Landscape and Urban Planning 183 (2019) 133–146

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

A GIS and object based image analysis approach to mapping the greenspace composition of domestic gardens in Leicester, UK

Fraser Baker[*,1], Claire Smith

Department of Geography, University of Leicester, University Road, Leicester LE1 7RH, United Kingdom

ARTICLE INFO

Keywords:
Domestic gardens
Object based image analysis
Urban greenspace
Worldview-2

ABSTRACT

Greenspace provides a range of environmental benefits for urban residents, and is considered an important resource in urban development strategies. However, city-wide greenspace benefit modelling approaches often overestimate greenspace within garden areas, or even omit gardens from such analysis. As combined garden areal extents are significant for UK urban areas, improved estimations of garden greenspace abundance are required to improve urban greenspace analysis. This study investigates the methodological implications of a GIS and Object Based Image Analysis (OBIA) remote sensing approach with very high resolution Worldview-2 imagery for classifying UK urban garden surfaces. Gardens for an approximate 7 km^2 study area of the city of Leicester, UK were classified with an overall accuracy ~86%. The study demonstrates the applicability of GIS and OBIA analysis for mapping UK urban garden surfaces, with the methodology detailed here useful as a framework for further UK garden studies. Improvements to the current methodology are also considered in lieu of data and methodological limitations. In addition, the resulting garden surface dataset was analysed to examine associations of garden greenspace proportions with physical garden characteristics. Low greenspace proportions are found to be particularly prevalent for Victorian Terraced housing types in the study area; with greenspace proportions also generally associated positively with garden areal extents. Identification of potential predictive characteristics for garden greenspace abundance may prove useful as proxy information for urban greenspace analysis in other UK urban areas.

Key findings

1. A successful combination of GIS and Object Based Image analysis remote sensing approach with Very High resolution imagery used to map Grass, Shrubs, Impervious and Building surfaces for a continuous study area of gardens within a UK urban area, with overall classification accuracy of ~86%. This approach offers urban planning stakeholders both the opportunity to improve city greenspace estimations as inputs into greenspace benefit models, as well as providing an effective method for monitoring dynamic change in garden greenspace resources across the city area.
2. Gardens with less than 50% greenspace cover are particularly associated with Victorian Terraced housing, which is a commonly found housing type in urban areas across the UK. This information is potentially useful for other localised investigations into gardens in other UK urban areas, as researchers have useful guidance of where generally low proportion greenspace gardens may be located.
3. In general there exists a positive association ($r = 0.42$) between garden areal extents and the proportion of garden that is greenspace. This association is weak to moderate at the individual garden level, owing to the heterogeneity of garden surface structures within the study area. However, when considering gardens as clusters of similar areal extents, this association is much stronger ($r = 0.84$–0.87), thus indicating that clusters of similar size gardens 'on the ground' may provide a robust indication of garden greenspace abundance for that area.

1. Background

The human derived benefits of urban greenspace (UGS) are well documented, with an increasing body of research devoted to the spatial quantification of UGS benefits across the urban landscape (Haase et al., 2014; Santos, Silva, & António Tenedório, 2017; Santos, Tenedório, & Gonçalves, 2016). Spatial analysis of this kind demonstrates the various benefits of localised UGS retention and improvement for urban residents. Proximity to UGS alone can improve the aesthetic of

* Corresponding author.
E-mail addresses: fraser.a.baker@stu.mmu.ac.uk (F. Baker), cls53@leicester.ac.uk (C. Smith).
[1] School of Science and the Environment, Manchester Metropolitan University, John Dalton Building, Chester Street, Manchester M1 5GD, United Kingdom.

https://doi.org/10.1016/j.landurbplan.2018.12.002
Received 24 July 2017; Received in revised form 27 November 2018; Accepted 4 December 2018
Available online 18 December 2018
0169-2046/

surrounding areas, benefitting local residents' psychological well-being and stress levels (Barton & Pretty, 2010; Thompson et al., 2012). UGS also provides a range of important environmental services such as localised climate regulation (Dimoudi & Nikolopoulou, 2003), surface water filtration (Pauleit & Duhme, 2000) and pollution particulate reduction (Maher, Ahmed, Davison, Karloukovski, & Clarke, 2013). These services mitigate associated urban environmental risks (e.g. pluvial flooding, urban heat island enhanced temperatures, harmful pollution levels), which can have negative implications for the health of urban residents (Namdeo & Bell, 2005; Patz, Campbell-Lendrum, Holloway, & Foley, 2005; Schmitt, Thomas, & Ettrich, 2004). All sources of UGS, from large-scale parks and urban forests, through to individual garden patches can thus play a role in regulating the urban environment.

Maintaining an extensive UGS network is now considered within long-term urban development plans of a number of local authorities in the UK (Johnson, 2013; Shaw, Colley, & Connell, 2007). However, despite these positive developments, there is further scope to refine benefit models through finer scale spatial mapping of UGS areas. Whilst studies of both general and public UGS (parks, urban woodlands, natural waterways etc.) have received widespread attention, studies into private UGS and in particular domestic gardens in the UK are somewhat lacking, with limited knowledge of UGS extent and quality for these areas (Cameron et al., 2012).

This is an issue, as it is estimated in the UK that between 35 and 47% of all UGS may be contained within urban domestic gardens (Loram, Tratalos, Warren, & Gaston, 2007). Due to limited knowledge in this context, current garden data sets may overestimate garden greenspace coverage significantly, as for example, in the recent Green and Blue Infrastructure Strategy for Manchester (Countryscape, 2015; MCC [Manchester City Council], 2015). In the technical analysis, garden areas were mapped from Ordnance Survey polygon data and used to update local UGS coverage statistics, by assuming that all garden units were 100% greenspace (Countryscape, 2015, p. 46). From studies where garden surfaces have been spatially quantified, this assumption may over-predict garden greenspace coverage for Manchester considerably (Baker, Smith, & Cavan, 2018; Perry & Nawaz, 2008; Verbeeck, Van Orshoven, & Hermy, 2011). Discrepancies between UGS analysis data and the actual UGS coverage on the ground, considering the extent of garden areal coverage within UK urban areas, undermines UGS benefit assessment at the city-scale.

1.1. Quantifying garden greenspace coverage

Whilst traditional in-situ surveying may be unavoidable for studies into garden bio-diversity and wildlife habitation, for example (Samnegård, Persson, & Smith, 2011; Thompson et al., 2003), quantification of the spatial extent of general garden surface types might better be served through GIS and remote sensing methods. Previous investigations into garden surface extents using traditional surveying techniques have typically surveyed a small sample of gardens and then statistically inferred the findings over the wider urban area (Warhurst, Parks, McCulloch, & Hudson, 2014; Zmyslony & Gagnon, 1998). In general, gardens in urban areas tend to vary widely in terms of features and surface composition (Smith, Gaston, Warren, & Thompson, 2005), and thus the large scale inference of garden properties holds obvious drawbacks, as heterogeneity of garden surfaces across the wider urban area may not be adequately represented through this type of analysis.

In comparison, other garden studies have demonstrated the value in interpretation of Very High Resolution (VHR) remotely sensed images for this purpose, as imagery of a suitable spatial resolution (< 2m) for the identification of small surface patches and objects within garden parcels is now readily available. For example, Perry and Nawaz (2008) manually digitized surfaces for garden plots in an area of Leeds, UK using both historical and contemporary geo-referenced VHR aerial imagery (approx. 60 cm resolution). The resulting information was then used to model surface runoff estimations for an increase in domestic garden imperviousness recorded over a thirty-three year period. Other studies have applied image classification techniques to improve upon the efficiency of extracting garden surface areas over manual techniques. For example, Mathieu, Freeman, and Aryal (2007) adopted an Object Based Image Analysis (OBIA) approach using VHR IKONOS imagery to classify urban garden types in Dunedin, NZ according to the categories of tree, shrubs and grass coverage within garden areas. Other studies have successfully used OBIA to quantify greenspace at the housing plot level for cities in semi-arid areas in the USA, with the purpose of modelling the amount of water used for replenishing garden vegetation (Al-Kofahi, Steele, VanLeeuwen, & Hilaire, 2012; Xie, 2009).

The quantification of garden surfaces over a continuous urban landscape holds a number of advantages over traditional survey methods, particularly as classification results are easily associated with parcel information in Geographical Information Systems (GIS) enabling a wide range of statistical analyses. Domestic gardens are UGS areas under dynamic management, with little legislative protection to prevent garden owners from degrading greenspace through private land management decisions (Sayce, Walford, & Garside, 2012). Results from a number of quantitative garden studies suggest a general declining trend of greenspace coverage in domestic garden areas in recent years (Perry & Nawaz, 2008; Verbeeck et al., 2011; Warhurst et al., 2014). Therefore, methods that allow the large-scale monitoring of surface changes in domestic gardens, will enable local authorities to assess the impact on UGS benefits at varying scales across the urban landscape.

1.2. Aims of study

The potential application of this approach for garden parcel mapping is yet to be fully explored for urban areas in the UK. Successful results for studies in other parts of the world may not transfer to towns and cities in the UK, due to differences in urban land cover morphology between different countries. The first aim of this study is therefore to assess the potentials and limitations of a combined GIS and VHR image classification approach for quantifying garden surface composition for a case study area in the UK. By creating a garden data set from the ground-up, specifically for potential UGS benefit modelling across a significant urban area, important insights on methods used will inform further research.

The second aim of this study is to use the derived garden parcel data set, to examine whether the proportion of garden greenspace coverage has any relation to physical garden characteristics, building on previous studies which have analysed greenspace abundance within individual gardens in relation to garden areal extents (Lin et al., 2017; Stone, 2004) and associated housing type (Verbeeck et al., 2011). General association of greenspace abundance to such characteristics may provide useful indicators of garden greenspace abundance for further research and planning purposes. For example, if low proportions of garden greenspace are particularly associated with small garden areas, or indeed a certain housing type, then this information can be used to inform proxy assignment of greenspace abundance in other garden data sets. More realistic estimations of garden greenspace will thus benefit UGS benefit modelling approaches as a whole. Furthermore, physical indicators may prove useful to guide localised study where information is required to identify gardens of certain greenspace proportions for site-based research.

2. Case study

2.1. VHR imagery classification methods

A complete overview of remote sensing image classification methods is beyond the scope of this paper, and only a brief rationale for the techniques used in the study are provided. In general image classification techniques involve the inference and assigning of classes to all image areas based on the properties of a sample of these image areas (pixels or objects), and as such offer a time efficient method for categorising image areas in comparison to manual digitisation techniques (Kampouraki, Wood, & Brewer, 2008). Whilst VHR imagery offers enhanced opportunities for detailed urban mapping, the fine spatial scale, conversely, provides a different set of challenges for image classification in comparison to those encountered with coarser (10 m +) imagery. Coarse resolution pixels will often cover many objects in an urban scene, whilst in VHR imagery the reverse is true; objects in may be covered by many pixels, which may then vary significantly in recorded values due to intra-object variation in light reflectance (Aguilar, Saldaña, & Aguilar, 2013). Thus the application of traditional pixel-by-pixel classification techniques with VHR imagery can result in multiple class coverage for single class objects (the 'salt and pepper' effect), which in turn results in poor thematic map accuracy (Shackelford & Davis, 2003).

To counter this issue OBIA methods have been developed. OBIA involves object creation through image segmentation (grouping of similar image pixels into vector objects), which in turn allows classification techniques using a range of object derived features, including shape, texture, object to object topology as well as spectral features (Blaschke, 2010). OBIA methods in conjunction with VHR imagery have been used successfully to classify surfaces in other urban based studies (Immitzer, Atzberger, & Koukal, 2012, Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011), and were thus implemented for the purposes of this study.

2.2. Study area

The general study extents cover an approximate 7.36 km^2 of Leicester, UK (Fig. 1). The area mainly consists of low-density residential suburban housing and areas of high greenspace abundance (allotment areas, parks etc.), with higher density housing and some industrial activity in eastern areas close to the city centre. The area contains a variety of common residential property types found within UK urban areas such as Victorian and modern terraced, semi-detached and detached housing, and thus covers a variety of domestic gardens for analysis (see Table 2 – for proportion of associated type gardens to total garden areal extents and total number of identified garden areas within study extents).

2.3. Reference data

The VHR imagery used in the study was recorded by the Worldview-2 (WV-2) satellite sensor (DigitalGlobe, 2013). WV-2 imagery comprises eight multi-spectral bands at approximately 2 m resolution, with a panchromatic band at approximately 0.5 m resolution (detailed WV-2 specs are provided in Table 1). The image was recorded on the 17th April 2011 (11:20:32 AM); due to the conditions at the time of recording, approximately 2% of the scene area is obscured by cloud, with a further 3% covered in varying degrees of cloud shadow (see Fig. 1). Additional effects of atmospheric scattering were also present in both the multi-spectral and panchromatic bands.

An Ordnance Survey MasterMap Topography layer (OSMT) covering the study area was downloaded in GIS format (Source: https://digimap.edina.ac.uk/; December 2014 version). The OSMT provides the positions of features such as buildings, road extents, property boundaries and landform features at a scale of 1:1250, which is suitable for the delineation of individual housing plots; and as such provided the base polygon and line features for the digitisation of Garden parcel polygons. The reported positional accuracy of topography features in this data set is $+/-0.5$ m (Root mean squared error @ 1:1250 scale), and was thus deemed suitable as a reference source for the geo-rectification of the Worldview-2 (WV-2) imagery, particularly as the process of this exercise is to obtain an accurate alignment of garden areas present in the OSMT and WV-2 imagery.

2.3.1. Image pre-processing

Pre-processing steps were undertaken to improve the quality of the original base imagery for further analysis. The initial step was to pan-sharpen the image using the HCS algorithm (see Padwick, Deskevich, Pacifici, & Smallwood, 2010). The pan-sharpened image was then exhaustively geo-rectified to the OS MasterMap data, using the Rubber Sheeting (Linear Method – Bilinear Interpolation) method in ERDAS Imagine. Suitable features in OSMT (easily identifiable in the WV-2 image) such as boundary intersections, building corners etc. were used as reference points.

Further radiometric calibration of the geo-rectified image was conducted to improve the quality and visual clarity of the image data. Firstly, the image was converted from radiometrically corrected image pixels (format specific to WV-2 imagery), to top-of-atmosphere spectral radiance according to the instructions provided by Updike and Comp (2010), as this is considered the minimum requirement in any processing of WV-2 data. To account for the atmospheric haze in the image the *Improved Dark Object Subtraction Method* (Chavez, 1988) was used to enhance image pixel values. The processed image was then converted to top of atmosphere reflectance (see – Updike & Comp, 2010), as conversion to reflectance can improve spectral differentiation between spectrally similar surfaces represented in the imagery (Pu & Landry, 2012).

2.4. Garden parcel polygon digitisation

A Garden Parcel layer, containing the polygon extents of individual domestic garden parcels within the general study area was digitised through analysis of discrepancies in the alignment of garden boundaries between the OSMT and features in the image. Alignment discrepancies occurred due to inconsistencies in the geo-rectification process, as well as temporal issues between the data sets i.e. where a garden area apparent in the imagery has been subsequently subdivided into additional plots of land in the later OSMT. Personal judgement was used to determine the most accurate reference data for boundary digitisation in such cases.

As domestic gardens are the unit of analysis in this study, only parcels associated with individual residential housing units were digitised; this excludes communal garden areas associated with purpose built flats, retirement villages, and land attached to commercial properties. For the majority of cases garden parcel polygons were digitised to encompass the whole residential plot area, which includes buildings as well as the associated private land (see Fig. 2). Main dwelling building areas are generally not considered components of actual garden areas and are thus excluded from quantification of actual garden greenspace in this study. Where front gardens were not present, in either the OSMT or the image data, then back garden areas only were digitised, with the main dwelling area omitted from the polygon. In cases where OSMT boundaries were incomplete or missing, then plots were digitised using the image as a guide; if this was not possible then plot areas were omitted completely (see Fig. 3 for complete extent of digitised garden plots). Garden areas completely obscured by cloud or cloud shadow were also excluded due to a lack of useable spectral information for surfaces in these areas.

Garden polygons were digitised to initially encompass a large sample of the associated main dwelling types defined in the English Housing Report from the UK Department for Communities and Local Government (DCLG [Department for Communities and Local Government], 2008; p. 159 – 160). To assign associated property types to Garden parcel areas, the DCLG classification was updated to take into account the distinction in garden types between Victorian era terraced properties and more modern terraced properties in the study (see Table 2).

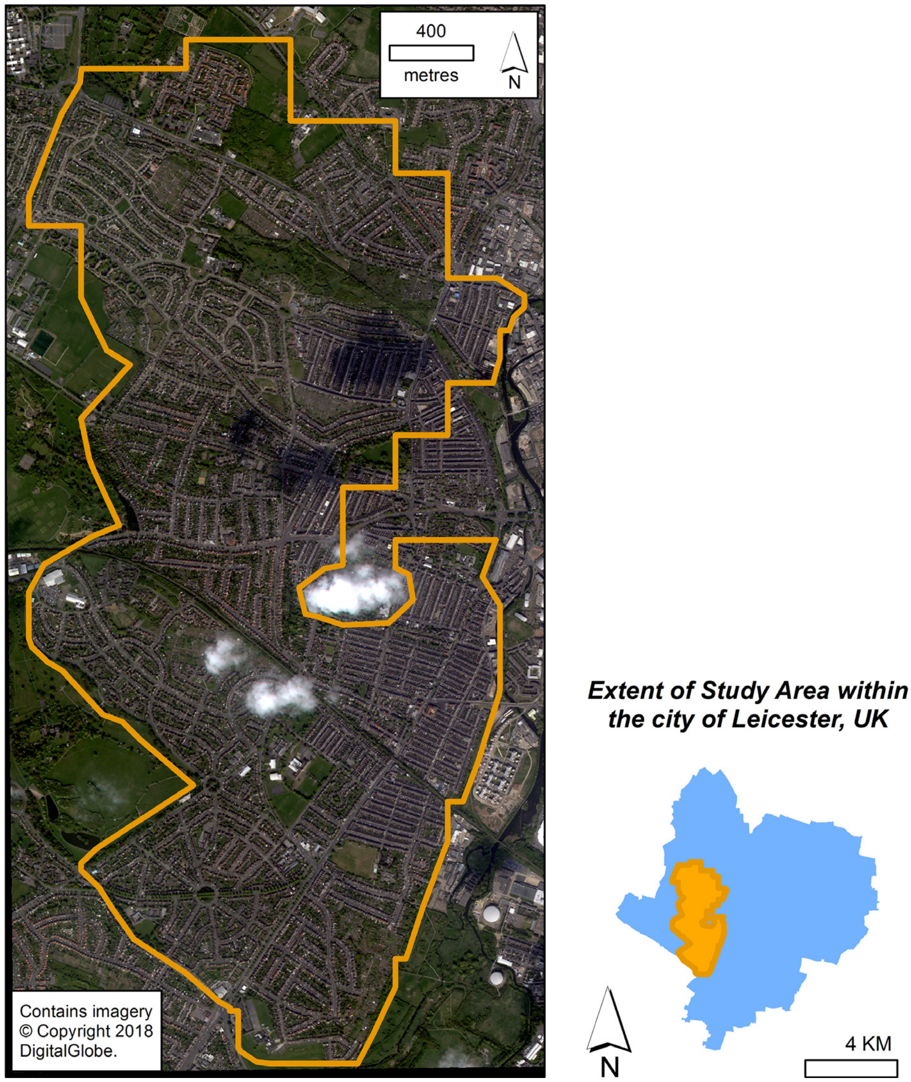

Fig. 1. Study Area and location within City of Leicester. Cloud and cloud shadow coverage evident in the WV-2 imagery.

Table 1
Specifications of Worldview – 2 (WV – 2) sensor (DigitalGlobe, 2013).

Sensor Bands:	Wavelength (nm)
Panchromatic	450–800
Coastal	400–450
Blue	450–510
Green	510–580
Yellow	585–625
Red	630–690
Red Edge	705–745
NIR	770–895
NIR-2	860–1040
Sensor Resolution:	
Panchromatic	0.46 m at nadir (down sampled to 0.5 m in imagery)
Multi-spectral	1.85 m at nadir (down sampled to 2 m in imagery)

2.5. Determining a classification scheme

As the study area contains a heterogeneous range of vegetative and hard surfaces, a mutually exclusive classification scheme (Congalton & Green, 2009) was devised to assign all image pixels to a relevant surface class. A general assessment of garden greenspace abundance arguably requires only two classes: greenspace and non-greenspace. However, a more detailed classification was determined for this study, as detailed components of general greenspace and non-greenspace surfaces can serve as useful input data into environmental models to calculate, for example, Land Surface Temperature and Surface Water Runoff values for urban areas (Gill, Handley, Ennos, & Pauleit, 2007). Such information is useful for the assessment of UGS resources for climate change adaptation strategies (Cavan et al., 2014) and therefore, a total of four classes suitable for such analyses were determined for final classification (see Table 3 for class descriptions).

2.6. Image features for classification

In order to improve differentiation between the classes, a number of additional image layers were created from the original WV-2 bands. Both the Normalised Difference Vegetation Index (NDVI = NIR-2 − RED/NIR-2 + RED) and the Normalised Difference Soil Index (NDSI = GREEN − YELLOW/GREEN + YELLOW) were calculated, as both indices are useful for distinguishing between vegetative and non-vegetative surfaces (Wolf, 2012). 8 principal component analysis (PCA) bands were created, as PCA bands have proven effective in separating urban covers in previous studies (Gao & Skillcorn, 1998); PCA2, PCA3 and PCA4 were found to be potentially useful in distinguishing between Grass and Shrubs, and were thus retained for further use. All additional layers were stacked with the original 8 WV-2 bands to create a composite 13 band study image.

Table 2
Classification of Property Types assigned to Garden Parcels.

Property Type	Housing Type	No. of Associated Gardens (% of total in brackets)	Combined area of associated gardens in km^2 (% of total garden area in brackets)
Detached (D)	House where none of the habitable structure is joined to another building (other than garages, outhouses etc.)	1056 (7.6%)	0.33 (16%)
Semi-Detached (S)	House that is attached to just one other in a block of two	5052 (36.3%)	0.58 (28%)
Modern Terraced (MT)	Medium/large terraced house: a house with a total floor area of approximately 70 m^2 or more forming part of a block where at least one house is attached to two or more other houses (includes end terraces)	3237 (23.2%)	1.04 (50%)
Victorian Terraced (VT)	Small terraced house: a house with a total floor area of approximately less than 70 m^2 forming part of a block where at least one house is attached to two or more other houses (includes end terraces); comprising of pre-1920 red brick terraces in the scene with relatively small garden areas	4579 (32.9%)	0.13 (6%)
TOTAL		13,924	2.08

2.7. OBIA classification

The classification was processed using eCognition Developer software (www.ecognition.com/suite/ecognition-developer). Multi-resolution segmentation, where single pixels are considered as separate objects and are then assessed and merged into larger segments based on local homogeneity criterion for selected image layers (Darwish, Leukert, & Reinhardt, 2003), was used for all segmentation levels in the classification process. A general threshold classification approach was adopted (in contrast to use of machine learning algorithms such as Nearest neighbour and Support Vector Machine) as this enables the user maximum control over the classification process, and allows fine scale refinement of rulesets for spectral and spatial/topological processing of uncertain object areas (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). As Garden parcels will inevitably contain small patches of difficult to classify surfaces, this approach was desired to allow subjective trial and error refinement of the classification process. As the date of image acquisition did not represent ideal vegetation conditions, due to inconsistencies in leaf-on cover between various plant species, sample selections of vegetation classes were thus required to incorporate a variety of intra-class objects of varying canopy coverage and general vegetative conditions.

The first stage involved classifying all areas of the image into three easily separated broad cover types; Non-Vegetation, Vegetation and Shadow (areas completely obscured by shadow). The image was segmented into small compact objects to ensure a minimum of unwanted class overlap, where for example an object may cover both non-vegetative and vegetative surface types (Segmentation Parameters: Based on 8 WV-2 Bands equally weighted; Scale Parameter 0.5, Shape 0.1, Compactness 0.5). For each of the three classes 150 sample objects were selected, with sample histograms compared to analyse suitable features for class separation. Additional object features such as mean brightness, image layer standard deviation and image layer ratios were created at this stage to increase the number of dimensions used in analysis. Objects with Mean NDVI > 0.6 were assigned to the Vegetation class; objects were assigned to shadow class with Brightness value < 0.05

Fig. 2. Garden polygons digitised over the Study Image.

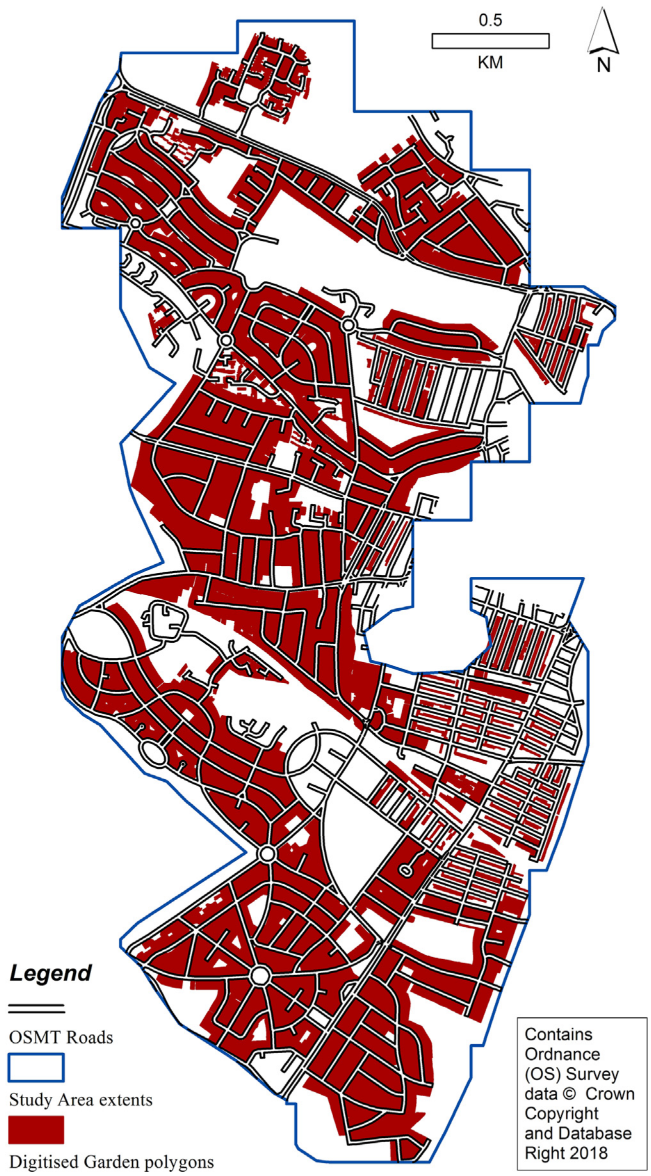

Fig. 3. Extents of Digitised Garden polygons within Study Area.

and Mean Red < 0.035; all other objects were assigned to Non-Vegetation (see Fig. 4).

By producing colour composite images of the scene using different band combinations, a selection of bands was identified on which visual differentiation between Grass and Shrubs was apparent (Fig. 5). Examination of differences between Grass and Shrubs sample distributions in all PCA bands confirmed potential class separability using these features. The Vegetation class only was thus re-segmented into larger and more compact areas (representing homogenous vegetation areas) using the selected image layers only (Segmentation Parameters: Coastal, Blue, Green, PCA2, PCA3, PCA4 Bands equally weighted; Scale Parameter 2, Shape 0.2, Compactness 0.5). From the re-segmented image, samples were selected (150 per class) representing Grass and Shrubs surfaces to determine separation thresholds were again derived from the Sample editor tool. Areas of shade in vegetated areas were difficult to assign to either vegetation class and were thus assigned to a Vegetation Shadow class with thresholds Ratio Blue > 0.075, NDSI > 0.028 and Ratio Coastal > 0.13. Grass Objects were assigned with Mean PCA4 > −0.003 and Mean PCA3 > −0.014, whilst all other objects were assigned as Shrubs.

The resulting image contained a certain degree of the 'salt and pepper effect' (see Section 2.1) with insignificant and difficult to identify objects intermixed within homogenously classified areas. The re-assignment of some objects was deemed necessary to improve map cohesion. Firstly, neighbouring objects of the same class were merged into larger homogenous objects, and then small areas (< 25 pixels) of all classes enclosed wholly by either the Shrubs, Grass or Non-Vegetation objects were assigned to the respective enclosing class. Small objects (< 11 pixels) completely surrounded by shadow, were assumed part of this class and were thus re-assigned. Vegetation Shadow appears on either the shaded side of trees/shrubs or on grass on the ground level; thus Vegetation Shadow objects with a relative border of > =80% to Shrubs objects were re-assigned to this class, if this condition was not met then the objects were assigned to Grass.

The final stage of classification required re-assignment of the remaining non-Vegetation Shadow objects to an appropriate class. Neighbouring objects of the same class from the previous level were merged into homogenous objects. Small areas of shadow (< 31 pixels) were considered as insignificant areas which could be assigned to the relevant neighbouring class. If these small objects had a relative border of > =50% with Shrubs, or > 50% with Grass, they were assigned to the respective class. All other shadow objects were assumed Non-Vegetation and were assigned as such. Due to the difficulty in distinguishing between Building roof surfaces and other Non-Vegetation surfaces (due to spectral similarity between these surfaces), Building polygons from OSMT were used to represent building areas in the classification. Due to the close alignment between OSMT and the study image, the use of ancillary OSMT building polygons was considered feasible, particularly as the use of ancillary building polygons has been used successfully in another study (see – Zhou & Troy, 2008). Approximately 16% of the classification area was reassigned as Buildings using the above method.

2.8. Analysis of proportion of greenspace in gardens to garden characteristics

To assess whether physical garden characteristics are associated with the garden greenspace abundance, the combined classified garden parcel Grass & Shrubs surface area was calculated as a proportion of total useable garden area (UGA), which was defined as garden parcel area exclusive of all building surfaces. This greenspace proportion (PropGreen) was analysed against both assigned property type (PropType) and UGA areal size (GA). PropGreen distribution was compared between PropType categories, whilst correlation analysis was deemed appropriate to analyse PropGreen to the continuous GA variable.

Correlation of GA to PropGreen was conducted both on an

Table 3
Image Class descriptions.

Class	Description
Building	Covers all building areas; represented by building polygons in the OS Mastermap Topography Layer
Grass	Covers significant grass areas; a predominate surface in the study area
Non-Vegetative	All non-building area OS mastermap (non-vegetative) hard surfaces; includes water (as there are insignificant areas of water in the scene) & Bare Soil (difficult to differentiate spectrally from other hard surfaces; similar properties to other hard surfaces in Surface Runoff calculations) and temporary structures in Gardens
Shrubs	All significant non-Grass vegetation surfaces; includes Trees, low-lying shrubs and other rough vegetative surfaces

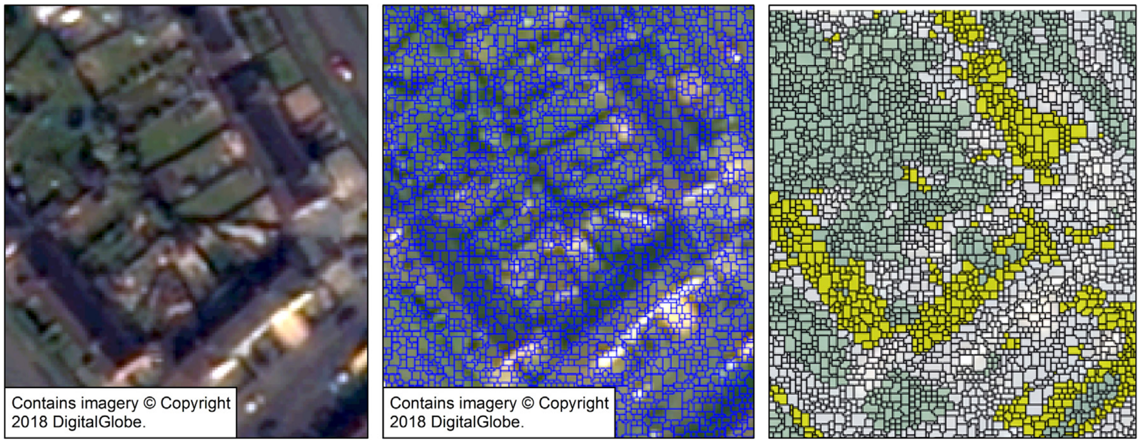

Fig. 4. Initial segmentation and object classification: (Left) Non-segmented Study Image; (Middle) Objects created after segmentation process; (Right) Objects classified to either Non-Vegetation (Grey), Vegetation (Green) or Shadow (Yellow) class. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

individual parcel basis using the full dataset, and through binning the parcel data according to GA values. Due to expected heterogeneity in garden parcel PropGreen values, data binning was implemented to reduce noise in this variable, and to assess whether amalgamation of garden units into larger groupings affected the relationship between the GA and PropGreen variables. The number of required bins was then set at 1000, 500, 250, 100, 50 and 25, with the number of observations for each bin calculated by dividing the total number of bins required by the total number of garden records (13,924 in total). Prior to assigning garden records to bins the dataset was re-ordered in ascending order on the GA variable. For each bin size number a new data set was created, with the mean PropGreen and mean GA values calculated from observations in each bin to enable correlation analysis.

3. Results

3.1. Classification results

Mapping accuracy was calculated for the classification results (Fig. 6) to make sure the map produced was of sufficient quality for further use, and also to provide information on any resulting classification errors (Bektas & Goksel, 2005). Validation points for this exercise were determined using the 'multivariate law' described by Mather and Koch (2010), where the number of samples for each class should be at least 30*p* (where *p* = number of features used in the classification). As classification followed a ruleset procedure, instead of using a typical classifier algorithm, features were counted as the 13 Study Image layers ($p = 8 \times WV\text{-}2\ \ Bands + 3 \times PCA\ \ Bands + NDVI\ \ index + NDSI$). The number of validation points for each class was therefore determined as 390 ($30 \times p = 390$). All class polygons were merged into single features, with the required number of validation points randomly placed in each class, to ensure a statistically unbiased distribution (Congalton & Green, 2009). For the majority of points the appropriate validation class was easily determined from the WV-2 image due to the high spatial resolution. However, where ambiguity existed in the image (due mainly to extremely small surface patches/objects in the scene or areas covered by dark shadow) then Google Earth imagery was used as a back-up reference. The date of the imagery used by Google Earth for Leicester is 27th September 2011 (Google Earth; http://www.google.com/earth/); although the WV-2 imagery was recorded an approximate five months previously, the temporal difference between images was not considered long enough to for large-scale changes in garden areas to have occurred.

Validation class labels were used to populate a confusion matrix (Table 4). Overall accuracy of the classification is 86.15%, which is above the 85% threshold generally regarded as an appropriate level of accuracy within the remote sensing community (Foody, 2008). Kappa = 0.815 (0 = agreement equivalent to chance; 1 = perfect no-chance agreement), indicating there is almost perfect agreement that the current confusion matrix values do not agree/disagree by chance (Viera & Garrett, 2005). The above two measures provide a general

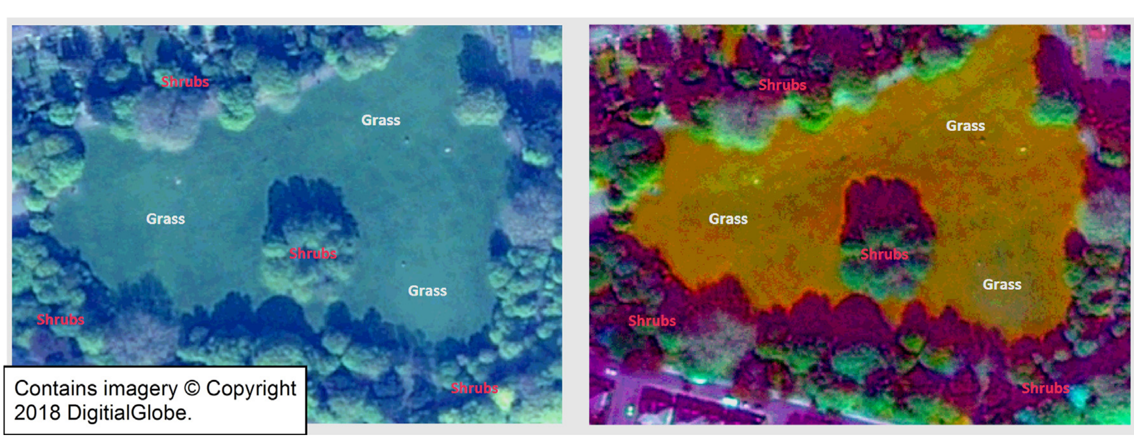

Fig. 5. (Left Image) 3-Band Composite: Red channel = Yellow, Green channel = Green, Blue channel = Blue; (Right Image) 6-Band Composite: Red channel = Coastal, PCA4, Green channel = Blue, PCA3, Blue channel = Yellow, PCA2. The additional PCA bands results in improved contrast between the two images, indicating Grass and Shrubs separability based on the PCA bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

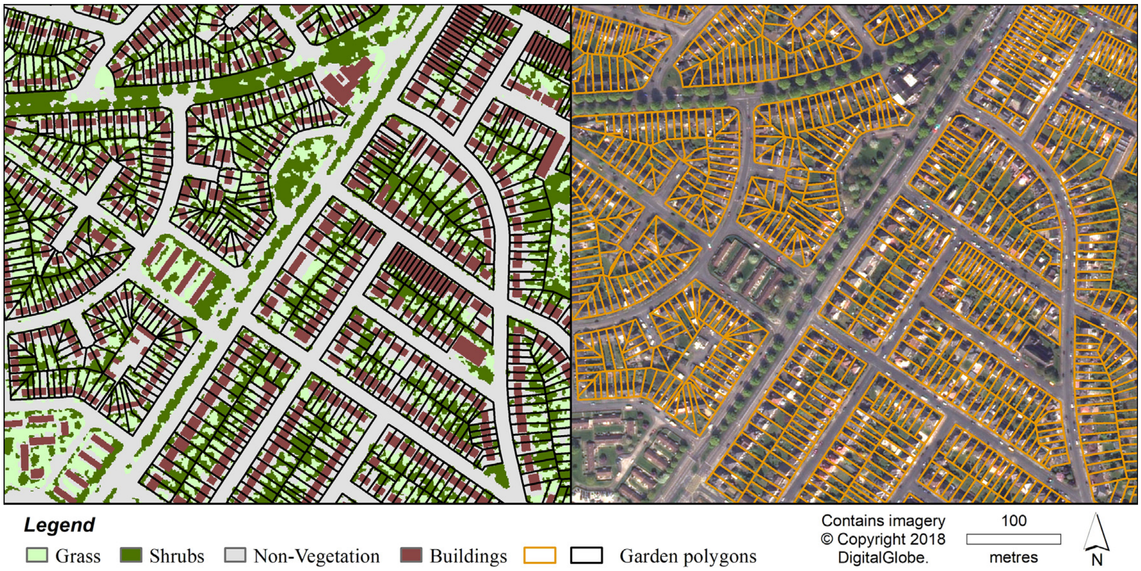

Fig. 6. Comparison between Classified Map and Worldview-2 imagery (with digitised Garden Parcels overlay).

Table 4
Confusion matrix & classification accuracy results.

Classes	Building	Grass	Non-Vegetation	Shrubs	Mapping Accuracy (%)
Building	364	7	17	2	83.87
Grass	7	329	17	38	69.55
Non-Vegetation	35	9	337	9	78.14
Shrubs	2	66	7	314	71.69

Overall Accuracy: 86.15%.
Kappa: 0.815.

indication that the classification exercise has been successful. For individual classes, mapping accuracy has been reported instead of user's and producer's accuracy, as this measure amalgamates errors of both omission and commission into a single useable estimation of class accuracy (FAS, 2015), and provides some context to the accuracy of classification between individual classes. Mapping accuracy was calculated using the following equation:

$$MA = \frac{NC}{NC+EO+EC} \cdot 100 \quad (1)$$

where MA is the Mapping Accuracy for an individual class; NC is the number of correctly assigned training points per class; EO is the errors of omission (non-NC row values for each class); EC is the errors of commission (non-NC column values for each class).

Due to the exhaustive geo-rectification of the base WV-2 image, the method of classifying Buildings using OSMT has resulted in a high level of mapping accuracy for this class. Errors occurring in this class are due to a combination of misalignment between the image and OSMT, and also inaccuracies due to the temporal difference between the image and the OSMT where building polygons differ in geometric extent to the appropriate building feature in the image. Both instances result in building polygons covering non-building areas in the WV-2 image thus causing a degree of misclassification, particularly with the Non-Vegetation class, as image buildings not aligned adequately to relevant OSMT polygons will almost certainly be classified as Non-Vegetation (see Fig. 7).

The NDVI proved to be an effective feature in separating Non-Vegetation from the vegetated classes, resulting in minimal confusion between these two class groups. Errors occurring here can be mainly attributed to a) the segmentation process, which to a certain degree will have resulted in mixed Non-Vegetation and Vegetation segments; b) incorrect reassignment of shadow segments; c) reassignment of extremely small segments to surrounding class. Also, due to the date of image acquisition some vegetation in the scene will not be fully senescent, and thus for some areas of vegetation, NDVI values will fall under the defined threshold. Grass and Shrubs have the lowest mapping accuracy, and this is mainly a result of spectral confusion between the two classes. Also re-segmentation of the vegetation class resulted in some mixed Grass and Shrubs segments resulting in further misclassification.

3.2. Analysis of proportion of greenspace in gardens to garden characteristics

The total area of all UGA in the study was 2.09 km^2, with 63.9% of this area classified as greenspace; UGA areal size values varied significantly in the data set, ranging from 4.5 m^2 to 2504 m^2 (median = 146 m^2). Analysis of mean PropGreen values against PropType indicates Victorian Terraced gardens contain a significantly lower proportion of greenspace in comparison to all other property types, which exhibit minimal difference in mean PropGreen values (see Fig. 10). This trend is again shown in a distribution boxplot (see Fig. 11); the distribution of PropGreen values is almost identical for Detached, Modern Terraced and Semi-Detached property types. Statistical testing between PropType categories was not conducted as the results are considered representative for the digitised garden parcel area only with a full population of data available for this analysis. Figs. 8 and 9 demonstrate spatial variation in garden parcel PropGreen values according to the spatial distribution of PropType parcels in the study area.

For PropGreen and GA analysis, a correlation coefficient was calculated using the Pearson product ($r = 0.42$, $p < 0.001$) method as it was difficult to predict the type of relationship between variables through examination of the scatterplot. The result shows a weak to moderate positive association between the GA and PropGreen variables, indicating that while some relationship is evident between the two variables, it is not strong enough to consider GA a useful predictor for PropGreen at the individual garden parcel level.

For the binned datasets both Pearson product and Spearman Rank correlation methods were used to assess linearity as well of strength of relationship between the GA and PropGreen variables (see Table 5).

Scatterplots for the Number of Bin data sets can be seen in Fig. 12. For all bin numbers a strong association between the variables is

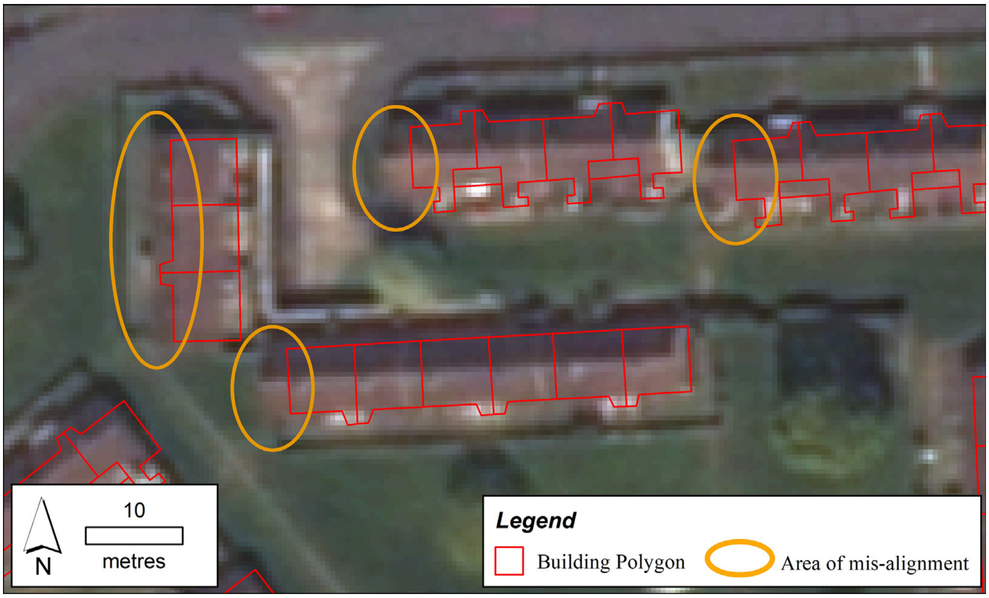

Fig. 7. Mis-alignment of OSMT building polygons, and building areas represented in the Study Image.

indicated in both correlation measures (all values significant at $p < 0.05$). Through examination of general patterns in the plots, and the results of the Spearman Rank analysis, indicate that all associations are non-linear in nature. As the results suggest, amalgamation of the data into a fewer number of bins results in stronger rho correlation values. Condensing the data through binning, indicates that GA may be a useful indicator of greenspace abundance when considering domestic gardens clusters with similar GA values.

4. Discussion

4.1. Classifying garden surfaces

For the purposes of this study, the mapping of general garden UGS abundance was a success. Quantifying detailed surfaces within garden parcels provides useful information on the quality or structure of garden greenspace, and is useable for general modelling applications. For example, Land Surface Temperature estimation using the urban energy exchange model (Cavan et al., 2014; Tso, Chan, & Hashim, 1991) requires knowledge of the evaporative fraction of an analysis area. The improved estimates of garden UGS cover, over simple assumptions of greenspace homogeneity (see Section 1), can thus improve temperature modelling on the neighbourhood scale (Gill et al., 2007).

However, within this context there are some limitations in the classified outputs. For example, the Non-Vegetation and Shrub class categories amalgamate surface types with various environmental properties. Non-Vegetation (e.g. Tarmac, Concrete) and pervious (e.g. Cultivated, Bare Soil, Water) surfaces contained within the Non-Vegetation class obscure important variation in surface infiltration properties for surface runoff models (USDA [United States Department of Agriculture], 1986; Warhurst et al., 2014). In addition, the Shrubs class incorporates all types of shrubbery, from small low-standing bushes through to mature trees. Distinction between various types of shrub vegetation can for example usefully enhance urban carbon sequestration (Davies, Edmondson, Heinemeyer, Leake, & Gaston, 2011) and biodiversity estimates (Goddard, Dougill, & Benton, 2010). The classification thus provides a useful base measure of garden greenspace, but can be further improved with 3D surface data to distinguish between tall standing features (e.g. trees, buildings, hedges, above ground shadow), and ground level features (e.g. grass, ground Non-Vegetation surfaces) (Chen, Su, Li, & Sun, 2009; Tansey, Chambers, Anstee, Denniss, & Lamb, 2009). In addition, other studies have augmented remotely sensed information with detailed site-surveyed estimates of garden surface properties (Baker et al., 2018; Davies et al., 2011). Thus scope exists within the existing methodology to improve the accuracy and number of classes within the classification process.

Furthermore, the exercise was limited (due to cloud free image availability) to using imagery captured in mid-spring (17th April) before full-growth (leaf-on) conditions for many plant species in the UK (Abernethy et al., 2017). This may have caused some classification issues, such as spectral confusion between Grass and Shrubs classes, in addition to non-leaf vegetation objects confused with areas of non-vegetation. Despite this issue, the classification proved to be reasonably accurate, with Google Earth imagery proving useful to validate difficult to distinguish class areas in the study area. In addition, pre-processing the image to achieve a decent alignment with the OSMT provided some issues. Whilst the Rubber Sheeting method allows a great deal of user control over the geo-rectification process, in comparison to other geo-rectification methods such as polynomial transformation, this method provides no estimation of error (Hughes, McDowell, & Marcus, 2006). As the garden parcel polygons are digitised from both the OSMT, and from features in the image itself, it proved difficult to quantify the degree of mis-alignment error between the two sets of data. In contrast to manual digitisation, the automated processing of OSMT alone (so that individual garden polygon features are merged in cohesive features for single garden areas) may be more appropriate (Baker et al., 2018). This would provide a useable reference data set to analyse the image geo-rectification process, which in turn would be readily updateable with revisions of OSMT.

4.2. Relation of garden greenspace to other garden indicators

As previously discussed, UGS has a wide range of benefits, and thus the PropGreen measure provides a general indication of the 'environmental friendliness' of a garden. Analysis of this measure against other garden indicators, can provide a general indication of the associated factors related to garden greenspace abundance which may be applied to in other research projects. As shown in the results, gardens with low proportions of UGS have a high association with Victorian Terraced properties; which is unsurprising given the significant difference in garden size and structure between Victorian Terraced and all other property types. For future research into urban gardens in the UK this finding may has some significance, as the Victorian Terrace property type is commonly found within UK. Identifying areas of Victorian

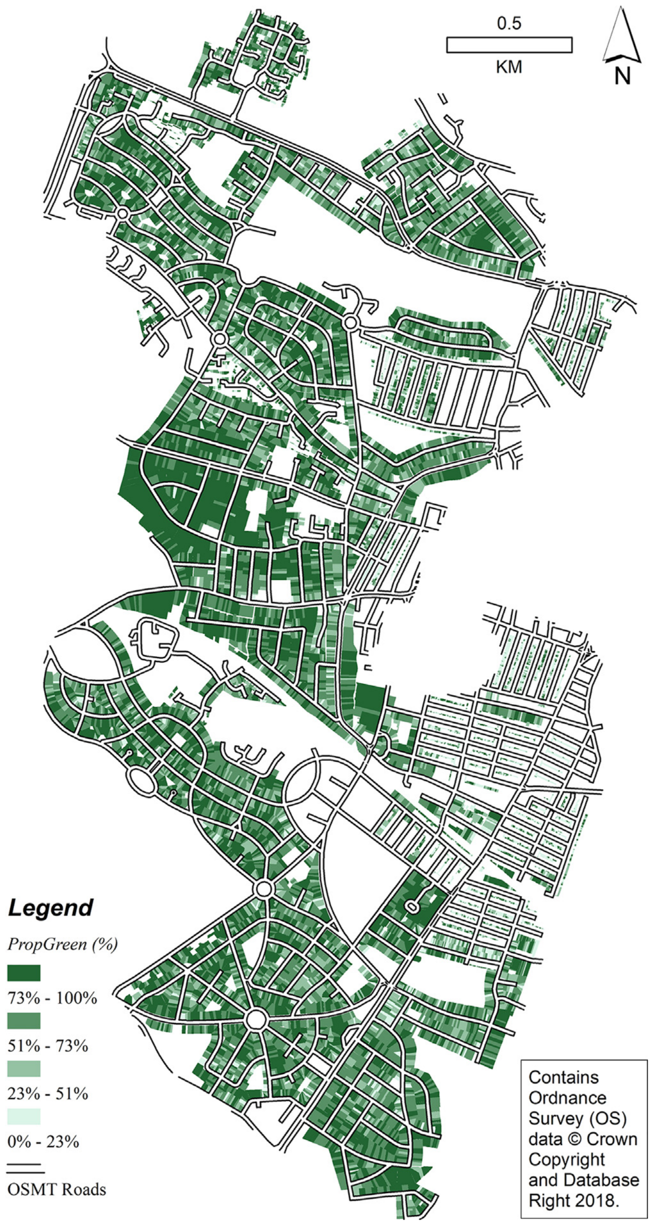

Fig. 8. Garden Polygons according to proportion of useable garden area that is greenspace (PropGreen).

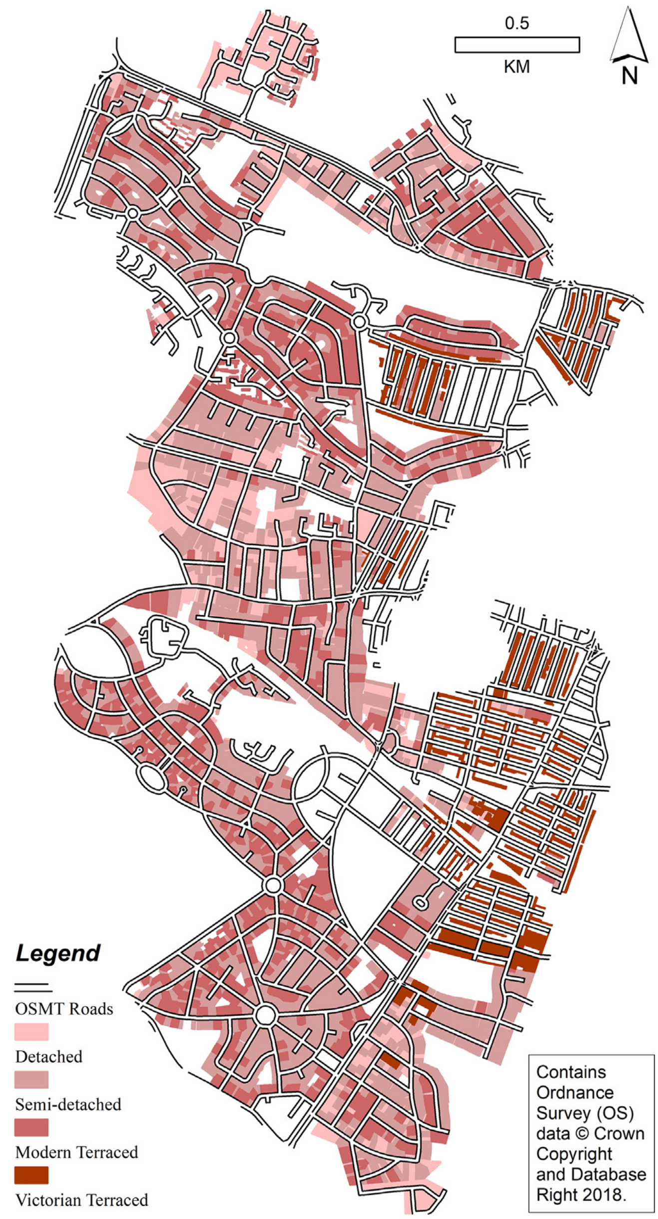

Fig. 9. Garden Polygons according to associated Property Type.

housing from OMST or Remotely sensed imagery etc. may potentially provide an indication of where a significantly high proportion of environmentally underperforming gardens are located in other UK urban areas.

The moderate to weak relationship between PropGreen and GA for individual garden parcels is supported in other studies. Stone (2004) found that in general the proportion of lot area that is impervious declined with increasing total lot area for residential housing plots in Olympia, WA. Verbeeck et al. (2011) also found a weak positive correlation between garden size and pervious garden (greenspace) area. However as these studies indicate, factors such as size of front garden, the distance of a property to street and age of housing also have an influence on the abundance of garden greenspace (Stone, 2004; Stone & Norman, 2006; Verbeeck et al., 2011). Evidence from UK studies suggests that current trends in increasing imperviousness are concentrated mainly in front garden areas, as people convert this space for off-street parking (Perry & Nawaz, 2008; Warhurst et al., 2014). In the contrast, the increasing size of back gardens, has been found to improve the abundance and diversity of greenspace surface cover for garden areas in Sheffield (Smith et al., 2005). Thus an improvement in the analysis conducted in this study may therefore involve processing the garden data set further, such as splitting garden parcels into front and back garden areas, and assessing greenspace variation according to this additional dichotomy. In addition, better indicators of garden greenspace may also be enhanced with analysis to other physical and socio-economic variables such neighbourhood development age, socio-economic status and surrounding morphology, as a number of studies suggest these variables may have some relation to residential garden greenspace levels (Lin et al., 2017; Mathieu et al., 2007; Pauleit, Ennos, & Golding, 2005).

The PropGreen to GA analysis on the binned dataset provided evidence of a stronger general relationship between the two variables. Whilst data binning may be considered a manipulation of data to present a biased view of inherent associations between variables; in relation to general indicative factors regarding garden greenspace abundance, this approach has some validity. A general observation of the garden parcel polygons, is that groups of adjoining garden areas are

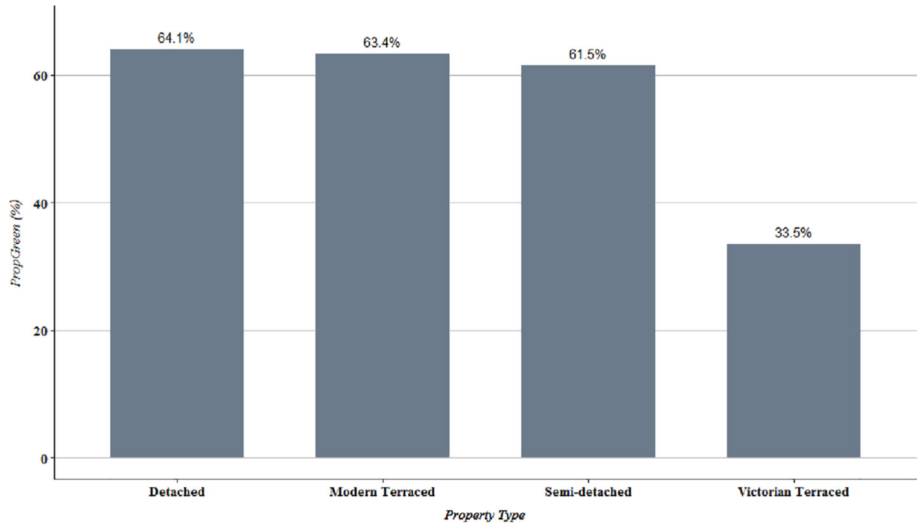

Fig. 10. Mean useable garden area that is greenspace per property type.

often of similar size. For example, this can be seen for rows of terraced housing with very similar sized gardens, or for larger adjoining garden areas associated with suburban detached properties. Whilst it is not valid to predict greenspace abundance for individual gardens according to GA, grouping gardens together into blocks of similar sized garden areas (e.g. postcode areas, housing estates) and then calculating mean garden area, may be a useful indicator of general garden greenspace abundance for these areas.

The above assertions have validity in the local context, as the findings can be used to update local green infrastructure estimations for further research. The completion date of analysis for the project was in August 2015; since mid-2017 the Ordnance Survey has provided the Mastermap Greenspace layer product for academic research (OS, 2017). This product identifies individual private garden polygons, which in turn could enable an extrapolation method of the findings from this study to the gardens in the wider urban area of Leicester. However, further work is arguably required to determine suitable methods for clustering gardens of similar characteristics into larger spatial blocks for analysis.

Table 5
Correlation values for Number of Bins data sets.

Number of Bins	Observations per Bin	Correlation values for GA and PropGreen values	
		Pearson (r)	Spearman (r_s)
)1000	13	0.84	0.84
500	27	0.87	0.90
250	55	0.86	0.93
100	138	0.86	0.96
50	277	0.85	0.98
25	556	0.86	0.98

5. Conclusion

The main findings of the study are:

- Successful demonstration of GIS and OBIA approach for mapping general surfaces within domestic gardens, with an overall accuracy of 86.15%.
- Significant differences in greenspace abundance found between

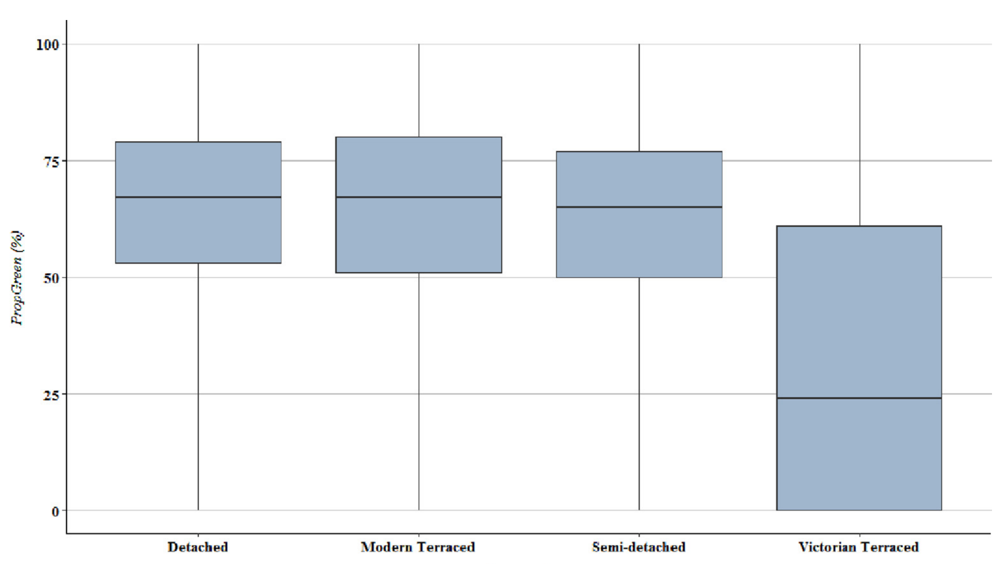

Fig. 11. Distribution of useable garden area that is greenspace values per Property Type.

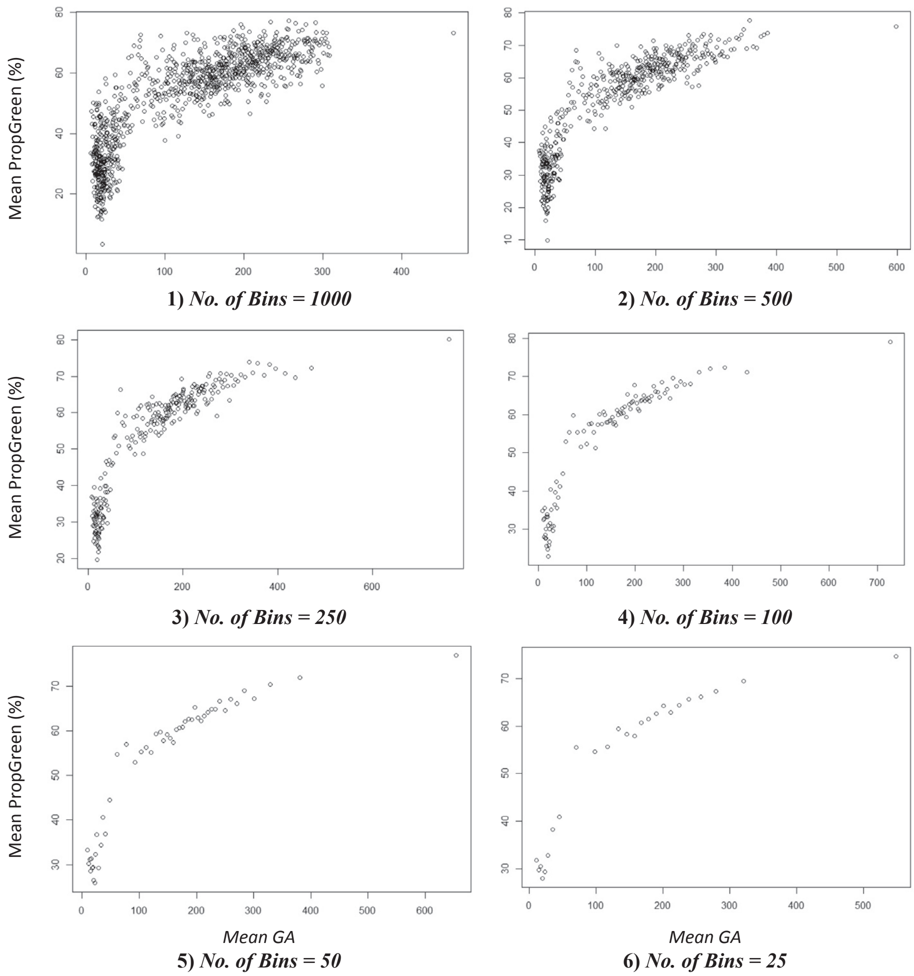

Fig. 12. Scatterplots of Mean Bin GA size (x-axis) and Mean Bin PropGreen (y-axis) for all No. of Bins.

Victorian Terraced housing (mean PropGreen = 34%) and non-Victorian Terraced housing (mean PropGreen = 62–64%) in the study area, which has possible use for indicating 'Environmental Deprivation' in domestic gardens for other urban areas of the UK.

- Moderate to weak positive association between useable garden area and greenspace abundance for individual garden areas ($r = 0.42$, $p < 0.001$).
- Stronger association between useable garden area and greenspace abundance exists in increasing amalgamations of garden records according to UGA extent groupings, indicating spatial clusters of similar size garden areas may provide some indication of greenspace abundance across study area.

By quantifying UGS cover within individual gardens, the study has demonstrated the benefits of automated classification of high-resolution imagery for this purpose. As high-resolution geospatial data is becoming increasingly accessible, such methods are applicable to continually monitor change in UGS resources and the benefits associated with them. Improvements to the method described here are perhaps needed for specific modelling purposes, however the findings of UGS abundance to garden size and property type can be used to guide further garden research in other UK urban areas.

Indeed the approach discussed here has wider impact in relation to UK urban development policy. High-resolution information on garden UGS is useful for local planning authorities to identify UGS need, and thus develop localised restrictions on the development of garden areas (Perry & Nawaz, 2008). This has particular relevance for areas in the UK for example, such as Greater London and South-East England, where housing demand and the resulting pressure on property prices has facilitated a trend for building new or extending existing homes onto back garden areas (Sayce et al., 2012). As practical implementation of localised urban development strategy requires detailed information UGS resources, the general approach to garden UGS mapping described here should be improved and extended over larger scales.

Acknowledgements

This manuscript is adapted from an original dissertation thesis completed for a Masters of Science (MSc) degree in Geographical Information Science (University of Leicester; course dates 09/2014 – 09/2015). Work relating to the dissertation was conducted between 05/2015 – 09/2015. The Worldview-2 imagery and GIS software was funded by the Department of Geography, University of Leicester. I would personally like to thank all staff and tutors associated with the MSc course for their excellent support and teaching, which supported the completion of the dissertation, and ultimately this manuscript. I would also like to personally thank my MSc supervisor Dr. Claire Smith and current PhD director of studies Gina Cavan (Manchester Metropolitan University) for their invaluable advice and support in publishing this work.

References

Abernethy, R., Garforth, J., Hemming, D., Kendon, M., Mc-Carthy, M., & Sparks, T. (2017). State of the UK Climate 2016: Phenology supplement. https://www.metoffice.gov.uk/binaries/content/assets/mohippo/pdf/uk-climate/state-of-the-uk-

climate/mo-phenology-supplement-v4.pdf (Last accessed 27.11.18).
Aguilar, M. A., Saldaña, M. M., & Aguilar, F. J. (2013). GeoEye-1 and WorldView-2 pan-sharpened imagery for object-based classification in urban environments. *International Journal of Remote Sensing, 34*(7), 2583–2606. https://doi.org/10.1080/01431161.2012.747018.
Al-Kofahi, S., Steele, C., VanLeeuwen, D., & Hilaire, R. S. (2012). Mapping land cover in urban residential landscapes using very high spatial resolution aerial photographs. *Urban Forestry & Urban Greening, 11*(3), 291–301. https://doi.org/10.1016/j.ufug.2012.05.001.
Baker, F., Smith, C. L., & Cavan, G. (2018). A combined approach to classifying land surface cover of urban domestic gardens using citizen science data and high resolution image analysis. *Remote Sensing, 10*(4), 537. https://doi.org/10.3390/rs10040537.
Barton, J., & Pretty, J. (2010). What is the best dose of nature and green exercise for improving mental health? A multi-study analysis. *Environmental Science & Technology, 44*(10), 3947–3955. https://doi.org/10.1021/es903183r.
Bektas, F., & Goksel, C. (2005). Remote sensing and GIS integration for land cover analysis, a case study: Gokceada Island. *Forest, 3548*, 12–30.
Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing, 58*(3), 239–258. https://doi.org/10.1016/j.isprsjprs.2003.10.002.
Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 65*(1), 2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004.
Cameron, R. W., Blanuša, T., Taylor, J. E., Salisbury, A., Halstead, A. J., ... Thompson, K. (2012). The domestic garden–Its contribution to urban green infrastructure. *Urban Forestry & Urban Greening, 11*(2), 129–137. https://doi.org/10.1016/j.ufug.2012.01.002.
Cavan, G., Lindley, S., Jalayer, F., Yeshitela, K., Pauleit, S., Renner, F., ... Kibassa, D. (2014). Urban morphological determinants of temperature regulating ecosystem services in two African cities. *Ecological Indicators, 42*, 43–57. https://doi.org/10.1016/j.ecolind.2014.01.025.
Chavez, P. S. (1988). An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. *Remote Sensing of Environment, 24*(3), 459–479. https://doi.org/10.1016/0034-4257(88)90019-3.
Chen, Y., Su, W., Li, J., & Sun, Z. (2009). Hierarchical object oriented classification using very high resolution imagery and LIDAR data over urban areas. *Advances in Space Research, 43*(7), 1101–1110. https://doi.org/10.1016/j.asr.2008.11.008.
Congalton, R. G., & Green, K. (2009). *Assessing the accuracy of remotely sensed data: Principles and practices.* CRC.
Countryscape (2015). *Manchester green infrastructure strategy: Technical report.* Countryscape (Last Accessed 16.08.15).
Darwish, A., Leukert, K. & Reinhardt, W. (2003, July). Image segmentation for the purpose of object-based classification. In: International Geoscience and Remote Sensing Symposium (Vol. 3, pp. III-2039). doi:10.1109/IGARSS.2003.1294332.
Davies, Z. G., Edmondson, J. L., Heinemeyer, A., Leake, J. R., & Gaston, K. J. (2011). Mapping an urban ecosystem service: Quantifying above-ground carbon storage at a city-wide scale. *Journal of Applied Ecology, 48*(5), 1125–1134. https://doi.org/10.1111/j.1365-2664.2011.02021.x.
DCLG [Department for Communities and Local Government] (2008). *English housing survey 2008: Stock report.* Department for Communities and Local Government (Last Accessed 16.08.15).
DigitalGlobe (2013). Worldview-2 Data-sheet. https://dg-cms-uploads-production.s3.amazonaws.com/uploads/document/file/98/DG_WorldView2_DS_PROD.pdf (Last Accessed 16.08.15).
Dimoudi, A., & Nikolopoulou, M. (2003). Vegetation in the urban environment: Microclimatic analysis and benefits. *Energy and Buildings, 35*(1), 69–76. https://doi.org/10.1016/S0378-7788(02)00081-6.
FAS [Federation of American Scientists]. (2015). Collecting Data at the Surface – Ground Truth; Imaging Spectroscopy. http://fas.org/irp/imint/docs/rst/Sect13/Sect13_3.html (Last Accessed 16.08.15).
Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing, 29*(11), 3137–3158. https://doi.org/10.1080/01431160701442120.
Gao, J., & Skillcorn, D. (1998). Capability of SPOT XS data in producing detailed land cover maps at the urban-rural periphery. *International Journal of Remote Sensing, 19*(15), 2877–2891. https://doi.org/10.1080/014311698214325.
Gill, S. E., Handley, J. F., Ennos, A. R., & Pauleit, S. (2007). Adapting cities for climate change: The role of the green infrastructure. *Built Environment, 1978-*, 115–133. https://doi.org/10.2148/benv.33.1.115.
Goddard, M. A., Dougill, A. J., & Benton, T. G. (2010). Scaling up from gardens: Biodiversity conservation in urban environments. *Trends in Ecology & Evolution, 25*(2), 90–98. https://doi.org/10.1016/j.tree.2009.07.016.
Haase, D., Larondelle, N., Andersson, E., Artmann, M., Borgström, S., Breuste, J., ... Kabisch, N. (2014). A quantitative review of urban ecosystem service assessments: Concepts, models, and implementation. *Ambio, 43*(4), 413–433. https://doi.org/10.1007/s13280-014-0504-0.
Hughes, M. L., McDowell, P. F., & Marcus, W. A. (2006). Accuracy assessment of georectified aerial photographs: Implications for measuring lateral channel movement in a GIS. *Geomorphology, 74*(1), 1–16. https://doi.org/10.1016/j.geomorph.2005.07.001.
Immitzer, M., Atzberger, C., & Koukal, T. (2012). Tree species classification with random forest using very high spatial resolution 8-band WorldView-2 satellite data. *Remote Sensing, 4*(9), 2661–2693. https://doi.org/10.3390/rs4092661.
Johnson, B. (2013). *The Greatest City on Earth.* London: Greater London Authority (Last Accessed 01.06.17).
Kampouraki, M., Wood, G. A., & Brewer, T. R. (2008). *Opportunities and limitations of object based image analysis for detecting urban impervious and vegetated surfaces using true-colour aerial photography. Object-based image analysis: Spatial concepts for knowledge-driven remote sensing applications*. Springer (Last Accessed 16.08.15).
Lin, B. B., Gaston, K. J., Fuller, R. A., Wu, D., Bush, R., & Shanahan, D. F. (2017). How green is your garden? Urban form and socio-demographic factors influence yard vegetation, visitation, and ecosystem service benefits. *Landscape and Urban Planning, 157*, 239–246. https://doi.org/10.1016/j.landurbplan.2016.07.007.
Loram, A., Tratalos, J., Warren, P. H., & Gaston, K. J. (2007). Urban domestic gardens (X): The extent & structure of the resource in five major cities. *Landscape Ecology, 22*, 601–615. https://doi.org/10.1007/s10980-006-9051-9.
Maher, B. A., Ahmed, I. A., Davison, B., Karloukovski, V., & Clarke, R. (2013). Impact of roadside tree lines on indoor concentrations of traffic-derived particulate matter. *Environmental Science & Technology, 47*(23), 13737–13744. https://doi.org/10.1021/es404363m.
Mather, P., & Koch, M. (2010). *Computer processing of remotely-sensed images.* Wiley.
Mathieu, R., Freeman, C., & Aryal, J. (2007). Mapping private gardens in urban areas using object-oriented techniques and very high-resolution satellite imagery. *Landscape and Urban Planning, 81*(3), 179–192. https://doi.org/10.1016/j.landurbplan.2006.11.009.
MCC [Manchester City Council] (July 2015). *Manchester's Great Outdoors: a Green and Blue Infrastructure Strategy for Manchester – 2015–25.* Manchester City Council Retrieved from: http://www.manchester.gov.uk/downloads/download/6314/manchester_green_and_blue_strategy (Last Accessed 01.06.17).
Myint, S. W., Gober, P., Brazel, A., Grossman-Clarke, S., & Weng, Q. (2011). Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sensing of Environment, 115*(5), 1145–1161. https://doi.org/10.1016/j.rse.2010.12.017.
Namdeo, A., & Bell, M. C. (2005). Characteristics and health implications of fine and coarse particulates at roadside, urban background and rural sites in UK. *Environment International, 31*(4), 565–573. https://doi.org/10.1016/j.envint.2004.09.026.
OS [Ordnance Survey]. (2017). Ordnance Survey releases open dataset and free map of Britain's Greenspaces. Available from: https://www.ordnancesurvey.co.uk/about/news/2017/os-releases-open-dataset-free-map-gb-greenspaces.html.
Padwick, C., Deskevich, M., Pacifici, F. & Smallwood, S. (2010, April). WorldView-2 pan-sharpening. In: Proceedings of the ASPRS 2010 Annual Conference, San Diego, CA, USA (Vol. 2630). http://www.asprs.org/wp-content/uploads/2013/08/Padwick.pdf (Last Accessed 01.06.17).
Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. *Nature, 438*(7066), 310–317. https://doi.org/10.1038/nature04188.
Pauleit, S., & Duhme, F. (2000). Assessing the environmental performance of land cover types for urban planning. *Landscape and Urban Planning, 52*(1), 1–20. https://doi.org/10.1016/S0169-2046(00)00109-2.
Pauleit, S., Ennos, R., & Golding, Y. (2005). Modeling the environmental impacts of urban land use and land cover change—A study in Merseyside, UK. *Landscape and Urban Planning, 71*(2–4), 295–310. https://doi.org/10.1016/j.landurbplan.2004.03.009.
Perry, T., & Nawaz, R. (2008). An investigation into the extent and impacts of hard surfacing of domestic gardens in an area of Leeds, United Kingdom. *Landscape and Urban Planning, 86*(1), 1–13. https://doi.org/10.1016/j.landurbplan.2007.12.004.
Pu, R., & Landry, S. (2012). A comparative analysis of high spatial resolution IKONOS and WorldView-2 imagery for mapping urban tree species. *Remote Sensing of Environment, 124*, 516–533. https://doi.org/10.1016/j.rse.2012.06.011.
Samnegård, U., Persson, A. S., & Smith, H. G. (2011). Gardens benefit bees and enhance pollination in intensively managed farmland. *Biological Conservation, 144*(11), 2602–2606. https://doi.org/10.1016/j.biocon.2011.07.008.
Santos, T., Silva, C., António Tenedório, J. (2017). Modelling urban thermal comfort: Evaluating the impact of the urban requalification project of Praça Duque De Saldanha and Avenida Da República in Lisbon. In: Proceedings of the 3rd International Conference on Geographical Information Systems Theory, Applications and Management (pp. 70–80). ISBN 978-989-758-252-3. DOI: 10.5220/0006324500700080. http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220/0006324500700080.
Santos, T., Tenedório, J., & Gonçalves, J. (2016). Quantifying the city's green area potential gain using remote sensing data. *Sustainability, 8*(12), https://doi.org/10.3390/su8121247.
Sayce, S., Walford, N., & Garside, P. (2012). Residential development on gardens in England: Their role in providing sustainable housing supply. *Land Use Policy, 29*(4), 771–780. https://doi.org/10.1016/j.landusepol.2011.12.002.
Schmitt, T. G., Thomas, M., & Ettrich, N. (2004). Analysis and modeling of flooding in urban drainage systems. *Journal of Hydrology, 299*(3), 300–311. https://doi.org/10.1016/j.jhydrol.2004.08.012.
Shackelford, A. K., & Davis, C. H. (2003). A combined fuzzy pixel-based and object-based approach for classification of high-resolution multispectral data over urban areas. *Geoscience and Remote Sensing, IEEE Transactions on, 41*(10), 2354–2363. https://doi.org/10.1109/TGRS.2003.815972.
Shaw, R., Colley, M., & Connell, R. (2007). *Climate change adaptation by design: a guide for sustainable communities.* TCPA (Last Accessed 16.08.15).
Smith, R. M., Gaston, K. J., Warren, P. H., & Thompson, K. (2005). Urban domestic gardens (V): Relationships between landcover composition, housing and landscape. *Landscape Ecology, 20*(2), 235–253. https://doi.org/10.1007/s10980-004-3160-0.
Stone, B. (2004). Paving over paradise: How land use regulations promote residential imperviousness. *Landscape and Urban Planning, 69*(1), 101–113. https://doi.org/10.1016/j.landurbplan.2003.10.028.
Stone, B., & Norman, J. M. (2006). Land use planning and surface heat island formation: A

parcel-based radiation flux approach. *Atmospheric Environment, 40*(19), 3561–3573. https://doi.org/10.1016/j.atmosenv.2006.01.015.
Tansey, K., Chambers, I., Anstee, A., Denniss, A., & Lamb, A. (2009). Object-oriented classification of very high resolution airborne imagery for the extraction of hedgerows and field margin cover in agricultural areas. *Applied Geography, 29*(2), 145–157. https://doi.org/10.1016/j.apgeog.2008.08.004.
Thompson, K., Austin, K. C., Smith, R. M., Warren, P. H., Angold, P. G., & Gaston, K. J. (2003). Urban domestic gardens (I): Putting small-scale plant diversity in context. *Journal of Vegetation Science, 14*(1), 71–78.
Thompson, C. W., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning, 105*(3), 221–229. https://doi.org/10.1016/j.landurbplan.2011.12.015.
Tso, C. P., Chan, B. K., & Hashim, M. A. (1991). Analytical solutions to the near-neutral atmospheric surface energy balance with and without heat storage for urban climatological studies. *Journal of Applied Meteorology, 30*(4), 413–424. https://doi.org/10.1175/1520-0450(1991) 030%3C0413:ASTTNN%3E2.0.CO;2.
Updike, T., & Comp, C. (2010). *Radiometric use of WorldView-2 imagery. Technical Note.* Digital Globe (Last Accessed 16.08.15).
USDA [United States Department of Agriculture] (1986). *Urban hydrology for small watersheds.* US Dept. of Agriculture, Soil Conservation Service, Engineering Division (Last Accessed 29.04.18).
Verbeeck, K., Van Orshoven, J., & Hermy, M. (2011). Measuring extent, location and change of imperviousness in urban domestic gardens in collective housing projects. *Landscape and Urban Planning, 100*(1), 57–66. https://doi.org/10.1016/j.landurbplan.2010.09.007.
Viera, A. J., & Garrett, J. M. (2005). Understanding interobserver agreement: the kappa statistic. *Family Medicine, 37*(5), 360–363 (Last Accessed 29.04.18).
Warhurst, J. R., Parks, K. E., McCulloch, L., & Hudson, M. D. (2014). Front gardens to car parks: Changes in garden permeability and effects on flood regulation. *Science of the Total Environment, 485*, 329–339. https://doi.org/10.1016/j.scitotenv.2014.03.035.
Wolf, A. F. (2012). Using Worldview-2 Vis-NIR multispectral imagery to support land mapping and feature extraction using normalized difference index ratios. pp. 83900N-83900N *SPIE Defense, Security, and Sensing*International Society for Optics and Photonicshttps://doi.org/10.1117/12.917717.
Xie, H. (2009). Using remote sensing and GIS technology for an improved decision support: A case study of residential water use in El Paso, Texas. *Civil Engineering and Environmental Systems, 26*(1), 53–63. https://doi.org/10.1080/10286600802003666.
Zhou, W., & Troy, A. (2008). An object-oriented approach for analysing and characterizing urban landscape at the parcel level. *International Journal of Remote Sensing, 29*(11), 3119–3135. https://doi.org/10.1080/01431160701469065.
Zmyslony, J., & Gagnon, D. (1998). Residential management of urban front-yard landscape: A random process? *Landscape and Urban Planning, 40*(4), 295–307. https://doi.org/10.1016/S0169-2046(97)00090-X.