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LETTERS

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Shortcomings of the normalized difference vegetation index as an exposure metric

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The health benefits of exposure to trees and plants is a rapidly expanding field of study. Research has shown that exposure is associated with improvements in a wide range of health outcomes including cardiovascular disease, birth outcomes, respiratory disease, cancer, mental health and all-cause mortality[1]. One of the challenges that these studies face is characterizing participants' exposure to trees and plants. A common approach is to use the normalized difference vegetation index, a greenness index typically derived from satellite imagery. Reliance on the normalized difference vegetation index is understandable; for decades, the imagery required to calculate the normalized difference vegetation index has been available for the entire Earth's surface and is updated at regular intervals. However, the normalized difference vegetation index may do a poor job of fully characterizing the human experience of being exposed to trees and plants, because scenes with the same normalized difference vegetation index value can appear different to the human eye. We demonstrate this phenomenon by identifying sites in Portland, Oregon that have the same normalized difference vegetation index value as a large, culturally significant elm tree. These sites are strikingly different aesthetically, suggesting that use of the normalized difference vegetation index may lead to exposure misclassification. Where possible, the normalized difference vegetation index should be supplemented with other exposure metrics.

The normalized difference vegetation index (NDVI) is a commonly used metric of exposure to trees and plants. For example, a 2018 review and meta-analysis of the health benefits of greenspace included 113 observational studies[1], 26 (23%) of which used NDVI as the primary exposure metric.

As a proxy for individual exposure to trees and plants, NDVI has much to recommend it. Landsat imagery, the most commonly used data source for NDVI, has been available since 1972 and, in 2008, the entire imagery archive became free and openly available[2], which provides researchers around the world easy access to a consistent exposure metric. The three Landsat satellite vehicles currently in operation, Landsat 7, 8 and 9, have a 16-day trajectory-repeat cycle, yet jointly acquire the spectral imagery needed to calculate NDVI every 8 days for any location on the Earth's surface. More recently, finer-resolution NDVI data have become commercially available (5-m resolution RapidEye[3] imagery, for example). Finally, a distal measure, like NDVI, may be less susceptible to bias compared with more personal measures of exposure such as self-reports or GPS tracking to assess exposure to greenspace[4].

NDVI measures the quantity of live plants by taking advantage of two spectral phenomena. First, plants preferentially absorb photosynthetically active radiation between 400 and 700 nm. Second, plants reflect near-infrared radiation (700 to 1,100 nm) that cannot be used photosynthetically and may cause tissue damage. NDVI is, therefore, simply a measure of photosynthetic activity. In consequence, natural scenes that are visually very different may have the same NDVI value. More fundamentally, people viewing scenes with the same NDVI value may perceive them to be profoundly aesthetically different. For some health outcomes, the inability of NDVI to distinguish between scenes that people judge to be aesthetically different may not be important. However, for other outcomes, the mechanisms involved are innately aesthetic. In addition to NDVI's visual inconsistency, natural scenes with the same NDVI value may have different impacts on sound and temperature, both of which have been shown to impact health[5,6].

Several studies have critiqued the use of NDVI as an exposure metric by comparing it with higher-resolution remotely sensed data and by examining the consistency of associations between NDVI and health across different buffer sizes[7–9]. However, to our knowledge, no studies have focused on NDVI's misspecification of the exposure of interest as a result of aesthetic inconsistency.

The mechanisms that mediate the relationship between exposure to trees and plants and improved health are only partially understood. However, certain pathways are probably important. These include improved air quality, stress reduction, better social connectivity, increased physical activity and more diverse microbial exposure[10–12].

Some of the mechanisms linking trees and plants to health do not have an aesthetic component. For example, the capacity of trees and plants to absorb air pollution is a biophysical phenomenon: pollution absorption is a function of leaf area[13], and leaf area is positively associated with photosynthetic capacity. Therefore, if the association between a health outcome and exposure to trees and plants is mediated primarily by improvements in air quality—as may be the case for some respiratory outcomes, for example—then NDVI may be an appropriate exposure metric. In contrast, other mechanisms do have a strong aesthetic component. For example, multiple studies have found that exposure to trees and plants can reduce short-term markers of stress such as heart rate, blood pressure and salivary cortisol[14,15]. Much of this impact is probably mediated aesthetically, because multiple studies have demonstrated that simply viewing images of a natural scene has a similar stress-reducing effect as being exposed to the scene itself[16]. Roger Ulrich, one of the pioneers of green-health research, noted that vision is by far our most

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Fig. 1 | Elm tree in Portland, Oregon. An American elm (*Ulmus americana*), planted in 1870, that is located at 1111 SW 10th Ave in Portland, Oregon (8 June 2020). Credit: Stuart White.

important sense in terms of yielding information about outdoor environments[17]. Ulrich later confirmed the importance of visually experiencing nature by showing that patients recovering from surgery in a room with a view of a natural scene recovered faster and took fewer opioids than patients who had a view of a brick wall[18].

Attention restoration theory, provides a theoretical framework for the restorative effects of viewing aesthetically pleasing natural scenes[19]. In particular, attention restoration theory posits that to be cognitively restorative a natural scene must be more than just green: "a restorative environment must be of sufficient scope to engage the mind. It must provide enough to see, experience, and think about so that it takes up a substantial portion of the available room in one's head"[19].

Stress reduction is not the only mechanism with an aesthetic component. A handful of studies have found an association between neighbourhood greenness and social connectivity[20,21]. Notably, these studies used exposure metrics based on participants' aesthetic judgements. For example, Sugiyama et al.[21] used a neighbourhood environment walkability scale[22] that included questions such as whether a neighbourhood contained 'pleasant natural features'. Van Dillen and De Vries developed an objective measure of greenspace quality that was significantly associated with stress and social cohesion. Importantly, the association with quality was stronger than the association with quantity[20].

Physical activity is another green-health mechanism that may be mediated aesthetically. Several studies have found a positive association between neighbourhood-level greenness and physical activity[23–25]. Further, one of these studies found that adults were 41% less likely to engage in recreational walking if they rated the aesthetics of their neighbourhood's greenspace as low[23]. This finding is consistent with research in the forestry literature showing that forest aesthetics influence recreational choices[26].

More recently, several studies have found an association between plant diversity and allergic, autoimmune and other inflammatory conditions[10,27]. These effects are unlikely to be explained by aesthetic or visual cues from the environment. Instead, they can be explained by the 'biodiversity hypothesis', which postulates that reduced biodiversity results in decreased diversity of environmental and human microbiota and that this, in turn, through immune, nervous and endocrine system changes, increases the risk of a range of common conditions, including allergies and asthma[28]. Nonetheless, similar to the limitations noted for aesthetic mechanisms, NDVI from a single imagery acquisition is not a viable plant-diversity metric, because broad groups of species (conifers and deciduous trees, for example) have comparable values due to similar reflectance regimes in the near-infrared and red parts of the electromagnetic spectrum[29].

This brief overview demonstrates that aesthetics are probably part of the causal pathways linking trees and plants with improved health outcomes. Therefore, to be valid and reliable, a metric of exposure to trees and plants must be aesthetically, or at the very least, visually consistent. In other words, scenes with the same score should be visually similar. To investigate NDVI's aesthetic and visual accuracy and consistency, we calculated the NDVI value of a large American elm (*Ulmus americana*) (Fig. 1) in Portland, Oregon. We chose this as our reference because research has shown that, across many different cultures, people prefer natural scenes that feature mature or iconic trees with wide, spreading canopies[30,31]. This elm was also the first tree enrolled in Portland's heritage tree programme, which formally recognizes trees for their unique size, beauty, age, historical or horticultural importance[32].

The crown of the elm tree has a Landsat 8 maximum annual NDVI value of 0.37095 and a planar area of 731 m^2. We identified

Fig. 2 | Nine scenes with the same mean NDVI as heritage elm tree. Foreground of nine 2014 Landsat 8 pixels in Portland, Oregon with the same NDVI value as the elm in Fig. 1 (20 October 2020). Credit: Stuart White.

233 pixels (each 30 m × 30 m) in Portland with the same NDVI value. Figure 2 shows photographs of nine of these pixels selected at random. Although aesthetic judgements are inherently subjective, most people would not find these scenes as aesthetically appealing as the elm because they lack the elements of the elm tree (large tree with a spreading crown) that research has shown to be appealing across cultures[30,31]. In this example, NDVI is neither visually nor aesthetically consistent. This suggests that relying solely on NDVI as an exposure metric in studies evaluating health may result in substantial exposure misclassification.

Higher-resolution NDVI data are becoming increasingly available, and these data may be able to better characterize highly heterogenous urban vegetation. In addition, higher-resolution data make it easier for analysts to incorporate measures of variation into exposure metrics. To calculate measures of variability, the resolution of the imagery must be smaller than the object of interest. Because the elm tree is approximately 30 m × 30 m, we repeated our analysis using 3-m resolution Planet data imagery. With the Landsat data, our analysis was constrained to 30 m × 30 m areas, the spatial extent of a single Landsat pixel, with the same mean NDVI as the elm. However, using 3-m resolution data, we were able to identify 30 m × 30 m areas with the same mean NDVI as the elm as well as the same s.d., because each 30 m × 30 m area now contained 100 pixels. We identified seventy-five 30 m × 30 m areas in Portland with the same mean NDVI and the same s.d. Figure 3 shows nine of these cells selected at random. As with the Landsat analysis, there are clear aesthetic differences between these nine scenes and the elm, although these differences are perhaps not as marked as in Fig. 2. This demonstrates that using higher-resolution data, as well as incorporating measures of variance, cannot completely solve the problem that scenes with the same NDVI values may be different visually and aesthetically.

The examples we present are extreme. The elm tree we chose has been formally recognized for its size and beauty. In addition, previous research has noted that the use of NDVI to describe small areas of greenspace may be problematic[8]. However, our choice was a deliberate one to illustrate NDVI's visual and aesthetic inconsistency. The attributes of the elm tree that make it beautiful are apparent to the human eye. It is equally apparent that these attributes are largely missing from any of the comparison scenes. This aesthetic inconsistency is a particular problem for green-health studies because many such studies are focused on urban areas where the

Fig. 3 | Nine scenes with the same NDVI (mean and SD) as heritage elm tree. Nine scenes in Portland, Oregon (images taken from Google Street View) with the same mean NDVI (0.531) and area-weighted s.d. (0.146) computed using co-temporal Planet imagery, as the crown of the elm in Supplementary Fig. 2.

majority of people live, and urban vegetation is highly heterogeneous and often specifically managed for aesthetic purposes.

We are not suggesting that NDVI should never be used in green-health research. Multiple studies have found an association between NDVI and a range of health outcomes. For example, a meta-analysis of 13 longitudinal studies found a significant protective effect of NDVI on mortality[33]. This suggests that NDVI contains useful information on the health benefits of exposure to trees and plants. However, it is essential that selection of an exposure metric be guided by an explicit causal model specifying the proposed mechanism linking trees and plants to health. In cases in which aesthetics probably play a major role in the causal process, it may be prudent to supplement NDVI with other green metrics. One option that is increasingly available is light detection and ranging (LiDAR) data. Some of the aesthetic qualities of the elm tree in our example are apparent in the corresponding LiDAR point cloud (Fig. 4a). For example, the LiDAR data identify the elm as a single tall tree rather than an ensemble of smaller ones with the same cumulative crown area. Where LiDAR data are unavailable or dated, point clouds derived from photogrammetry can be used. For example, National Agriculture Imaging Program imagery is acquired in a 2–3-year cycle across the conterminous United States[34]. Similar photogrammetry-derived data are available in other countries, although resolution, coverage and repeat cycle vary.

Supplementing NDVI with additional exposure metrics may also be useful from a policy perspective because there are many ways to increase greenness exposure, some of which may provide more desirable co-benefits than others. For example, does a stand of mature trees offer the same health benefits as a grass field with nearly the same NDVI value? Similarly, does exposure to diverse trees and plants provide more health benefits than an equally green monoculture?

However, even with new data sources, all quantitative metrics are unavoidably reductive. No vector of numbers can fully capture the beauty of a natural scene. One possible solution is to use mixed quantitative–qualitative methods. Quantitative measures of trees and plants could be supplemented by carefully calibrated qualitative indices that consistently capture aesthetic judgements.

The approaches we suggest are more data-intensive and costly than using NDVI alone. However, if an exposure metric as coarse as NDVI can reveal useful information, then investments in more sophisticated exposure metrics will likely yield new insights into the

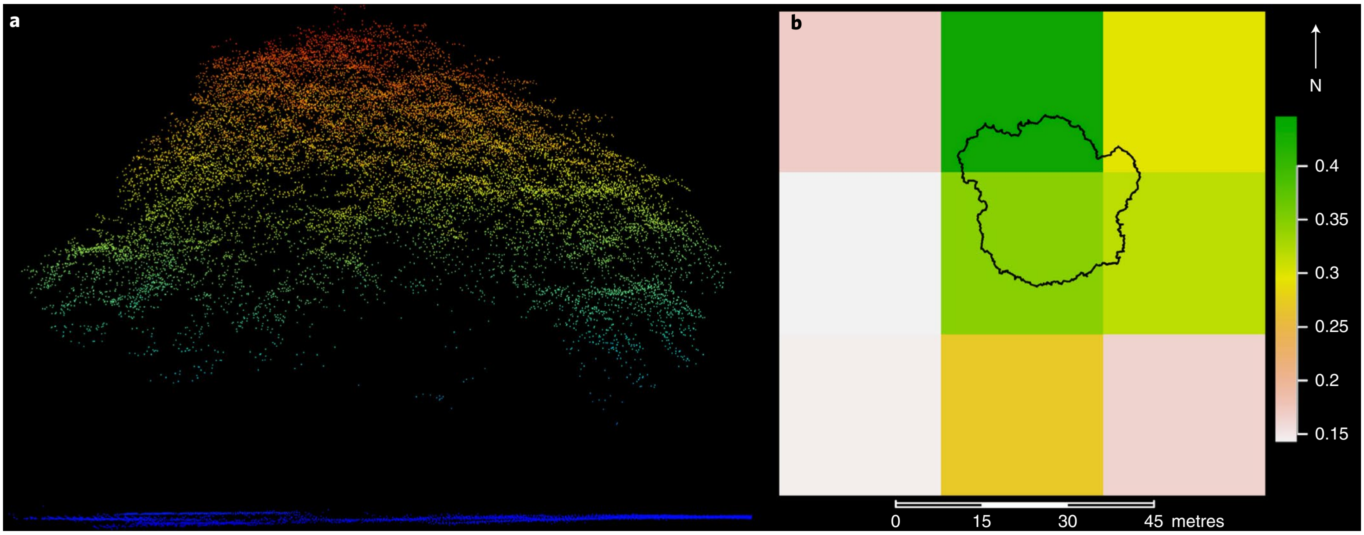

Fig. 4 | a. LiDAR point cloud of heritage elm tree. b. Heritage elm tree superimposed on NDVI raster. a, Lateral view of the elm crown (shown in Fig. 1) and underlying surfaces as represented in a 2014 dense, height-coloured LiDAR point cloud. **b**, Horizontal crown extent of elm shown in Fig. 1 superimposed on Landsat 8 derived NDVI raster.

health benefits of being exposed to trees and plants, and bring us closer to identifying effective green-health interventions.

Methods

To calculate the planar footprint of the elm, we used the most recent (August 2014), publicly available, high-density LiDAR data for Portland (Fig. 4a). We intersected the crown footprint with co-temporal Landsat 8 maximum annual NDVI data (Fig. 4b). Maximum NDVI was based on three cloud-free scenes dating from 6 July to 11 November 2014. The NDVI value for the crown was 0.37095, which is the mean of the four cells intersected by the crown, weighted by the respective intersection areas. We queried the city-wide NDVI raster and identified 233 cells with the same value. We randomly selected 9 of these 233 cells using an iterative process, so that each cell was at least 500 m from an already selected cell. We then field-visited and photographed the area represented by each cell, so that the leading edge of the 30 m cell filled the frame. Because of access and safety issues this was an approximate process. Supplementary Fig. 1 shows the location of each cell in relation to nearby roads and buildings. To ensure that there were no major changes in vegetation or land use on the cells between 2014 and 2020, we examined 0.5-m resolution airborne imagery for 2020, 2016 and 2012 over each candidate cell and discarded those that had any noticeable changes. Three candidate cells were discarded before we identified the nine cells shown in Fig. 3.

The planar extent of the elm's crown is 731 m^2, which is comparable with the area of a single Landsat cell (900 m^2). However, because the crown intersects four cells, its NDVI value is influenced by other objects that are completely or partially within those cells. One simple consequence is that the elm is not among the 233 cells with an NDVI value of 0.37095 because no single cell in Fig. 4 has this value. This is a well-documented[35] scale issue whose effects can be partially ameliorated only by using finer-resolution imagery and complex and computationally intensive techniques, which are often financially, logistically or practically unfeasible.

We replicated our analysis using 3-m resolution 2017 Planet satellite data, obtained from NASA, and subject to the Earthdata End User License Agreement. We used 2017 data, rather than 2014, because 2017 was the earliest multispectral Planet dataset available to us that included the near-infrared channel necessary for the computation of NDVI. Maximum NDVI was based on 18 cloud-free days dating from 26 May to 28 September 2017. We used the same crown boundary, delineated using 2014 LiDAR data, to compute NDVI distribution metrics for the elm tree using 3-m resolution data (Supplementary Fig. 2). The mean NDVI for the crown, computed as the area-weighted mean of pixel or pixel portions within the boundary was 0.531, and the area-weighted s.d. was 0.146.

To find scenes within Portland that had the same NDVI values as the elm (both mean and s.d.), we passed a 30 m × 30 m pixel kernel (moving window) over the Planet maximum NDVI raster, and for each kernel instance we computed the mean and s.d. (we used a 30 m × 30 m kernel, because it the same size as a single Landsat pixel). Using a tolerance of 0.25%, we found that seventy-five 30 m × 30 m scenes had the same mean and s.d. as the elm tree. Figure 3 shows a random selection of 9 of these 75 scenes.

The analysis in this paper was performed using open-source R software (v.4.0.2; https://www.R-project.org/) and the 'raster' package (v.3.5-2; https://CRAN.Rproject.org/package=raster).

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

High-density Oregon Department of Geology and Mineral Industries (DOGAMI) LiDAR data were obtained from ftp://lidar.engr.oregonstate.edu/OREGON LIDAR CONSORTIUM PROJECT DATA/OLC METRO 2014/ Landsat 8 data were obtained from Google Earth Engine[36]. The 3-m multispectral, satellite imagery was obtained from Planet[37].

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G.H.D., D.G., M.D. and J.D. developed the original idea. G.H.D. and D.G. conducted the analysis. G.H.D., D.G., M.D., Y.L.M., J.P.D. and J.D. wrote and edited the paper.

Competing interests
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