

Improving models of urban greenspace: from vegetation surface cover to volumetric survey, using waveform laser scanning

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Summary

1. Urban greenspace has a major impact on human health and quality of life, and thus the way in which such green infrastructure is constructed, managed and maintained is of critical importance. A range of studies have demonstrated the relationship between the areal coverage and distribution of vegetation and the provision of multiple urban ecosystem services. It is not known how sensitive findings are to the spatial resolution of the underlying data relative to the grain size of urban land cover heterogeneity. Moreover, little is known about the three-dimensional (3D) structure of urban vegetation and delivery of services, and addressing such questions is limited by the availability of data describing canopy structure from the tree tops to the ground.

2. Waveform airborne laser scanning (lidar) offers a new way of capturing 3D data describing vegetation structure. We generated voxels (volumetric pixels) from waveform lidar (1.5 m resolution), differentiated vegetation layers using height as a determinant, and computed statistics on surface cover, volume and volume density per stratum. We then used a range of widely available remote sensing products with varying spatial resolution (1 to 100 m) to map the same greenspace, and compared results to those from the waveform lidar survey.

3. We focused on data from three urban zones in the UK with distinct patterns of vegetation cover. We found -3% , $+7.5\%$ and $+26.1\%$ differences in green surface cover compared with, respectively, town planning maps (< 10 m resolution), national land cover maps (25 m) and European land cover maps (100 m). There were differences of -59.1% , $+12.4\%$ and -2.4% in tree cover compared with global (30 m resolution), European (25 m) and national (1 m) estimates. Waveform lidar captured sub-canopy structure and detected empty spaces in the understorey which contributed a 16% bias in the total green volume derived from non-waveform lidar observations.

4. We conclude that waveform lidar has a key role to play in estimating important quantitative metrics of urban green infrastructure, which is important because urban greenspace is highly fragmented and shows high levels of spatial and volumetric heterogeneity.

Key-words: 3D, airborne, lidar, mapping, remote sensing, voxel, waveform laser

Introduction

The last decade has seen an explosion of research interest in measuring and mapping the provision of ecosystem services within urban areas (including, but not limited to, carbon storage, noise reduction, air pollution reduction, pollination, biodiversity, and human health and well-being; Elmqvist *et al.* 2013; Gaston, Ávila-Jiménez & Edmondson 2013; Haase *et al.* 2014; Derksen, van Teeffelen & Verburg 2015). This has arisen for three reasons (Gaston, Ávila-Jiménez & Edmondson 2013). First, whilst urban land cover remains relatively restricted at a global scale, it is the fastest growing land use, can be very extensive at a regional scale, and can thus account for the delivery of substantial proportions of regional ecosystem services (Elmqvist *et al.* 2013). This significance can be

enhanced because urbanization tends disproportionately to occur in areas that are relatively rich in many services (e.g. in areas at lower elevations, of greater natural primary production; McDonald, Marcotullio & Guneralp 2013). Second, particularly in regions that have otherwise extensively experienced alternative forms of intensive land use (e.g. intensive agriculture), cities and towns can have higher levels of some ecosystem services than are found elsewhere (e.g. carbon storage; Davies *et al.* 2011; Edmondson *et al.* 2012). Third, it has become increasingly clear that the local delivery of some ecosystem services, particularly those associated with human health and well-being, may be critical to redressing some of the challenges of urban living (Elmqvist *et al.* 2015; Sandifer, Sutton-Grier & Ward 2015).

Whatever the motivation, key to the measurement and mapping of the vast majority of ecosystem services within cities and towns is a detailed knowledge of the extent and structure of the

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greenspaces within their bounds. It is well established that (i) the overall coverage of such greenspaces is often much greater than was long thought, particularly when both public and private (e.g. domestic gardens) spaces are accounted for (Gaston *et al.* 2005); and (ii) this overall coverage is almost invariably comprised of huge numbers of individual greenspace patches, with the small ones often contributing a substantial proportion of both the total number and the overall coverage, and hence of the benefits that greenspace provides (Cameron *et al.* 2012; Gaston, Ávila-Jiménez & Edmondson 2013). The spatially variable structure and fragmentation makes the measurement and mapping of urban greenspaces particularly challenging, and even more so is the measurement and mapping of key land cover components within those fragmented, small spaces (e.g. tree cover, vegetation volume; Gaston, Ávila-Jiménez & Edmondson 2013).

Most urban ecology research to date has used one of three methods for the two-dimensional characterization of urban greenspace: (i) analysis of historical town planning maps, inventories or cadastral plans; (ii) analysis of regional-extent satellite remote sensing data from one or more of a range of systems operating at different spatial resolutions; and (iii) analysis of fine-grained commercial satellite data (e.g. IKONOS) or airborne remote sensing data including airborne laser scanning (e.g. lidar) and aerial photography. These three approaches have various limitations. First, the fine-grained maps (i) usually focus on publicly maintained gardens and spaces, neglecting privately owned features, and whilst they can convey information about the historic layout of a town or city these data may rapidly lose their currency, therefore failing to capture information about the changing nature of the greenspace. Second, maps derived from freely available satellite remote sensing datasets (here we refer specifically to medium resolution data from systems such as Landsat which have a spatial resolution typically of between 25 and 30 m) are commonly used to produce land cover datasets (EEA 2006; Morton *et al.* 2011) of final resolution ranging from 25 to 1000 m, describing variables such as green cover or tree cover (Kempeneers *et al.* 2011; Hansen *et al.* 2013). The coarse spatial resolution of these data in comparison to the grain size of features and patterns in urban spaces inevitably results in mixed pixels and as a result reliance on such data means that smaller greenspace patches are frequently misclassified (Momeni, Aplin & Boyd 2016). Finer grained maps derived using what may be considered more 'scale appropriate' data (i.e. with spatial resolutions finer than 10 m) provide one solution to this problem (Pu 2011; Pu & Landry 2012; Jeanjean *et al.* 2015). However, to date these data have been exploited principally to assess the extent of greenspace rather than its structural composition, and to deliver two-dimensional data, or at best two-and-a-half dimensional data (e.g. in the case of a canopy height model derived from discrete return lidar; Sankey *et al.* 2013). Whilst it is possible to exploit discrete return lidar data to model 3D canopy characteristics, previous work has illustrated the lack of sub-canopy information in discrete return airborne lidar data (see figs 11 and 13 in

Hancock *et al.* 2017). Neglecting to measure the three-dimensional character of urban greenspace means that a critical component of its 'quality' is overlooked (Wang, Weinacker & Koch 2008).

Recent developments in laser scanning technology have made available new advanced systems that are capable of waveform scanning (Anderson *et al.* 2016). These waveform lidar systems offer a potential solution to the gap in urban greenspace volume data. Waveform lidar is different from traditional (i.e. 'discrete return') lidar in that it is capable of measuring the reflected laser intensity as a function of range (Mallet & Bretar 2009). This gives information on all objects visible to the airborne laser scanner (see Fig. 1), but requires signal processing to extract target properties. Once processed (a non-trivial task requiring system pulse and attenuation to be calibrated; Hancock *et al.* 2015, 2017; Anderson *et al.* 2016), the resulting waveform is made up of the distribution of objects within the footprint. The final product has great potential to detect fine-grained vegetation structure beneath complex canopies. The extra information contained within waveform lidar has been used to measure biomass (Drake *et al.* 2002), forest structure (Hyde *et al.* 2005), land cover (Reitberger, Krzystek & Stilla 2008), urban forest species, leaf area index and carbon storage (Alonso *et al.* 2016), but there are currently only a few papers evidencing their application fully to characterise 3D urban vegetation structure (Mallet, Soergel & Bretar 2008; Guo *et al.* 2011; Yan, Shaker & El-Ashmawy 2015), and none that have specifically assessed within canopy variation and understory (Anderson *et al.* 2016). Hancock *et al.* (2017) provide a comprehensive review of literature describing the *status quo* of vegetation surveying using different laser scanning technologies and are the first to demonstrate an improvement over past studies in the 3D mapping of vegetation canopies using airborne waveform lidar, over large areas at fine scales (sub-2 m resolution).

The aims of this paper are threefold:

1. To identify differences between estimates of urban green surface cover derived from (i) a new waveform lidar voxel dataset (described fully in Hancock *et al.* 2017) and (ii) those from satellite data products. We aim to explore the extent to which small patches of greenspace and private garden space are neglected by the latter due to their coarser spatial resolution. In exploring these differences, it will then be possible to highlight biases in analyses of urban greenspace utilizing such satellite data products.
2. To quantify differences in estimates of urban tree cover derived from other remote sensing data products at a range of scales as compared to our own waveform lidar analysis.
3. To quantify surface and volumetric differences in urban greenspace derived from measurements of discrete canopy height maxima (e.g. such as would be achieved from discrete return lidar analysis) using waveform lidar and to apply the first validated volumetric model from waveform lidar data (described fully in Hancock *et al.* 2017) to generate estimates of vegetation structure per stratum with information on volume of vegetation density.

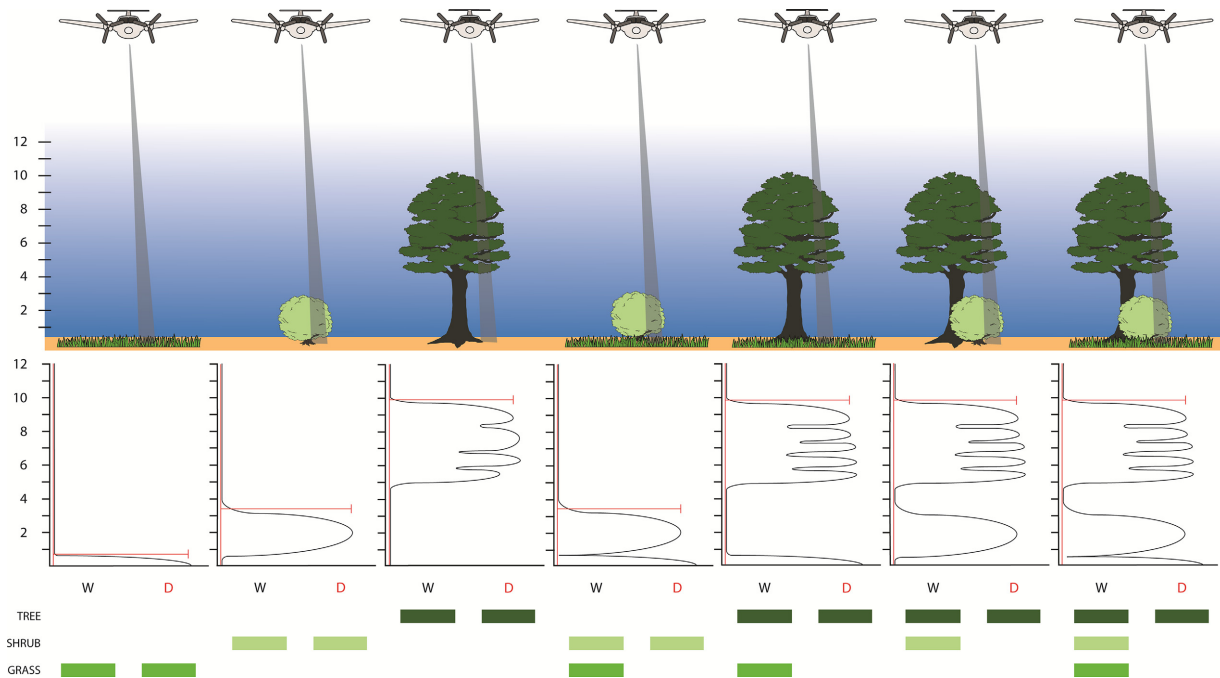


Fig. 1. Representation of presence-absence of vegetation cover layers according to discrete canopy height products (D in red) and full-waveform lidar products (W in black). The discrete canopy height representation detects canopy cover and is unable to detect understory vegetation or grass covered by shrubs. We consider this model as a two and a half rather than a three-dimensional green cover characterization.

Materials and methods

STUDY AREA

This study was conducted in the ‘Cranfield triangle’, a region in southern England, U.K., comprising the three adjacent towns of Milton Keynes (52°02′N, 0°45′W), Luton (51°53′N, 0°25′W), and Bedford (52°58′N, 0°28′W) with population sizes and density of, respectively, c. 230 000 and 2500/km²; c. 240 000 and 4800/km²; c. 160 000 and 2200/km² (2011 Census, UK). Overall, the survey area encompassing all three towns occupied an area of 166 km², and comprises a diverse array of urban forms, history, and management (Hebbert 2008). Milton Keynes is a ‘new town’ built in the 1960s with designed green corridors, a gridded road pattern and squared districts with planned greenspace. Bedford is a smaller county town arising from a medieval layout with much of the greenspace found along the banks of the Great Ouse River. Finally, Luton has large areas characterised by dense Victorian terraced houses (modest construction with very small, usually paved garden ‘yards’) alongside large industrial areas. These three towns thus represent an array of sizes, shapes, types and contexts of greenspace against which the objectives of the research could be tested.

REMOTE SENSING DATA CAPTURE

The Natural Environment Research Council Airborne Research and Survey Facility collected remote sensing data from a piloted Dornier 228 aircraft between June and September 2012 during four flights. The aircraft was flying at 1.5 km altitude over Milton Keynes (achieving 7 footprints per m²) and 2.6 km altitude over Luton and Bedford (achieving 2 footprints per m²) and carrying different sensors: a standard digital camera (Leica Camera AG, Wetzlar, Germany, model RCD105 CH39), an imaging spectrometer (Eagle) and a waveform-

capable lidar instrument (Leica Camera AG, model ALS50-II). The maximum scan angle for the lidar sensor was 8°. The spectrometer covered the wavelength region from 407.08 nm (blue) to 1007.10 nm (near infrared) in 253 bands. The hyperspectral data from Eagle were provided at 2 m resolution, with the exception of a small area of Luton for which they were at 4 m spatial resolution due to flying height restrictions near a major commercial airport. The hyper-spectral data was examined for across-track angular effects, and none were found. The following sections of the manuscript detail the image processing approaches and data comparison exercises undertaken to address the major research questions.

QUANTIFICATION OF VEGETATION SURFACE, VOLUME AND VOLUME DENSITY IN VERTICAL STRATA

The first stage in processing the acquired remote sensing data was to produce a binary layer describing the distribution of green and non-green spaces across the towns. For this purpose, the Eagle imaging spectrometer data were most useful because they could be processed at 2 m grid resolution to generate a simple Normalized Difference Vegetation Index (NDVI; Tucker 1979) for discriminating vegetated (NDVI ≥ 0.2) from non-vegetated areas providing a binary map of greenspace distribution; the 0.2 NDVI threshold was chosen following Liang (2004).

A ground DEM was generated with lastools (Isenburg 2011) and vegetation height determined. This was used for a more detailed classification of the type of vegetation stratum (grass, shrubs and trees) present within the regions classified above as being ‘green’. Vegetation strata were classified using the NDVI dataset and the waveform lidar data where: Grass – NDVI ≥ 0.2 and height < 0.5 m; Shrubs: NDVI ≥ 0.2 and height between 0.5 and 4 m; Trees: NDVI ≥ 0.2 and height > 4 m; All greencover: NDVI ≥ 0.2 and height > 0; and Not

green: $\text{NDVI} < 0.2$. The height thresholds were chosen to make our classification scheme comparable with other datasets which define trees as being taller than 4 m (Kempeneers *et al.* 2011; Hansen *et al.* 2013). Subsequently, as an additional and necessary step, we computed a further tree layer which utilised a 3 m rather than 4 m threshold in vegetation height to allow a further comparison with another tree dataset (Bluesky 2015); note, this did not affect the shrub or grass layers because this enquiry related only to the tree canopy. The threshold of 0.5 m distinguishing between grass and shrubs was chosen for two reasons – UK grasses in urban areas rarely exceed this height, and secondly this was the minimum available vertical grain size permitted by our voxel dataset. Using these thresholds, we processed waveform lidar to quantify the 2D surface cover of the stratum type.

The waveform lidar data were processed as described in Hancock *et al.* (2017) and the open-source code to perform the same processing is available from <https://bitbucket.org/StevenHancock/voxelate>. This allowed gap fraction estimates to be generated along each beam by denoising (Hancock *et al.* 2011), deconvolving (Hancock *et al.* 2008) and correcting for attenuation (Harding *et al.* 2001). Gap fractions for each beam were averaged into voxels of 1.5 m by 1.5 m (horizontal) by 50 cm (vertical) resolution.

We then used the voxel data and converted the signal into a binary dataset where the presence of a signal in the voxel was used to indicate the presence of vegetation. A threshold was applied to those data, using 1% within voxel cover as a minimum requirement for classifying a voxel as having vegetation present – this was used to filter noise error (Hancock *et al.* 2015). Finally, we projected the 3D voxel presence of each stratum into its corresponding 2D surface projection on the ground and quantified the surface cover for each stratum individually. To provide a comparable dataset showing discrete canopy height maxima (such as might be used in a discrete return lidar dataset), we also computed the same surface projection on the ground using the uppermost altitudinal signal in the positive voxel layer, and assumed that all voxels below this point were positive (i.e. containing vegetation, as one would treat a discrete return lidar; Fig. 1). We refer to this as a discrete canopy height product in the text hereafter, although it is different from the same measurement that would be delivered by a discrete return algorithm applied independently. Note that we intentionally chose not to use the standard discrete return lidar product here because, as Anderson *et al.* (2016) report, such products show biases compared to waveform lidar and quantifying these biases is not the topic of this paper. We accept that this is a somewhat simplistic estimation of the true biases because it is possible, theoretically, to model sub-canopy vegetation from discrete return lidar data. However, the Leica ALS50-II data used in this study has been shown to be incapable of mapping understorey vegetation at fine resolution (Hancock *et al.* 2017), so we suggest that the resultant statistics that are calculated and reported later in the manuscript are likely to overestimate the biases. They should however provide an initial useful comparative insight into the two methodologies.

Finally, the quantification of vegetation volume per stratum was undertaken by accumulating the number of positive voxels from the discrete canopy height product and waveform lidar. To compute volume density, we accumulated voxel signals per stratum.

COMPARISON WITH EXISTING METHODOLOGIES

To allow comparison with published datasets describing urban greenspace, we computed statistics within administrative units (UK Census Area Statistic ward) and selected all ward units where at least 99% of their spatial extent was contained within the coverage of our waveform

lidar survey flight zone (Fig. 2). Within these administrative units, we determined the surface coverage of vegetation (both green cover and tree cover) using the following datasets:

Green cover datasets

We used data from Richardson & Mitchell (2010) as green cover estimates for each ward administrative unit. These estimates (hereafter referred to as the ‘town planning map’ TPM6; the ‘6’ in the notation refers to the nominal spatial resolution of the data as being 6 m) are based on high resolution Ordnance Survey MasterMap products which are the most comprehensive and updated vector datasets available for the UK. MasterMap data are provided at scales as fine as 1 : 1250 for most urban areas, hence the estimates from Richardson & Mitchell (2010) should include all vegetated areas larger than 5 m² in area, but critically for urban systems, this product excludes domestic gardens.

Two supplementary green cover estimates were calculated, using a 25 m resolution national land cover map for the UK (NLC25; Morton *et al.* 2011) and the 100 m resolution European land cover map (EULC100; EEA 2006). For both, we distinguished vegetated and non-vegetated features within layer classes, resampled data at 2 m resolution and summed surface cover to make them comparable with estimates from our other datasets.

Tree cover datasets

Tree cover estimates were derived from national, European and global datasets, respectively, we used the national tree map for the UK (Bluesky 2015) at 1 m resolution (NTM1); the European tree map (Kempeneers *et al.* 2011) at 25 m resolution (EUTM25); and the global tree map (Hansen *et al.* 2013) at 30 m resolution (GLTM30). The NTM1 is a commercial airborne remote sensing derived map while the latter two maps (EUTM25 and GLTM30) are derived from optical satellite measurements that are freely available. To integrate the GLTM30 in our comparison, we downloaded the cloud-free and normalized top of atmosphere reflectance multispectral imagery (bands 5, 4 and 3), computed NDVI and applied the same threshold of $\text{NDVI} \geq 0.2$ to distinguish the presence/absence of tree cover in grid pixels. For all three tree cover estimates, we resampled data at 2 m resolution to compare estimates with our data.

DESCRIBING DIFFERENCES BETWEEN DISCRETE CANOPY HEIGHT PRODUCTS AND THOSE DERIVED FROM WAVEFORM LIDAR

We compared 3D mapping from two airborne lidar products, a discrete canopy height product that estimated canopy greenspace volume, using spot-height canopy maxima and waveform lidar products describing the full 3D structural elements of the vegetation canopy from the top to the ground and its density (see Fig. 1). The discrete canopy height product used here assumed that all vegetation volume below the top canopy was full of vegetation, and did not quantify empty space, whilst the waveform lidar product enabled quantification of this.

Results

GREEN COVER SURFACE AREA MAPPING

We found positive and negative biases between green covers according to the different datasets we compared to waveform

Fig. 2. Location of the overall study area within the UK (left) and details of the three towns considered (right). The black zones in the right panel define the flight missions on which the lidar data were collected; the areas coloured in white (Bedford), red (Milton Keynes) and yellow (Luton) define the ward administrative boundaries within the flight zones and considered here for data comparison.

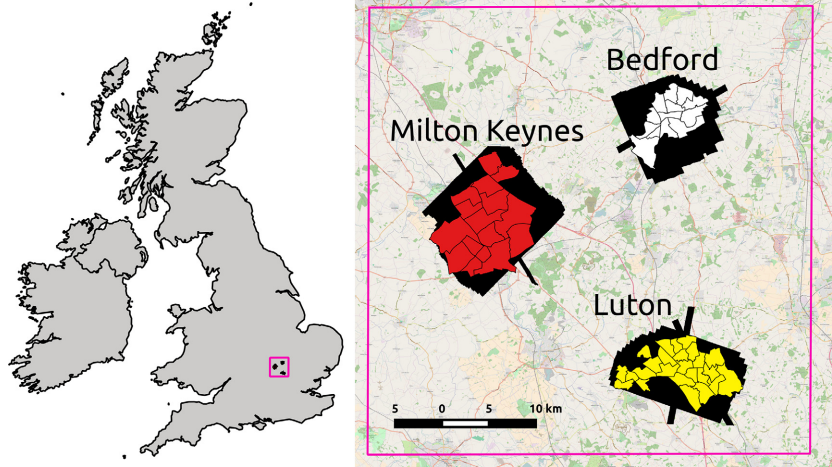


Table 1. Percentage of green cover surface estimates from different remote sensing sensors and methodology in three towns in the UK and in the overall study area

	Our waveform lidar analysis 1.5 m resolution	TPM6 Town planning map ~6 m resolution	NLC25 National land cover 25 m resolution	EULC100 European land cover 100 m resolution
Milton Keynes	43.9	50.7	41.5	22.0
Bedford	45.3	47.6	36.6	13.8
Luton	38.2	35.7	23.6	9.1
All urban sites	42.4	45.4	34.9	16.3

lidar (Table 1). The TPM6 overestimated greenspace (with the exception of for Luton) (Table 1 and Fig. 3) while the EULC100 and NLC25 underestimated greenspace in all three towns (Table 1 and Fig. 5). We expected underestimations of green cover from the TPM6 because these data are known to exclude private gardens and small green patches ($<6 \text{ m}^2$), but instead we found positive biases of +6.8% and +2.3 for Milton Keynes and Bedford while Luton was less green (−2.5%) according to this comparison (Table 1, Figs 3 and 5). The 25 m resolution NLC25 map showed differences of between −2.4% (Milton Keynes), −8.7% (Bedford) and −14.6% (Luton) in green cover (Table 1, Figs 3 and 4) compared to our data from waveform lidar. The 100 m resolution EULC100 showed an even larger underestimation (−21.9% Milton Keynes, −31.5% Bedford and −29.1% Luton) of green cover. In summary, we found overall underestimation biases in green cover increased as the spatial resolution of the land cover product was coarsened.

TREE COVER MAPPING

Table 2 shows that of the three datasets compared, the strongest agreement was found between the 1 m NTM1 and our waveform lidar data, with differences of +2.6% (Milton Keynes), 2.2% (Luton) and +1.9% (Bedford). A visual comparison of the products is shown in Fig. 4 for a section of the town of Luton, and a zoomed area with clear detail is shown in Fig. 5e–h.

The EUTM25 data showed larger differences as compared to metrics derived from waveform lidar estimates of −9.7%

(Luton), +12.0% (Bedford) and +14.4% (Milton Keynes), with the greatest biases in the most tree covered town (Milton Keynes; Table 2). The EUTM25 was designed to capture large forest stands while omitting sparse trees and lines of trees. We found the greatest biases in tree cover estimates derived from the GLTM30, which we have shown to be poor in describing tree cover in the diverse and heterogeneous urban system (see Table 2, Figs 4 and 5). From this last comparison we found overestimations of +56.5% (Bedford), +56.8% (Luton) and +61.5% (Milton Keynes) while using the GLTM30 as compared to our own analysis.

3D MAPPING: OVERALL VOLUME AND VOLUME DENSITY OF VEGETATION

The waveform lidar capability allowed us to generate stratified results showing the distribution of grass, shrubs and trees, including those in the understorey in the three towns. These results show that Milton Keynes was the ‘greenest’ town in terms of tree volume, followed by Bedford and Luton (Table 3). This is not an unexpected result, because Milton Keynes was a designed new town with directed planting and planned urban greenspace, whilst Luton and Bedford show older urban forms with more dense housing and fewer parks.

The volume density of vegetation in trees (Table 4) was higher in Milton Keynes, while shrubs were similarly dense in Milton Keynes and Bedford and less dense in Luton. Grass volume density is higher in Bedford as compared to the other two towns (see Table 4).

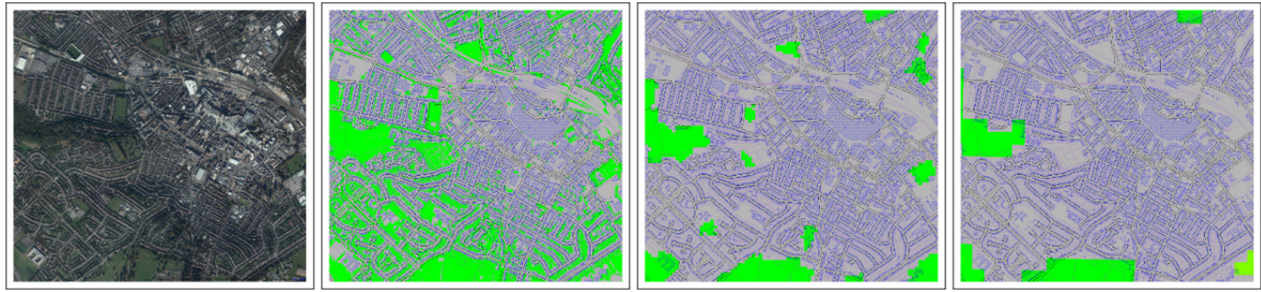


Fig. 3. An overview of green cover distribution in Luton, derived using three different remote sensing methods. Aerial photograph (left image) and green cover distribution (from left to right: Waveform lidar from our analysis (1.5 m resolution), national land cover (NLC25) at 25 m resolution and European land cover (EULC100) at 100 m resolution).

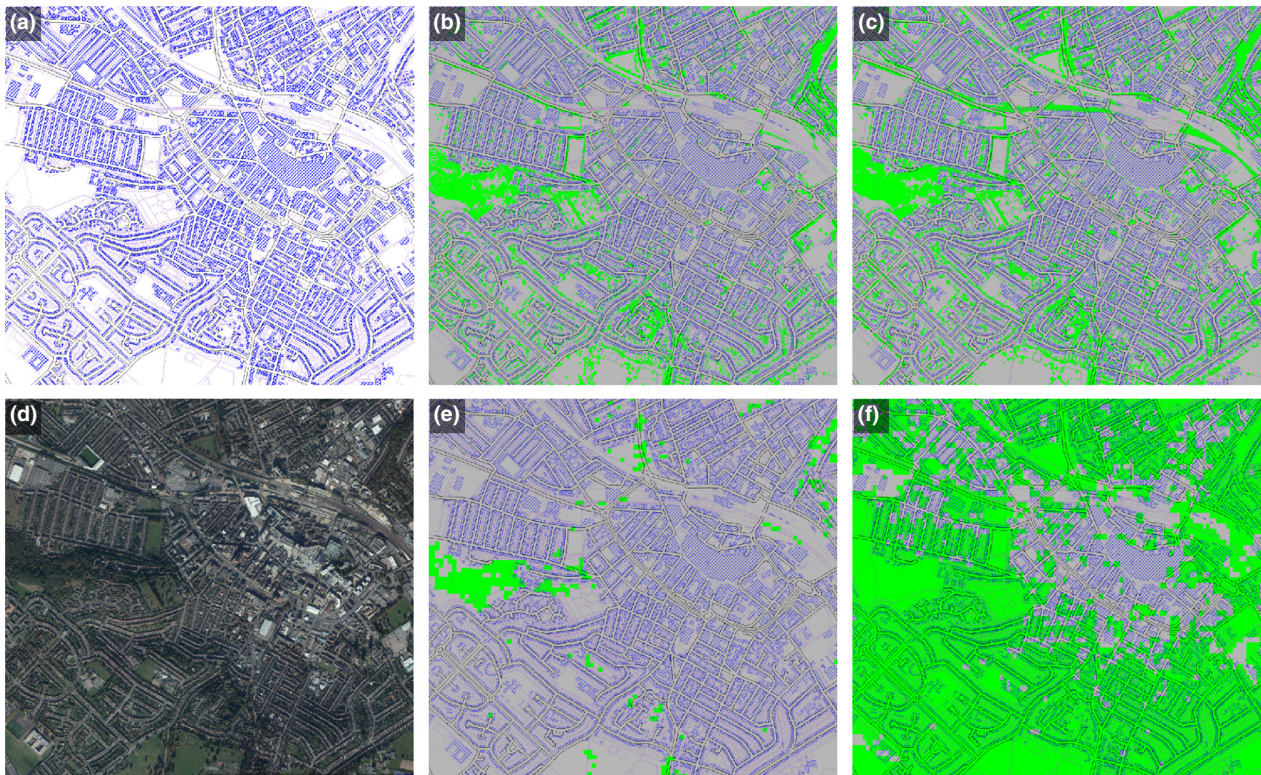


Fig. 4. An overview of tree cover distribution models for an area of south west Luton mapped, using different remote sensing methods. (a) Houses (blue) and roads (black) from the UK Ordnance Survey Mastermap vector layer; (b) waveform lidar (1.5 m resolution); (c) NTM1 – National tree map (1 m resolution); (d) Aerial image; (e) EUTM25 – European tree map at 25 m resolution; (f) GLTM30 – Global tree map at 30 m resolution.

Our comparisons of vegetation volume reveal that if one relies on fine-grained discrete canopy height products (e.g. products derived from lidar DSMs) to describe the urban greenspace, one first overlooks the ‘hidden’ vegetation beneath the canopy object that shows its surface expression to the remote sensing instrument. In this way, the canopy top hides between 34.0% (Bedford), 23.2% (Milton Keynes) and 21.3% (Luton) of shrubby vegetation and between 19.5% (Bedford), 15.4% (Luton) and 12.0% (Milton Keynes) of grass vegetation (Table 5).

In using waveform lidar data, these components of greenspace are made visible. Secondly, if one relies on a discrete canopy height product and assumes that the entire volume

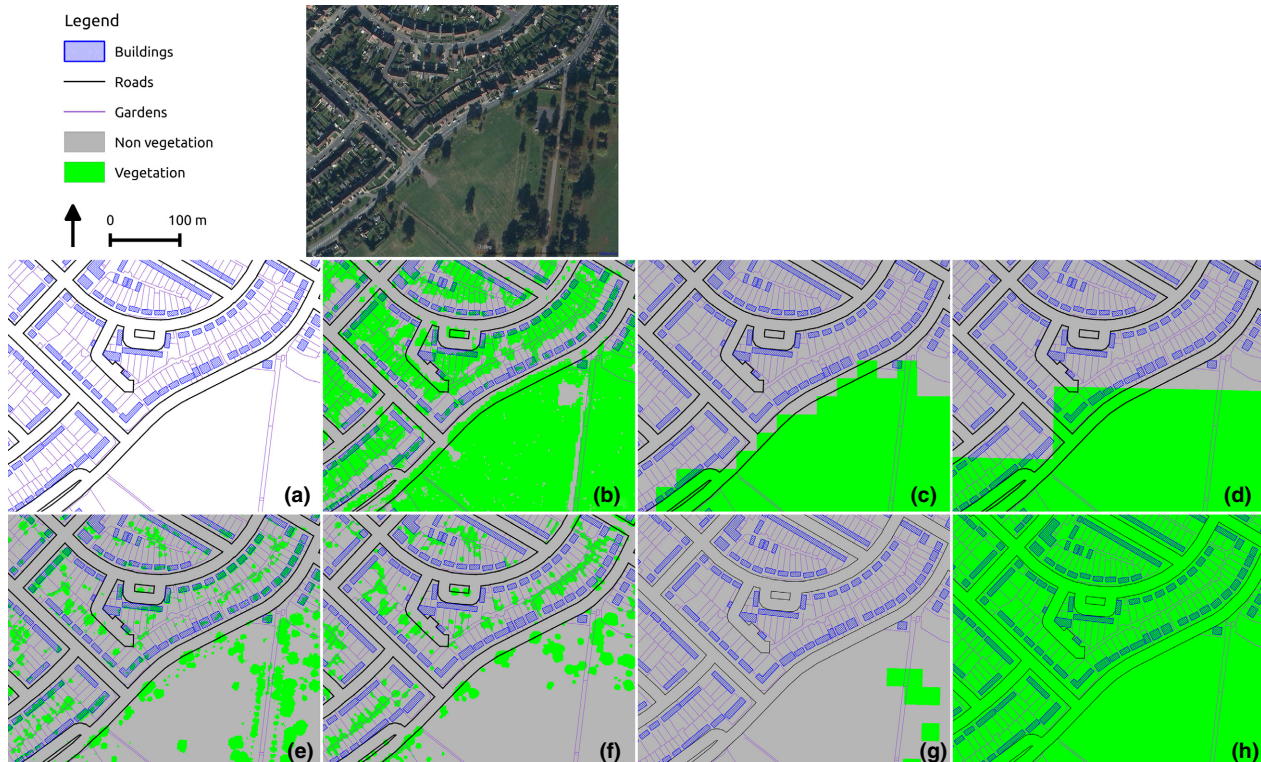
from the measured canopy top to the ground is filled with vegetation, then there will be an overestimation in vegetation volume by up to 18.5% (Table 3), because there are ‘voids’ in green volume beneath canopy tops that are not measurable from non-waveform systems.

Discussion

Urban greenspace mapping has been used in a broad range of contexts, including those of ecosystem services (Rudd, Vala & Schaefer 2002; Roe *et al.* 2013), microclimate (Ren, Ng & Katzschner 2011), atmospheric pollution (Jeanjean *et al.* 2015), climate change (Gaffin, Rosenzweig & Kong 2012),

Table 2. Percentage of tree cover estimates from different remote sensing sensors and methodology in three towns in the UK and in the overall study area

	Our waveform lidar analysis 1.5 m resolution	NTM1 National tree map 1 m resolution	EUTM25 European tree map 25 m resolution	GLTM30 Global tree map 30 m resolution
Milton Keynes	21.2	23.8	6.8	82.7
Bedford	14.6	16.4	2.6	71.1
Luton	12.4	14.6	2.7	69.2
All urban sites	17.1	19.5	4.7	76.2

**Fig. 5.** Green cover and tree cover distribution in a southern neighbourhood of Luton captured from different remote sensing approaches. Upper image: Aerial photograph; (a) Houses, gardens and roads from UK Ordnance Survey Mastermap vector layer; (b) Green cover from our waveform lidar analysis at 1.5 m resolution; (c) Green cover from NLC25 – National land cover at 25 m resolution; (d) Green cover from the EULC100 – European land cover (EEA 2006) at 100 m resolution; (e) Tree cover from our waveform lidar analysis at 1.5 m resolution; (f) Tree cover from NTM1 – National tree map at 1 m resolution; (g) Tree cover from EUTM25 – European tree map at 25 m resolution; (h) Tree cover from GLTM30 – Global tree map at 30 m resolution. Note: Green cover from TPM6 is not shown because estimates are provided as ha per ward administrative unit.

sociology (Watkins *et al.* 2017), and politics (Heynen 2006). By way of example, there has been a great deal of research into the relationships between human health/well-being and the

Table 3. Volume of vegetation estimates per stratum

	Grass	Shrubs	Trees	Overall	Empty volume %
Milton Keynes	1920	6991	1077	19 685	18.5
Bedford	2199	6982	7741	16 922	11.4
Luton	1810	5541	5745	13 097	13.1
All urban sites	1940	6532	8598	17 070	15.9

Cubic meter per ha of vegetation presence and difference to discrete canopy height estimates.

distribution of urban vegetation based on greenspace estimates derived from remotely sensed data of similar spatial resolutions to the satellite-derived datasets compared in this study (see Table 1 in Supporting Information for references), including (i) broad grain size land cover maps capable of detecting objects larger than 2 ha; (ii) land cover maps with a spatial resolution of 100 m; (iii) land cover maps with a spatial resolution of between 25 and 30 m; (iv) optical remote sensing products with a spatial resolution between 20 and 30 m; (v) land cover maps with a 10 m spatial resolution; and (vi) town planning maps which are able to detect vegetation at sub-10 m spatial resolution, but which omit private gardens.

The work presented in this paper has demonstrated that in urban systems which have a highly heterogeneous land

Table 4. Vegetation density per stratum

	Grass	Shrubs	Trees	Overall
Milton Keynes	331	526	615	1472
Bedford	577	517	349	1443
Luton	393	390	277	1061
All urban sites	398	481	457	1336

Values $\times 100$ accumulated voxels signals per surface area.

Table 5. Percentage underestimation of green surface area cover detected from discrete canopy height products in comparison with estimates from waveform lidar

	Grass	Shrubs	Trees
Milton Keynes	12.0	23.2	3.1
Bedford	19.5	34.0	2.8
Luton	15.4	21.3	2.7
All urban sites	14.5	24.7	2.9

Data from three towns in the UK.

cover distribution, including private gardens, these widely used medium spatial resolution products (20 m and coarser) deliver unreliable data with biases in green cover estimates ranging from +7.5% to +26.1% (Table 1), and in tree cover estimates ranging from +12.4 up to -59.1% (Table 2) when compared to our 1.5 m waveform lidar derived dataset. Biases were reduced as the spatial resolution of the remote sensing product increased for both green cover and tree cover estimates (i.e. -3% comparing urban green cover waveform estimates with the TPM6; -2.4% comparing tree cover waveform estimates with the national tree map). Mitchell, Astell-Burt & Richardson (2011, p. 11), evaluating three different greenspace indicators with varying spatial resolution, commented that indicators with different 'origins' (i.e. spatial resolution) showed 'considerable agreement on the amounts of greenspace they detected and in their association with mortality and morbidity'. However, critically, they explained that, 'these indicators did disagree in more socio-economically deprived areas, and this is probably because such areas have fewer larger greenspaces'. Our work, using fine-grained data from three towns with varying spatial patterns, has highlighted the importance of considering the impact of the resolution of the imaging product on the quality of the inferences that can be determined. The discrepancies reported here between the waveform lidar data and, for example, CORINE landcover data as used by Mitchell, Astell-Burt & Richardson (2011), were as large as 31.5% (Table 1 EULC100 in Bedford) – so these heterogeneously distributed patches of private gardens and other greenspace are a major proportion of the overall urban green area which are not captured by coarse resolution products. This is particularly important when considering the multiple impacts on human health, for example, because nature close to home is visited more frequently and is most important in delivery of health benefits (Soga *et al.* 2015).

Whilst the grain size problem with mapping in urban systems is not a new finding (e.g. Aplin & Atkinson 2001; Grafius *et al.* 2016; Momeni, Aplin & Boyd 2016), and waveform lidar has been used recently to characterize urban vegetation at very fine spatial resolution (Alonzo *et al.* 2016), here we quantify the biases in comparison to medium and fine spatial resolution datasets. We advise that these biases are strongly dependent on the grain size and spatial distribution of greenspace features within the urban extent with biases up to 61.5% if relying solely on GLTM30 data. In improving the grain of urban greenspace mapping, it will be possible to determine the impacts of urban greenspace distribution on a broad set of ecosystem services that humans benefit from.

Finally, our work has shown the importance of characterising urban greenspace not as a two-dimensional attribute but as the three-dimensional volume and its density. In using waveform lidar we have been the first to capture detail at high (<30 m) spatial resolution in the urban canopy structure, describing the complex understorey components, and quantifying the empty volumetric space within the canopy (i.e. 11.4% to 18.5% in Table 3). Even with recent developments in photogrammetric workflows, and widespread availability of aerial acquired stereo photography that can deliver sub-meter sampling of greencover, unlike waveform lidar, these technologies are not able to measure the sub-canopy structure. We have also reported on the density of vegetation in the urban volume which is impossible to achieve using any of the other datasets compared. This has shown that there are great differences in the density of vegetation in tree, shrub and grass strata across different urban forms (e.g. vegetation density is higher in trees for Milton Keynes, in shrubs for Bedford and in grass for Luton).

Potential adopters of our methodology will be faced with computational challenges in translating the waveform signal into voxel data due to the complex issues of multiple scattering and signal attenuation, to give just two examples. In this respect, we provide an open source code to process the voxel data, full details of which can be found in Hancock *et al.* (2017) and at <https://bitbucket.org/StevenHancock/voxelate>

It is important to consider that waveform lidar has a high economic cost both in terms of acquisition and processing of data, and in storage of voxel layers which have high data volumes. However, waveform lidar is emerging as a new strand in geospatial surveying and with NASA's forthcoming Global Ecosystems Dynamics Investigation (GEDI) mission (due to be operational from the International Space Station in 2019) and the increasing number of lidar sensors being sold with this capability (Anderson *et al.* 2016), there is opportunity for its reproducibility in time and space.

Authors' contributions

S.C. and K.A. conceived the ideas and designed methodology; S.C., K.A. and S.H. collected and analysed the data; S.C., K.A. and K.G. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Data accessibility

Waveform lidar and optical data from the NERC-ARSF flight (reference: 'RG 12/10') are archived at the Centre for Environmental data Analysis portal (CEDA) (<http://www.neodc.rl.ac.uk/>).

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Supporting Information

Details of electronic Supporting Information are provided below.

Table S1. Bibliographic references of researches looking at the relationships between human health/wellbeing and the distribution of urban vegetation based on greenspace estimates derived from remotely sensed data of similar spatial resolutions to the datasets compared in this study.