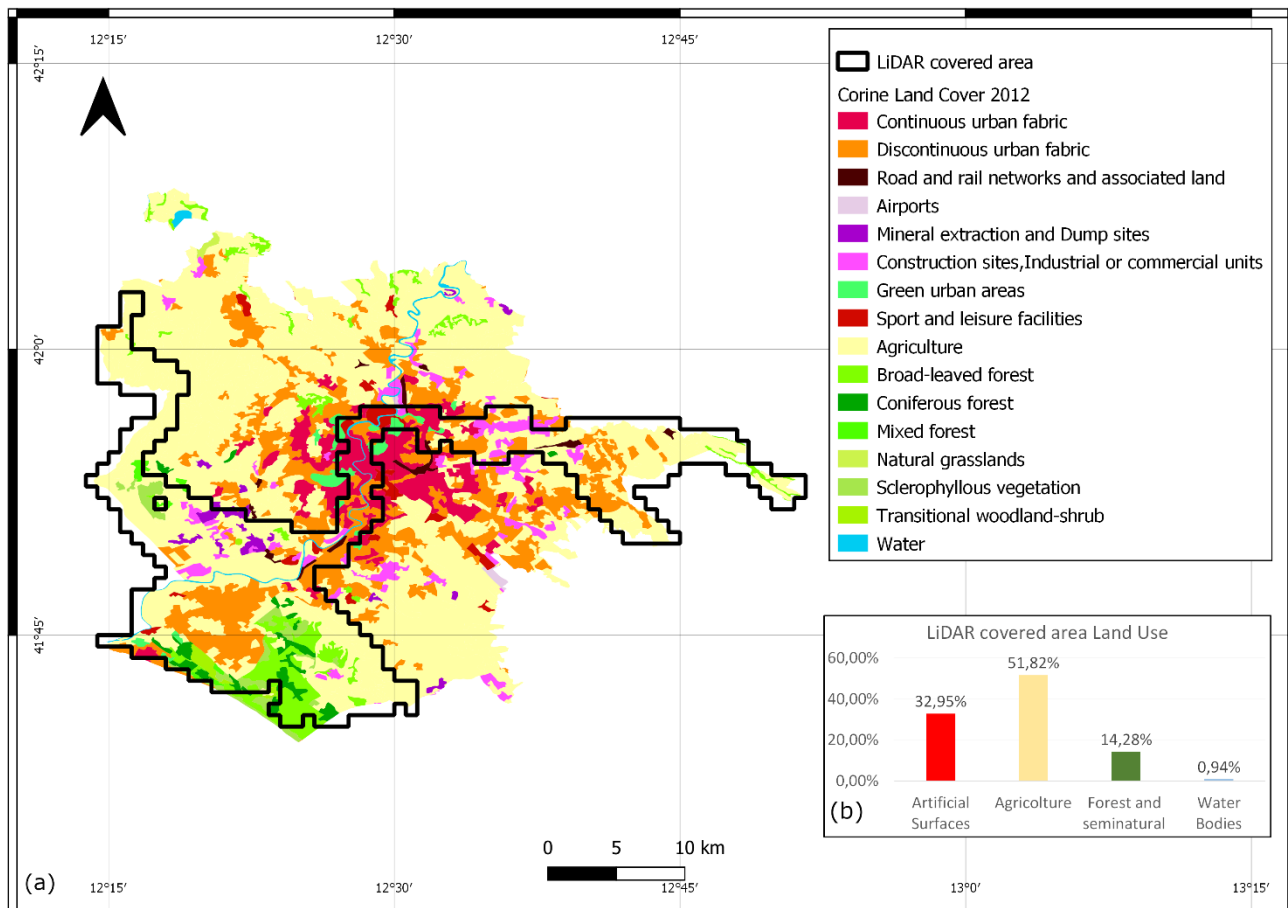


Figure 1. Corine Land cover 2012 selected classes an LiDAR coverage area of the municipality of Rome (a). Frequency distribution of LiDAR coverage over Artificial Surfaces, Agriculture, Forest and seminatural and Water bodies classes (b).

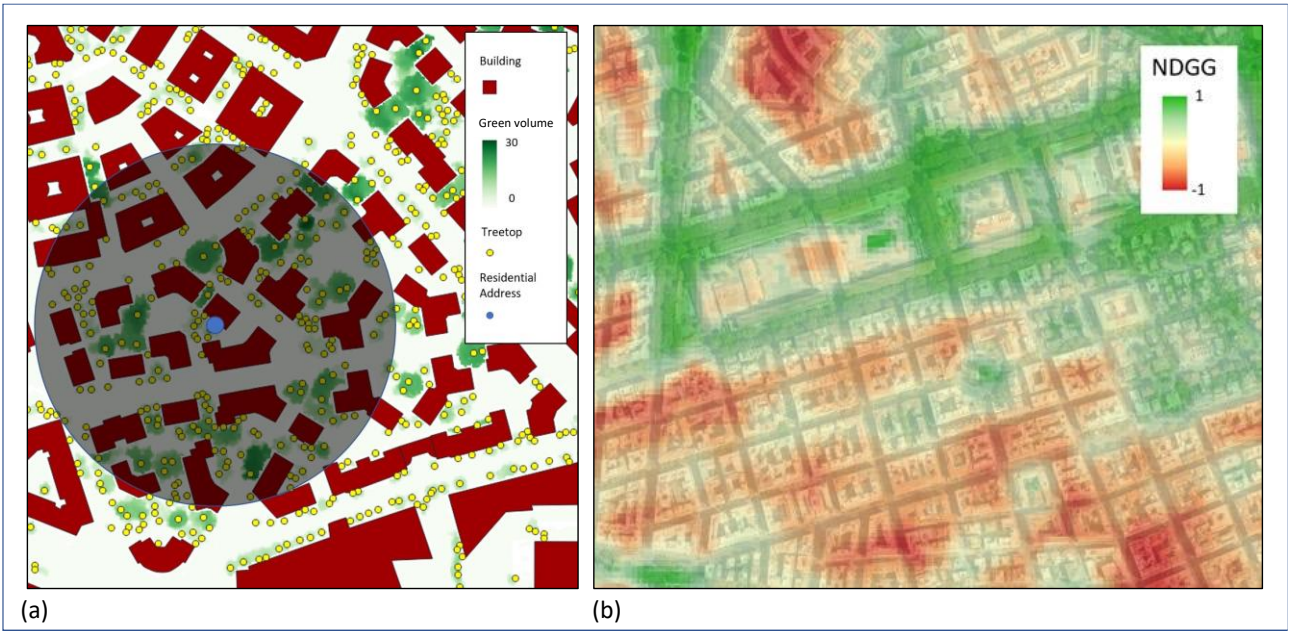


Figure 2. Figure showing the extraction of the three-dimensional green and gray indicators (a) and the Normalize Difference Green-Gray index (b).