



Article

Mapping Urban Green Infrastructure: A Novel Landscape-Based Approach to Incorporating Land Use and Land Cover in the Mapping of Human-Dominated Systems

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Abstract: Common approaches to mapping green infrastructure in urbanised landscapes invariably focus on measures of land use or land cover and associated functional or physical traits. However, such one-dimensional perspectives do not accurately capture the character and complexity of the landscapes in which urban inhabitants live. The new approach presented in this paper demonstrates how open-source, high spatial and temporal resolution data with global coverage can be used to measure and represent the landscape qualities of urban environments. Through going beyond simple metrics of quantity, such as percentage green and blue cover, it is now possible to explore the extent to which landscape quality helps to unpick the mixed evidence presented in the literature on the benefits of urban nature to human well-being. Here we present a landscape approach, employing remote sensing, GIS and data reduction techniques to map urban green infrastructure elements in a large U.K. city region. Comparison with existing urban datasets demonstrates considerable improvement in terms of coverage and thematic detail. The characterisation of landscapes, using census tracts as spatial units, and subsequent exploration of associations with social–ecological attributes highlights the further detail that can be uncovered by the approach. For example, eight urban landscape types identified for the case study city exhibited associations with distinct socioeconomic conditions accountable not only to quantities but also qualities of green and blue space. The identification of individual landscape features through simultaneous measures of land use and land cover demonstrated unique and significant associations between the former and indicators of human health and ecological condition. The approach may therefore provide a promising basis for developing further insight into processes and characteristics that affect human health and well-being in urban areas, both in the United Kingdom and beyond.

Keywords: health and well-being; GIS; remote sensing; urban ecosystems; social–ecological systems

1. Introduction

The links between the natural environment and human well-being have become increasingly highlighted in recent years. Studies that have investigated these links span numerous research agendas including public health [1–4], urban planning [5–7], landscape ecology [8,9], ecosystem services [10,11] and environmental justice [12–14]. Despite the broad range of perspectives taken, the fundamental metrics through which the natural environment has been represented in research on the topic have so far paid limited attention to the multi-faceted character of the landscapes in which many people live. In highly managed environments such as urban areas, landscape heterogeneity, function and use are highly modified by human activity. As a result, it has been difficult to describe such landscapes using traditional land use and land cover classification techniques [15–20]. With the availability of new data, particularly high-resolution multi-spectral imagery, this situation is now changing. New data availability has also coincided with a greater push from research and practice to better represent urban social–ecological systems as a means to understand the multiple benefits of green and blue spaces for human health and well-being [21,22]. In particular, the concept of green infrastructure has emerged as a promising framework to understand, manage and enhance the multiple benefits delivered by green and blue spaces, particularly in highly fragmented landscapes such as those affected by the process of urbanisation [23].

A primary aim of a green infrastructure approach involves the maximisation of physical and functional connectivity whilst optimising multi-functionality in terms of social, ecological and economic benefits [24,25] and seeking resilience through landscape diversity [26]. The effective mapping of such attributes therefore necessitates the ability to characterise land cover (form) and land use (function) simultaneously. An appreciation of green infrastructure that takes into account both physical form and functional properties likewise has the potential to consolidate divergent views of what comprises green infrastructure itself. For example, as Mell [25] argues, environmental practitioners, academics and local social–ecological actors tend to view green assets as either a visual/physical phenomenon or as a functional element in the wider infrastructural landscape. For this reason, green infrastructure typologies vary widely depending on the emphasis placed on either land use (function) or land cover (form). Developing a more social–ecological characterisation of landscape features that contribute to green infrastructure may go some way towards bridging such dichotomous perspectives. The landscape characteristics that may be derived from combining land cover and land use data should be applicable to analyses investigating the environmental benefits afforded by green spaces to urban inhabitants. It is known, for example, that urban green and blue spaces bring a range of health promoting benefits [4,11,26] but that such spaces are unequally distributed, disadvantaging the most socioeconomically deprived communities [14,27]. In order to address such inequalities in the planning process, assessments of landscapes and landscape features that relate simultaneously to both social provisions (i.e., function) and environmental quality (i.e., form) could support the design of an urban green infrastructure that promotes social and ecological resilience [28] in tandem. This is also important given that some aspects of form help to determine some elements of function, such as an enhanced cooling effect from trees over grass or higher aesthetic value of diverse land covers in urban settings [29,30].

Social–Ecological Research and the Representation of Urban Green and Blue Spaces

The association between urban form, landscape and socioeconomic conditions has long been recognised [31,32] and research on the topic continues to provide insight in studies focussed on social-ecological dynamics and human well-being, particularly in an urban context [33–35]. The underlying premise of a green infrastructure approach relates to the multiple benefits that may be obtained from well-connected ecological networks for human well-being. However, studies into health and well-being benefits of urban nature have come largely from the public health and social sciences. Understandably, these disciplines have tended to pay more attention to human processes and outcomes with relatively little emphasis on characterising the physical and ecological characteristics of

the natural environment in their assessments. There has been considerable use of broad density-based metrics. For example, Maas [36,37] employed dominant land cover (agricultural, natural and urban green) at a 25 m spatial resolution in their assessments on proximity to greenery and population health in the Netherlands. This resulted in street trees and roadside greenery being largely excluded from the model [37]. Furthermore, the emphasis was on using categories to estimate a percentage green space cover. Mitchell and Popham's [2,3] seminal work exploring the socioeconomic subtleties in the strength of the relationship between green space and health in the United Kingdom, used 5 m percentage green space cover. However, this indicator did not discriminate between the type, quality or accessibility of spaces that are categorised as green. Similarly, research has failed to consider the relevance of landscape-based metrics as indicators of environmental quality. Therefore, the development of new spatial data that account for the qualities of landscapes in which people live, as opposed to a purely quantitative consideration of green space cover, are needed. Such novel datasets allow more sophisticated approaches to analysing urban human well-being as well as being useful for a range of other purposes, such as urban planning.

Information on green infrastructure types, such as differentiating formal parks from informal or incidental green spaces, as well as cover, is a necessary step in describing landscapes from an anthropocentric perspective [38]. These nuances may help to explain negative associations between green space quantity and self-reported health in low-income suburban areas [2]. It may also challenge the notion that people of different socioeconomic backgrounds experience the same kinds of green spaces and in similar landscapes, an idea contested in research into environmental justice and urban design (see [14] for a review). Accordingly, it is important to consider how land cover and land use data can be effectively married in refined assessments of urban landscape types for the analysis of associated health and well-being outcomes.

Elsewhere, there have been useful developments that put greater emphasis on physical form and environmental function in the characterisation of urban areas, including a wider consideration of urban function. For example, Urban Morphology Types were designed to provide more homogenous analysis units from the perspective of environmental functionality [39–41]. However, the applicability of a UMT approach for health and well-being studies is ultimately hampered due to two main reasons. The first is due to difficulties integrating data on population, demographics, socioeconomic indicators and health which tend to use census tract data. Such statistical units are therefore integral to understanding the social–ecological character of the localities of urban inhabitants. It follows that, in research where social and ecological outcomes are at the fore, there are still strong arguments to make census units the primary analytical and geographical framing. Typologies that seek to characterise neighbourhoods at scales consistent with area-level statistical reporting are therefore a logical step in the advancing of studies into urban health and well-being indicators. Secondly, the methods to develop these datasets have been highly resource-intensive and demanded great sampling effort to achieve desirable levels of accuracy. For this reason the land cover estimates, though detailed, are generalised to a type and not to a location. Furthermore, given that they are time-consuming to conduct, they tend to be updated relatively infrequently. The more recent availability of very fine ≤ 10 m spatial resolution multi-spectral satellite imagery, has paved the way for semi-automating some of the classification tasks and allowing better classification of heterogeneous urban areas [42]. While it is still not possible to estimate the full range of urban land covers achieved in the aforementioned studies, there is now the opportunity to develop locally specific urban landscape characterisations for health and well-being studies to a level which was not previously possible. For example, some of the processed datasets available in the U.K. context and their characteristics are shown in Table 1. Limitations in the use of such data relate to the size of minimum mapping units (MMUs) that provide limited detail for spatial analysis of land use in cities, inconsistencies and the relative infrequency of updating.

Table 1. Attributes of commonly used processed datasets covering urban areas in the United Kingdom.

	Urban Atlas	Corine Land Cover	Land Cover Map
Minimum mapping units	0.25 ha	25 ha	0.5 ha
Input data resolution	2.5 m	25 m	25 m
Available years	2006; 2012	1990; 2000; 2006; 2012	2007; 2015
Number of land use/land cover classes	27	44	21
Thematic accuracy	≥80%	≥85%	-

The principal advantage of such datasets is their breadth of cover, providing a national and continental repository of thematic land use. They are limited, however, in their ability to offer information on landscape structure and patterns of vegetation. Furthermore, Urban Atlas [43] and U.K. Land Cover Map [44] data reveal inconsistencies resulting from variation in mapping units and resolution (see Figures 5 and 7). These inconsistencies, although expected for datasets employing different mapping units and resolution, are relevant given the prevalent use of both of these datasets in international research into urban environments (e.g., [39,45–51]) and policy guidance [22].

Most recently in 2017 the U.K. national mapping agency (Ordnance Survey) has produced a fine-scale vector dataset of urban green space using spatial data at the highest available resolution for the United Kingdom. The data are available under licence (OS Mastermap Greenspace Layer [52]) as well as in open-access format (OS Open Greenspace Layer [53]). The latter is less detailed, including fewer land use classes, but benefits from a greater extent, covering some peri-urban and rural areas not considered in the Mastermap Greenspace Layer. It overcomes a number of the limitations presented by previous datasets but its focus is on identifying green and blue land parcels and associated land use. It is much less refined in terms of its consideration of form (land cover) and, therefore, the quality of green spaces and how green and blue spaces come together in landscape types. The need to develop more integrated and detailed measures of landscape character than those offered by contemporary measures of land use or land cover presents a current research imperative. A landscape-oriented dataset should provide not only increased interpretability in terms of resolution, but equally a classification schema that supports the creation of meaningful landscape metrics and subsequent typologies. A novel method for incorporating both land use and land cover into a landscape-oriented representation of a large city catchment (Greater Manchester, UK) is presented here as an example of how such a shortcoming can be addressed. The method has three elements: (1) the use of remote sensing and GIS techniques to combine measures of land use, land cover and associated landscape metrics in the characterisation of neighbourhoods according to census units; (2) employing data reduction methods to identify common attributes of urban landscapes for the creation of meaningful typologies for social–ecological research; and (3) a demonstration of the merit of the approach through analysis of social–ecological relationships in a large U.K. urban conurbation.

2. Materials and Methods

The methodology presented here demonstrates the possibility of integrating currently available land use data such as those published by the U.K. Ordnance Survey with a land cover classification derived from high-resolution satellite imagery. The resulting composite dataset exhibits the ability to capture landscape features (integrating land use and land cover), indices, and a related typology congruent with existing socio-geographic units (U.K. national census tracts). Use of the latter as spatial extents for processing and analysis is particularly advantageous given that they reflect statistical units at which population, socioeconomic and health-related data are regularly reported. The primary use of recently available high-resolution remotely sensed data with global coverage (Sentinel 2A satellites, launched 2015 [54]), combined with a universally applicable classification scheme based on simple ecological stratification, highlights the potential of the method for work in other urban and human-dominated landscapes in a range of climates. The capacity to integrate elements of function and form in human-dominated landscapes and reflect multiple social and ecological dimensions of

use and quality presents a key opportunity for explorations of human health and ecological condition in social–ecological systems.

2.1. Overview

Greater Manchester comprises an extensive conurbation (1276 km²) with a population of approximately 2.8 million [55] that covers multiple areas of urban to rural transition but that is essentially defined by the distribution of urban centres within the 10 local authorities that make up the coterminous landscape of the city region. A novel composite spatial dataset covering the conurbation of Greater Manchester was achieved through a combination of remote sensing and GIS techniques that drew on the strengths of separately but freely available spatial data. The resulting dataset was then compared with other open-source and widely used datasets covering the same study area (Urban Atlas 2012 and Land Cover Map 2015). The methodology may provide a useful template for developing refined green infrastructure maps for other cities, particularly from the perspective of informing more detailed analyses of links between the urban environment and health and well-being. In order to assess the potential uses of the data, a number of example analyses are also carried out, namely to consider gradients observed in associations with indicators of health and social deprivation. The method consisted of three practical stages. Stages one and two achieved the processing and integration of land use and land cover data towards the characterisation of discrete landscape features (element one described in the previous section). Stage three involved the subsequent computing of landscape indices and, through data reduction techniques, the creation of a landscape typology (element two) towards the validation of the dataset with social–ecological analyses (element three).

2.2. Stage One: Automatic Land Cover Classification of Sentinel 2A Data and Data Processing

Copernicus Sentinel S2A (available since 2015) data were obtained from the Copernicus Scientific Data Hub (scihub.copernicus.eu/dhus). S2A multi-spectral imagery consists of 13 spectral bands with a swath width of 290 km. The spatial resolution of the bands are 10 m (for visible and near infrared bands), 20 m (for 6 red-edge and shortwave infrared bands) and 60 m (for 3 atmospheric correction bands). False colour infrared images were processed using bands 3 (green), 4 (red) and 8 (near infrared), all at 10 m resolution (Red:Green:Blue: 8:4:3). The Sentinel 2A mission has a re-visit time of five days.

A supervised classification approach was then employed to train a maximum likelihood automatic classifier. Around 100 training samples were used (after e.g., [42,56]). The results of the automatic classification divided the study area into five classes based on cover by water and levels of vegetative succession: built/impervious; a ground layer consisting of grasses and ground vegetation; a field layer consisting of forbs and shrubs; a canopy layer and a fifth class for areas of water. A simplified woodland stratification scheme was chosen as a widely acknowledged succession-related classification and, being common to temperate and tropical biomes, should be widely replicable for measures of greenness, biomass and structure and therefore suitable for a variety of environmental applications. The accuracy of the resulting classification was improved by incorporating digitised tree canopy data available from a local environmental NGO: City of Trees [57], which served principally to correct misclassification of *Calluna vulgaris* (ling heather) as tree cover in upland areas. Areas that showed evidence of such misclassification were clipped, re-classified and mosaicked with the original dataset. Additionally, a data layer for canals, rivers and open water from the Ordnance Survey Open Rivers layer 2017 [58] was added to improve cohesion of water-classified pixels in more urban areas. These vector datasets were rasterised and combined with existing pixel classes using map algebra and reclassification. All spatial processing and analysis were carried out using ArcMap 10.4.1. Accuracy assessment was enabled through ground-truthing (200 sampling points) based on 2017 Edina Digimap aerial photography [59] and cross-tabulated.

An overview of the data processing workflow for the landscape assessment is presented in Figure 1.

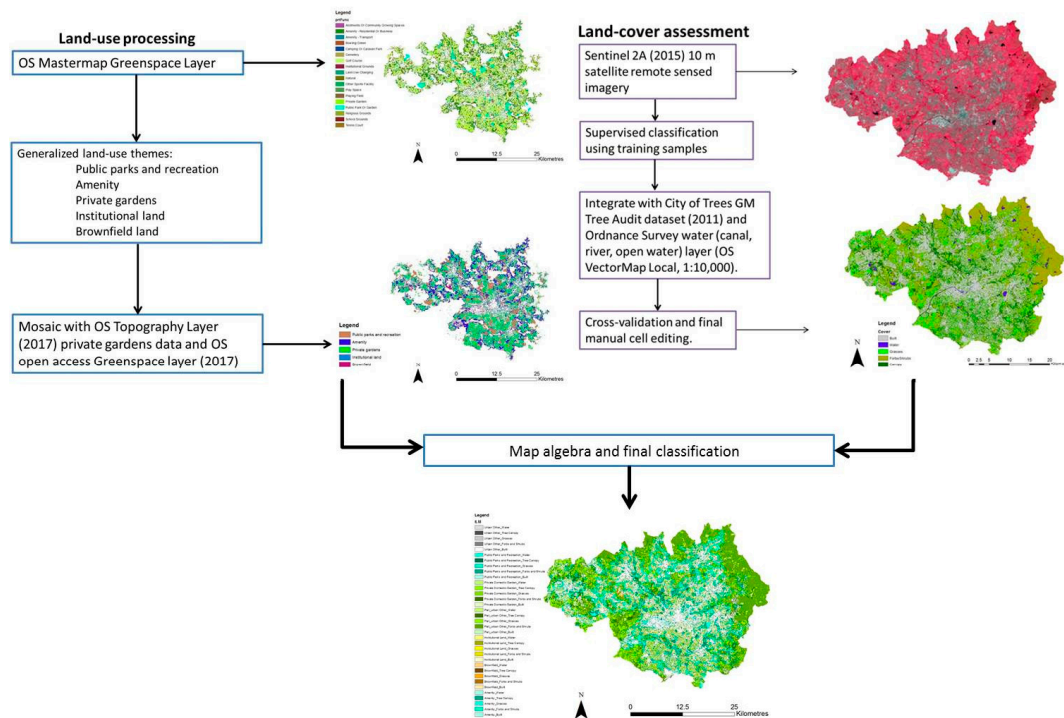


Figure 1. Data processing workflow.

2.3. Stage Two: Generalisation and Incorporation of Land Use Data

The land cover classification was subsequently enhanced with data on land use from the OS Mastermap Greenspace Layer (downloaded through the Edina Digimap Service from <http://digimap.edina.ac.uk>) through a four-step process. Firstly, the OS Mastermap Greenspace Layer was converted to 10 m raster cells to render it compatible with the land cover data. Secondly, the resulting raster layer was mosaicked with data from the rasterised OS Open Greenspace Layer, which has a wider spatial extent but less detail (data on publically accessible green spaces available at: <https://www.os.uk/opengreenspace>) and with data for private gardens extracted from the OS Mastermap Topography Layer ([60] also available from <http://digimap.edina.ac.uk>). This served to increase the spatial extent of data on these respective land use types. Thirdly, the items in the Primary function (land use) attribute of the resulting raster layer were generalised to represent common themes. The data were generalised in order to highlight common functional traits related to elements of green infrastructure (e.g., to combine similar usage types such as playing fields and other sports facilities) and also to reduce the number of classes for use in the statistical analyses presented in this paper. A fully disaggregated version of the dataset, covering all 18 land uses and with attributes denoting urban and peri-urban contexts is described in the supplementary materials. An open-access version of the dataset is available through the following link: http://huckg.is/d/ILM_Open.zip.

The 18 land use categories presented in the land use data were aggregated into the following five classes: amenity, public parks and recreation, private gardens, institutional land, and land use changing. The latter class was renamed brownfield land in the final classification as a more commonly used signifier of this type of land use in the United Kingdom. An additional two classes, urban other and peri-urban other, comprised urban and non-urban areas outside the extent of the OS Mastermap Greenspace Layer. The latter were classified according to their inclusion in the 2015 U.K. Land Cover Map. The sequential classification of land use and attribution of land cover is summarised in Figure 2. The fourth step employed map algebra to create a final layer with values corresponding to all possible combinations of land use and land cover, as individual landscape features. This resulted in a classification scheme consisting of 35 unique values. The classification scheme of the final Integrated

Landscape Dataset (ILM) provided a suitably aggregated dataset that reduced the number of values to near zero for each landscape feature at the LSOA level whilst providing an easily transferable thematic structure. This schematic approach, based on designations used within the OS urban land use classification and Land Cover Map, and land cover derived from freely available remotely sensed data, renders the data and the methodology employed immediately transferable at a national scale and to international contexts where comparable levels of land use data exist.

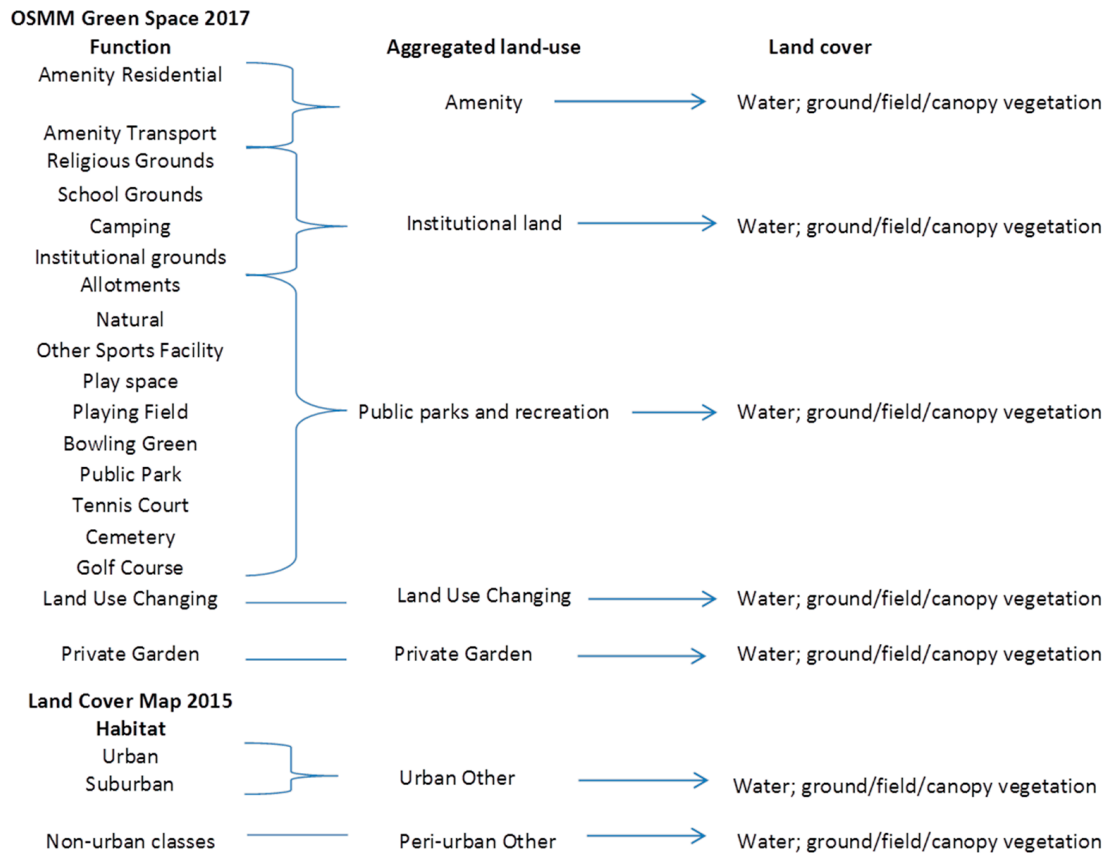


Figure 2. Decision tree of land use aggregation.

2.4. Consideration of Spatial Units

Much data are already available in spatial units that seek to capture local socio-geographic homogeneity, such as in the case of U.K. census data. The boundaries that are described by such units provide a useful spatial template for the development of effective landscape metrics and associated datasets. Given the increasing centrality of the natural environment in approaches to understanding human well-being, the generation of landscape typologies coterminous with spatial units employed in the gathering and dissemination of socio-demographic data is desirable from a spatial analysis point of view. Not only do such geographical units provide the basis for the reporting of a range of local area statistics, such as national census data, they also commonly delineate socioeconomically coherent spatial units. For example, in England and Wales, census reporting units (known as Lower Super Output Areas (LSOAs)) are designed to be socially homogenous in nature reflecting tenure, dwelling type and socioeconomic status [61]. They are also determined according to population and accordingly their spatial extent is a reflection of local population density. The spatial character of LSOAs is, furthermore, often shaped by elements of green (e.g., woodland), blue (e.g., watercourses) and grey infrastructure (e.g., major roads) in the landscape (Figure 3). Accordingly such socio-geographic units present a useful spatial template for the development of a landscape typology related to human-dominated systems, such as those in urban areas.

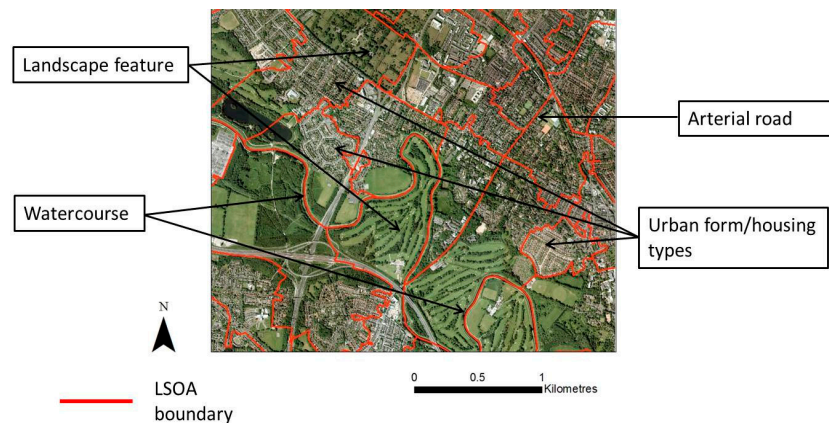


Figure 3. Boundaries of socio-geographic statistical units (Lower Super Output Areas) in South Manchester, UK. Source: Boundary data, ONS (2011); Aerial imagery, Edina (2017).

2.5. Stage 3: Validation of the Dataset

2.5.1. Statistical Comparison with Existing Urban Land Use Data

Validation was carried out based on a comparison with existing datasets and the reporting of classification error statistics. The selected comparators were Urban Atlas 2012, LCM 2015 and OS Mastermap Greenspace Layer 2017 for the same area (see Table 1). To investigate more closely the relative efficacy of the integrated landscape dataset for capturing vegetation and water cover across the Greater Manchester city region as indicators of its green infrastructure, histograms were generated of total percentage green and blue space cover per Lower Super Output Area [62] for the ILM, LCM, Urban Atlas, and the Primary Function and Form layers of the OS Mastermap Greenspace Layer. In the case of the latter two datasets, all land use values comprising water or vegetation classes according to the available technical reports were included in the calculation. For the ILM, all cells classed as water or vegetation were included.

2.5.2. Calculation of Landscape Indices and Correlations with Socioeconomic and Landscape Characteristics

The stratified approach to land cover using simple vegetative and water layers allowed for the generation of a range of landscape indices with which to explore the study area. The QGIS Landscape Ecology plugin LecoS 2.0.7 [63] was used to calculate values across a range of metrics using a vector overlay method that permitted the rapid computation of indices matching the neighbourhood-scale LSOAs. Values were computed for landscape indices reflecting diversity, Shannon's Index (SHDI), and connectivity, landscape division (LD) and canopy patch Euclidean distance nearest neighbour (ENN). These metrics were chosen given the centrality of landscape heterogeneity and connectivity in productive and resilient green infrastructure networks [12,64].

To assess the capacity of the ILM to reflect ecological and social variability in the study area landscape values for percentage cover at the LSOA-level for individual landscape feature were tested as correlates (Spearman's Rank) with landscape indices (LD and canopy ENN) and social deprivation indices related to premature mortality. The latter was quantified using the indicator years of potential life lost, an age- and sex-standardised measure of premature death, which is a sub-domain of the English Index of Multiple Deprivation [65]. Correlations were computed controlling for the sub-domain income deprivation from the same dataset to give a more accurate impression of the distinct relationship between landscape features and local health status.

In the case of landscape indices, landscape features describing tree cover for each of the seven land use classes were tested for correlations with measures of connectivity and, in the case of socioeconomic deprivation indices, all landscape features associated with amenity, private gardens and public

parks and recreation land use classes were included in the analysis. The hypothesis here was that individual landscape features, as unique green infrastructure elements, should similarly exhibit unique relationships with social-ecological characteristics in a given landscape. Accordingly, if the hypothesis holds, the creation of an integrated landscape approach to mapping green infrastructure can inform analysis and decision-making in human-dominated landscapes.

2.5.3. Generation and Assessment of Landscape Types

The 35 landscape features of the final ILM layer were used to group LSOAs into landscape types. In order to generate a landscape type for each LSOA, values for percentage cover by each of the landscape features as well as values for the landscape indices SHDI and LD were entered into a data reduction (*k*-means clustering ([66]) algorithm to group LSOAs. In order to test the ability of the method to create landscape types that effectively delineate social and ecological characteristics, types resulting from the *k*-means clustering were explored for patterns of variation in percentage green and blue cover per LSOA, Shannon's Diversity Index (SHDI) and Index of Multiple Deprivation scores. The same analysis was also performed for comparison on LSOAs grouped into quantiles (corresponding to the same number of percentile groups as for landscape types) according to total green and blue cover. The rationale for this was to test whether the landscape typology, ranked according to green/blue cover extent, exhibited patterns of socioeconomic deprivation and landscape diversity that simply replicated those generated as a result of a simple stratification of LSOAs by percentage green/blue space cover. If the latter were so, then the creation of such a typology would be invalidated as simply reflecting a coarse quantitative view of the relationship between green space and social-ecological characteristics. However, if exhibiting different patterns to those of a simple quantile stratification a landscape typology approach can, thereby, be validated as one that goes beyond the broad linear interpretation of social-ecological dynamics. All statistical operations were carried out in SPSS v. 23.

3. Results

Initial interrogation of the five-category land cover classification (see Figure 4) demonstrated satisfactory levels of accuracy (overall accuracy 85%) consistent with internationally recognised standards [67,68]. The dataset resulting from this initial classification is presented in Figure 4.

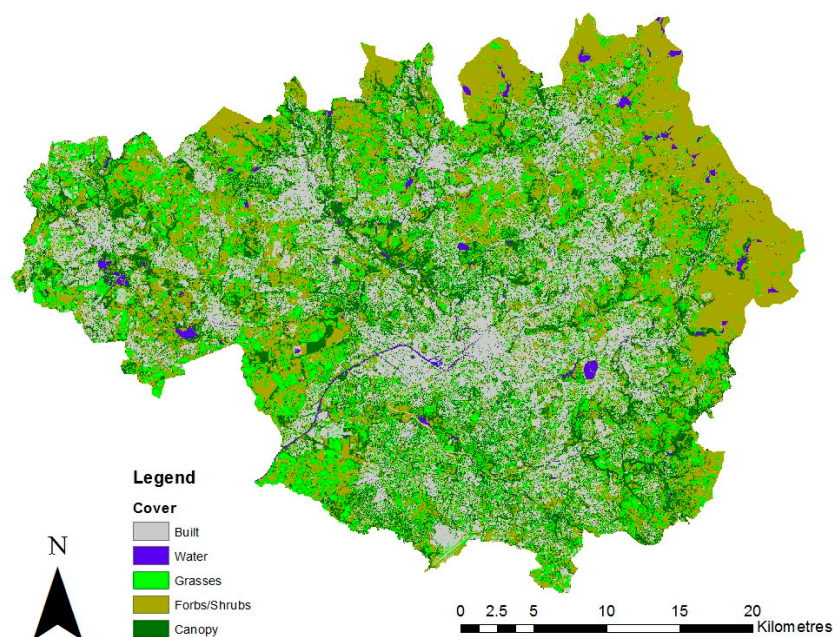


Figure 4. Result of the initial classification (Overall Accuracy 85%; Cohen's Kappa 0.86). Contains City of Trees (2011), Ordnance Survey (2017) and European Space Agency (2016) data.

3.1. Statistical Assessment of the Dataset

Figure 5a–d give the frequency distributions of total percentage green space cover per LSOA within Greater Manchester (N = 1673) derived from Urban Atlas 2012, UK LCM 2015 (as the sum of all green and blue land use classes), and the OS Mastermap Greenspace Layer values for land use and land cover. Figure 6 shows the distribution of values for green and blue space per LSOA for the ILM.

In addition to this comparison of frequency distributions of percentage green and blue cover, examples of the UA, LCM and OS Mastermap Greenspace Map with the Integrated Landscape Map are shown for an area of mixed land use in South Manchester. Figure 7a–e further compares with a high-resolution (25 cm) Edina 2017 aerial image given of the same area for reference in Figure 7f.

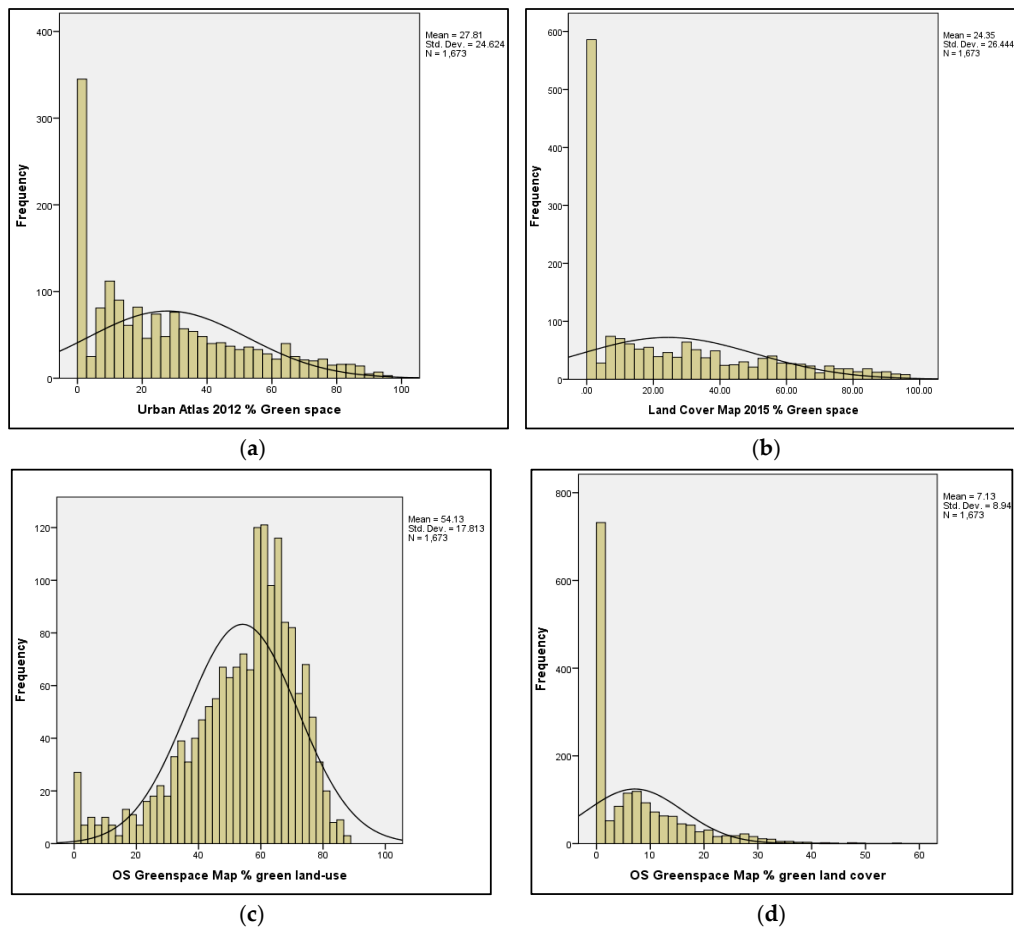


Figure 5. Frequency distribution of green space cover in local urban neighbourhoods. Top left, (a): Urban Atlas (EEA, 2012); Top right (b): Land Cover Map (Rowland et al. 2017); Bottom left (c): OS Mastermap Greenspace Layer, land use (Ordnance Survey, 2017); Bottom right, (d): OS Mastermap Greenspace Layer, land cover (Ordnance Survey, 2017).

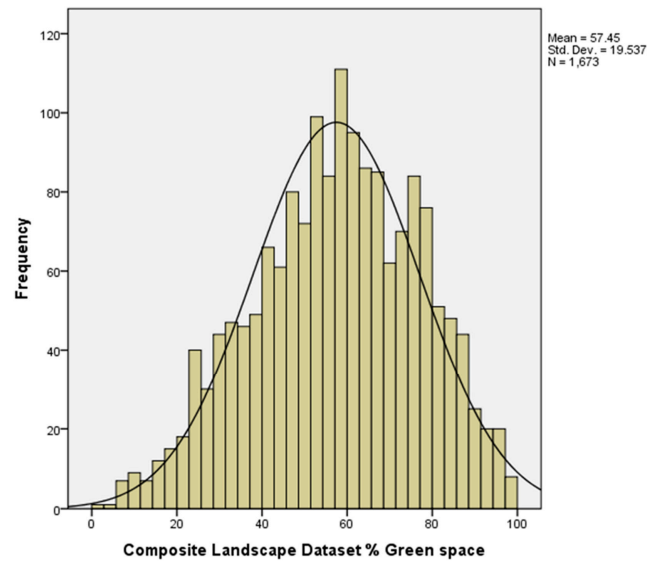


Figure 6. Distribution of green land cover values: Integrated Landscape Map.

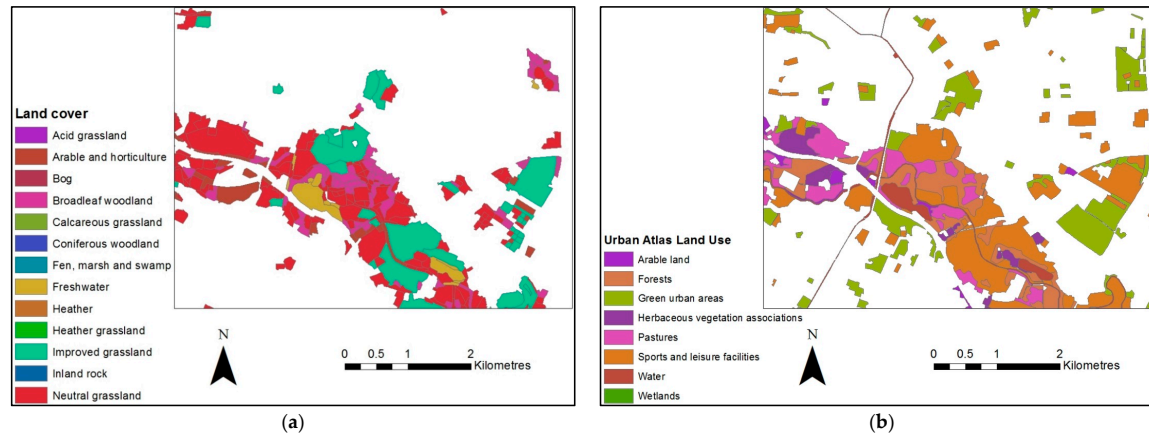


Figure 7. Cont.

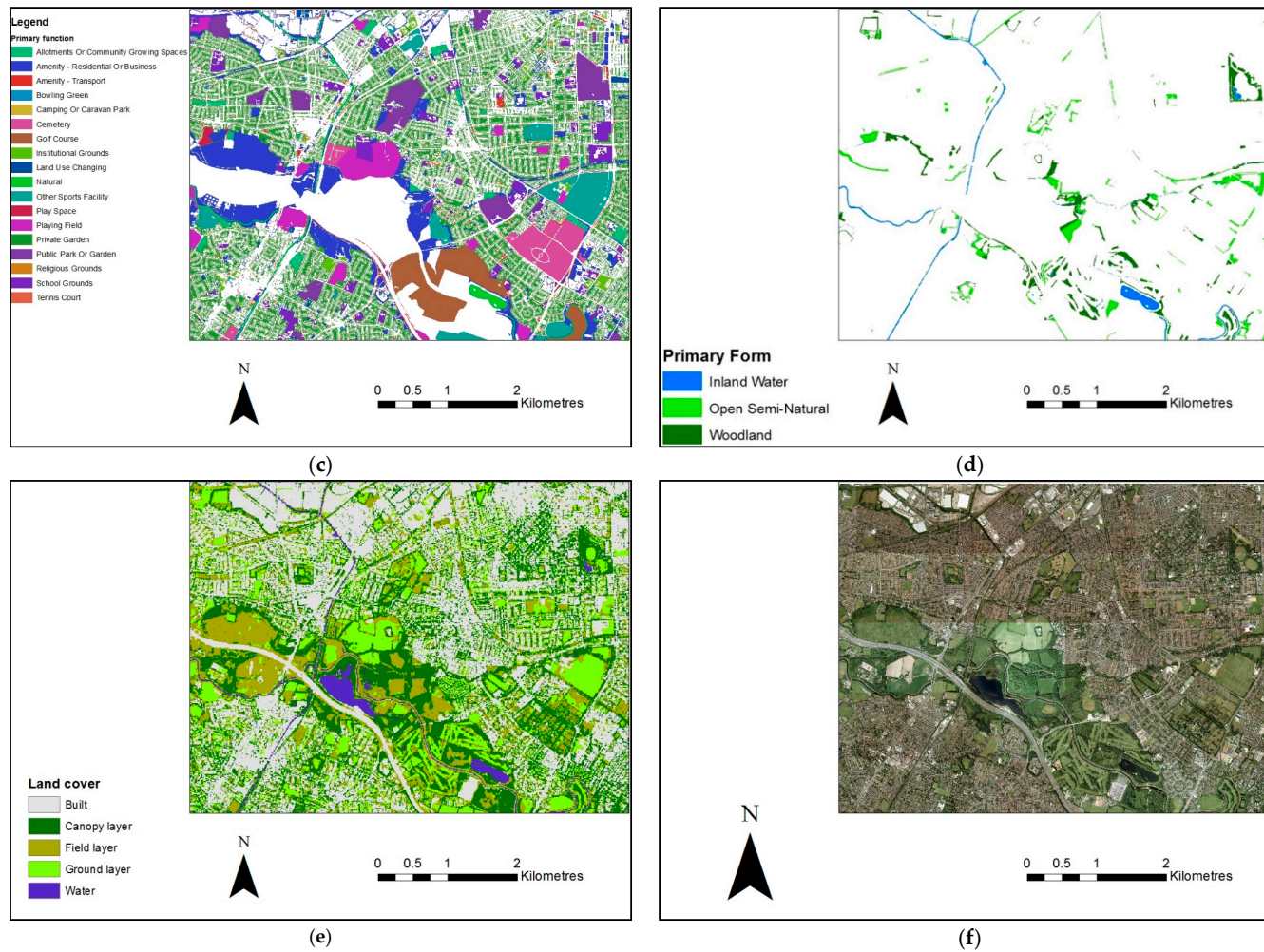


Figure 7. (a) (Top left) UK LCM 2015 (Rowland et al., 2017); (b) (top right) Urban Atlas 2012 (EEA, 2012); (c) (centre left) OS Mastermap Greenspace: land use (Ordnance Survey, 2017); (d) (centre right) OS Mastermap Greenspace: land cover (Ordnance Survey, 2017); (e) (bottom left) composite land cover map from stage one of the method and (f) aerial photograph (25 cm) of the same area (Edina, 2017).

3.2. Final Classification and Exploration of Social–Ecological Relationships

The results of the final classification of pixels into a 35 landscape features is presented in Figure 8. In the classification scheme, cells denote land use and land cover combinations where different colours (e.g., yellow, green, red) delineate use and the tone from light to dark indicates built, water, grasses, forbs and shrubs, and canopy cover, in that order. Table 2 presents correlations observed between selected landscape features and an indicator of health deprivation (premature mortality). Table 3 documents correlations with landscape indices reflecting connectivity.

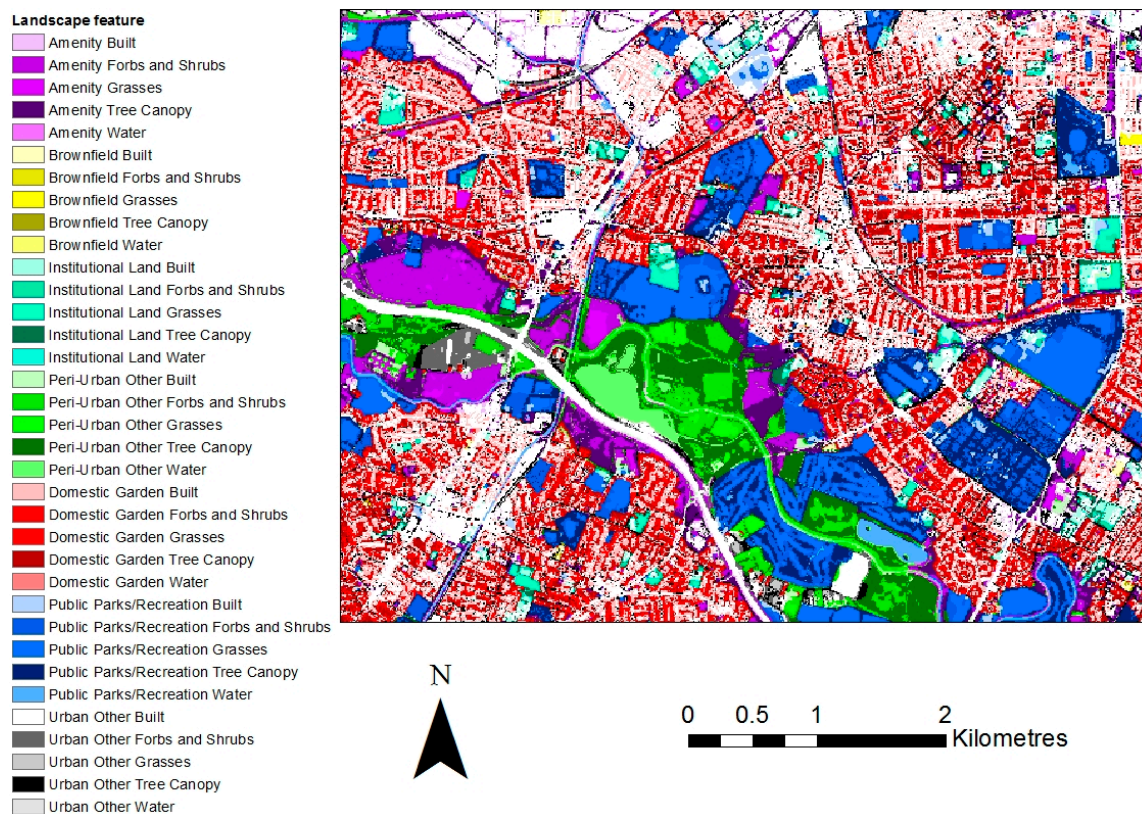


Figure 8. Final classification of the ILM dataset into 35 classes of landscape features (contains Ordnance Survey, 2017; European Space Agency, 2016 and City of Trees 2011 data).

The correlations shown in Table 2 demonstrate the different associations that can be observed between the discrete landscape features identified in the ILM and an indicator of local health status. Of particular note is the strength of association between higher plants and shrubs in private garden settings and years of potential life lost in comparison with, for example, correlations between the same land cover in public parks and this health indicator. Likewise, markedly different correlations can be seen between the latter and discrete land cover types (e.g., forbs/shrubs versus trees) occurring within the same land use (e.g., private gardens).

Table 3 demonstrates the variety in both strength and direction of correlations that occurs between landscape features of the ILM and different measures of connectivity in the landscape. For example, tree cover in the Other Urban category, which primarily describes incidental cover outside of the 18 land use categories of the OS Mastermap Greenspace Layer, shows a significant association with habitat fragmentation (Landscape Division) whilst simultaneously contributing to canopy connectivity. By contrast, tree cover situated in amenity areas bears the inverse relationship with both measures of landscape cohesion.

Table 2. Correlation matrix: selected ILM landscape features with years of potential life lost indicators. * denotes $p < 0.05$.

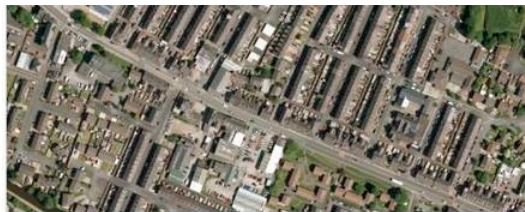
Control Variable: Income Deprivation Score		Public Parks and Recreation Grasses	Public Parks and Recreation Forbs and Shrubs	Public Parks and Recreation Tree Canopy	Amenity Grasses	Amenity Forbs and Shrubs	Amenity Trees	Private Garden Grasses	Private Garden Forbs and Shrubs	Private Garden Trees
Years of potential life lost indicator	Correlation	−0.066 *	−0.074 *	−0.026	−0.102 *	−0.109 *	−0.036	−0.176 *	−0.263 *	−0.132 *
	Significance (2-tailed)	0.007	0.002	0.285	0.000	0.000	0.139	0.000	0.000	0.000

Table 3. Correlation matrix: selected ILM landscape features with landscape division and canopy connectivity (Euclidean nearest neighbour) * denotes $p < 0.05$.

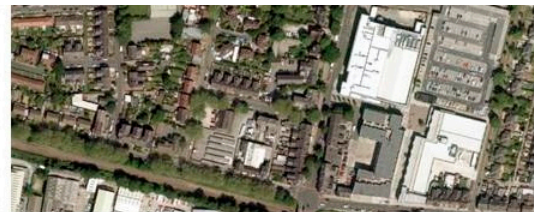
		Peri-Urban Other: Tree Canopy	Brownfield: Tree Canopy	Institutional Land: Tree Canopy	Private Domestic Garden: Tree Canopy	Amenity: Tree Canopy	Public Parks and Recreation: Tree Canopy	Other Urban: Tree Canopy
LD	Correlation Coefficient	−0.095 *	0.062 *	0.082 *	−0.201 *	−0.218 *	0.257 *	0.253 *
	Sig. (2-tailed)	0.000	0.012	0.001	0.000	0.000	0.000	0.000
Canopy ENN	Correlation Coefficient	0.066 *	0.158 *	−0.049*	−0.313 *	0.274 *	0.274*	−0.283 *
	Sig. (2-tailed)	0.007	0.000	0.046	0.000	0.000	0.000	0.000

3.3. Development of the Landscape Typology

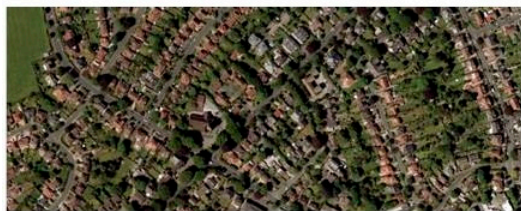
Figure 9 presents examples of the landscape typology resulting from the *k*-means clustering of LSOAs according to cover by landscape features. Table 4 offers descriptive statistics for all eight types, highlighting the differences in mean values of land use, land cover and landscape indices upon which the typology is established. Figure 10 shows their spatial distribution.



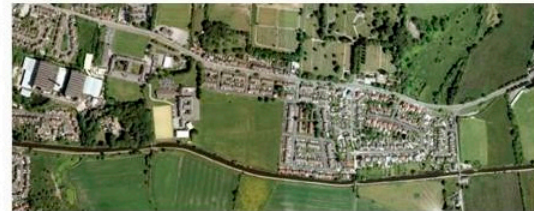
Dense Greyscape



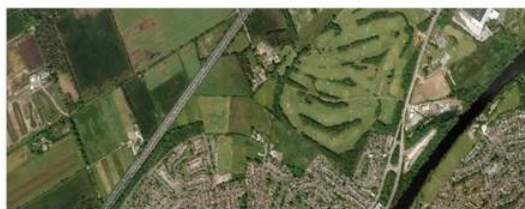
Garden City



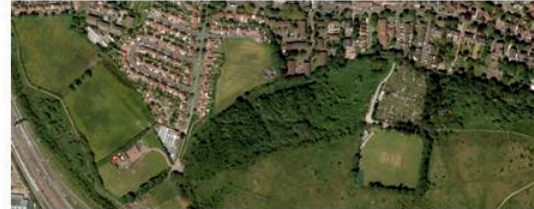
Leafy Residential



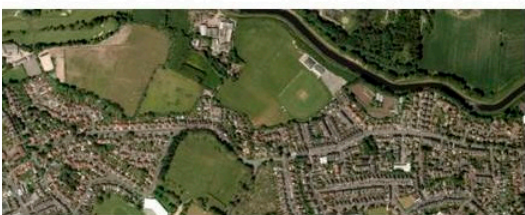
Peri-urban Fringe



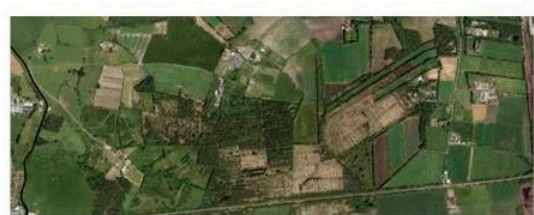
Encapsulated Countryside



Amenity Suburbs



Parklands



Rural Hinterland

Figure 9. The eight landscapes types resulting from the case study area with indicative labels based on the characteristics in Table 4 (Edina, 2017).

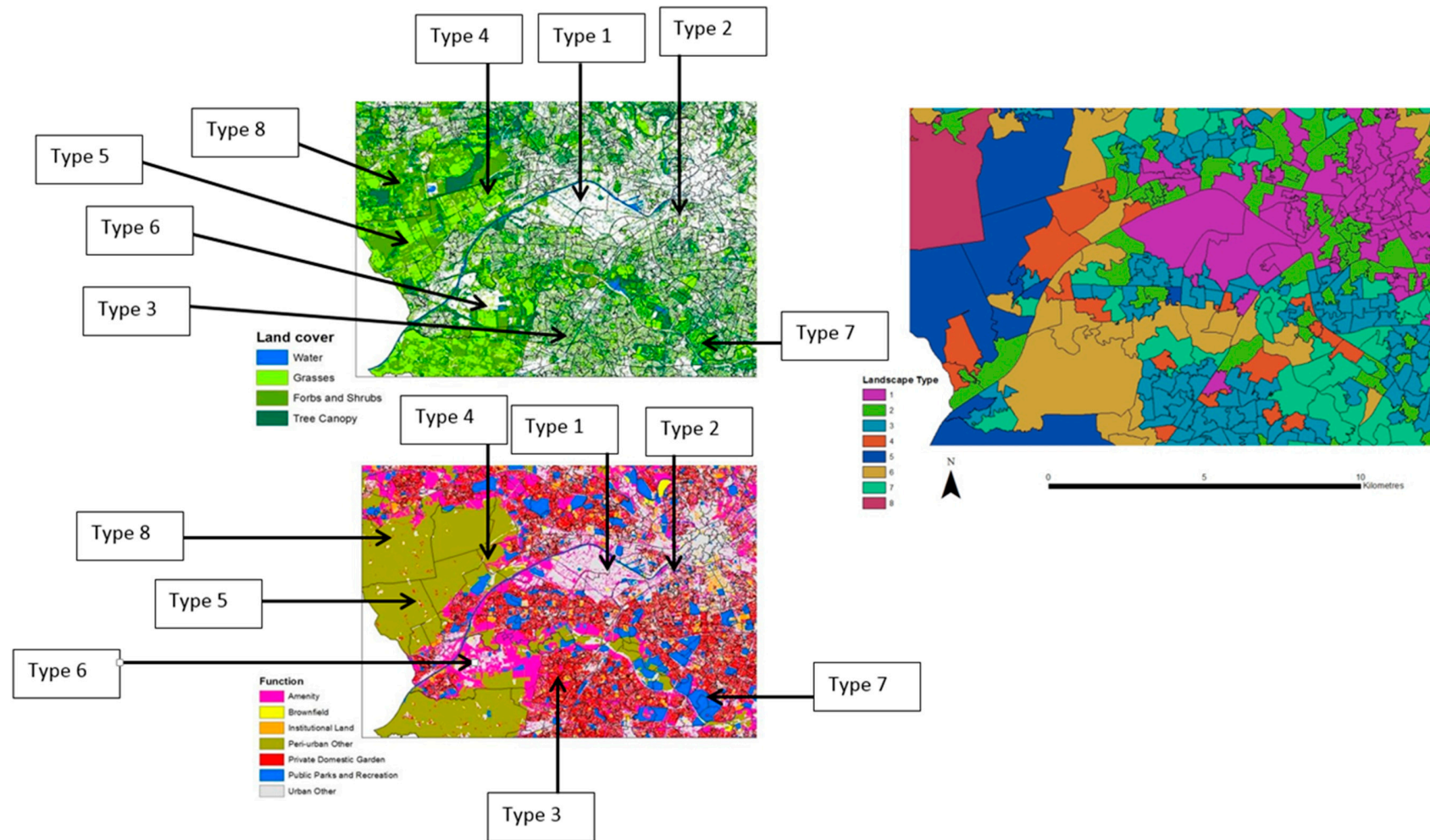


Figure 10. Examples of landscape types in the southwest of Greater Manchester. Source: LSOA boundary data from ONS, 2011. Key: Type 1: Dense Greyscape; Type 2: Garden City; Type 3: Leafy Residential; Type 4: Peri-urban Fringe; Type 5: Encapsulated Countryside; Type 6: Amenity Suburbs; Type 7: Parklands; Type 8: Rural Hinterland.

The distribution of all types included in the final landscape classification throughout the Greater Manchester area is presented in Figure 11.

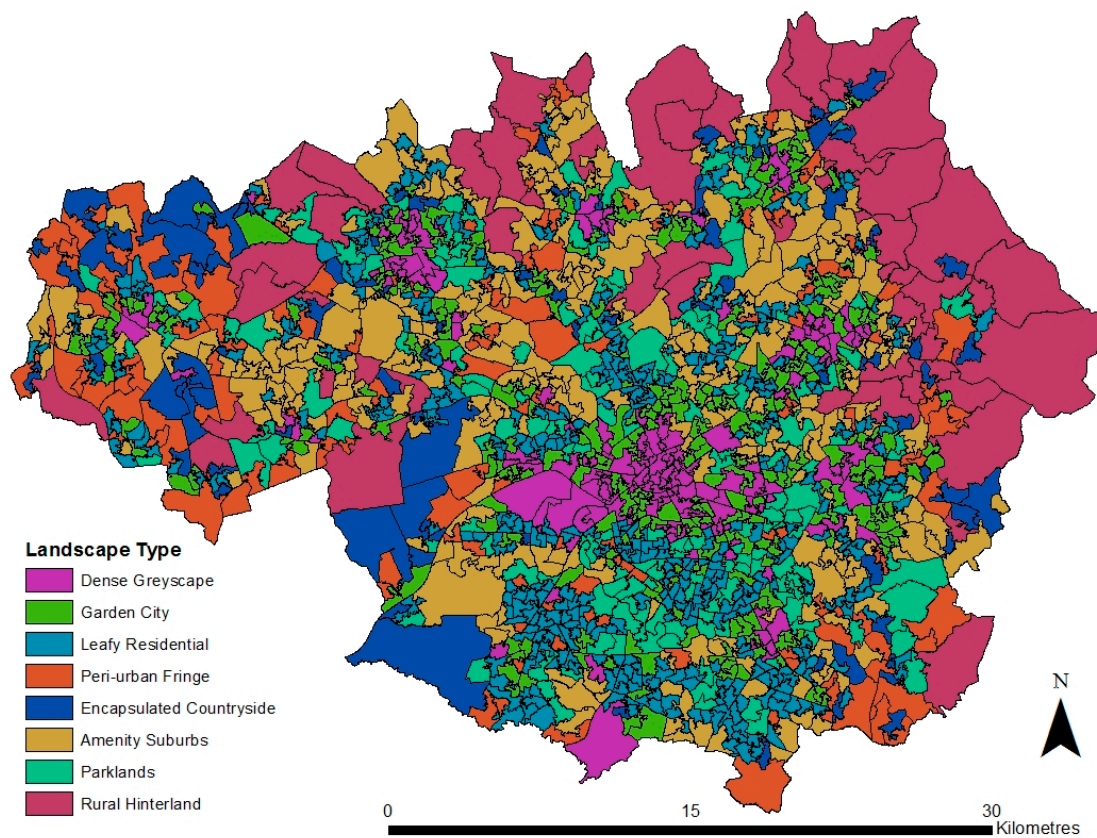


Figure 11. Distribution of LSOAs in Greater Manchester according to their landscape type with indicative labels (see Table 4; source: LSOA boundary data from ONS, 2011).

A comparison of the distribution of index of multiple deprivation scores (IMD) and Shannon’s diversity index (SHDI) according to both the eight landscape types and eight quantile groups for green and blue cover is presented in Figure 12a–d.

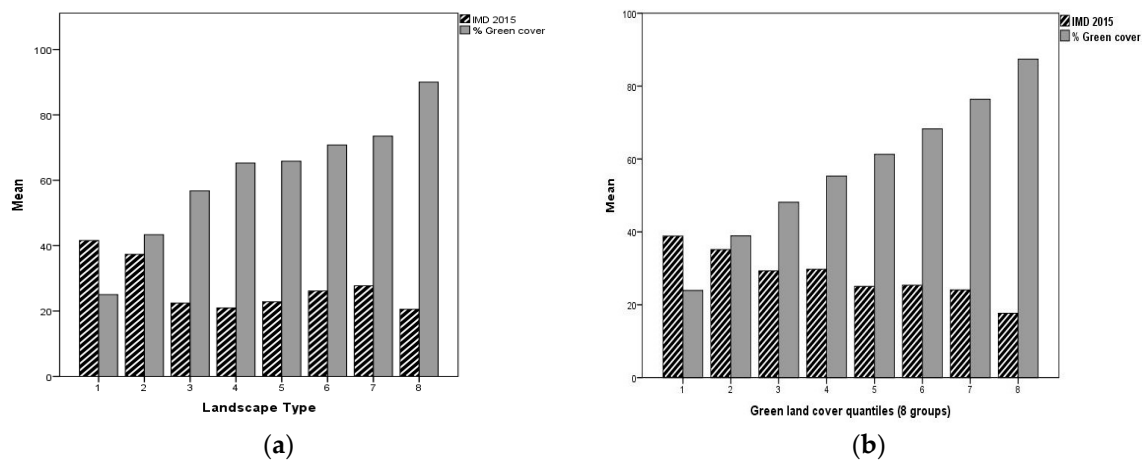


Figure 12. Cont.

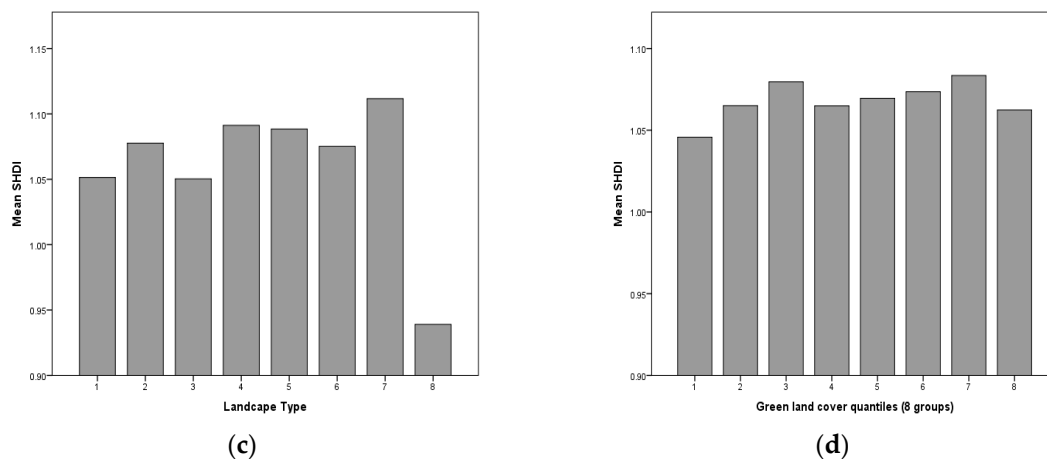


Figure 12. (a): Landscape types arranged in ascending order of green space cover and mean IMD score; (b): Eight quantile groups by percentage green/blue cover and respective mean IMD scores; (c): Landscape types arranged in ascending order of green/blue space cover and mean Shannon’s diversity index; (d): Eight quantile groups by percentage green space cover and Shannon’s diversity index (SHDI). Key: Type 1: Dense Greyscape; Type 2: Garden City; Type 3: Leafy Residential; Type 4: Peri-urban Fringe; Type 5: Encapsulated Countryside; Type 6: Amenity Suburbs; Type 7: Parklands; Type 8: Rural Hinterland.

The association between green and blue space cover and both the SHDI and IMD 2015 indicators for LSOAs in Greater Manchester exhibit markedly different patterns when stratifying LSOAs by landscape type (Figure 12a,c) compared to a quantile stratification of according to green and blue space cover (Figure 12b,d). The negative association that can be observed between IMD and green/blue space cover in Figure 12b stands in contrast to the non-linear trend exhibited when stratifying the study area according to the landscape typology derived from the ILM. Likewise, although in neither case was a linear relationship observed between green and blue space cover and SHDI, the stratification of the study area by landscape type (Figure 12c) reflects greater variance in landscape diversity than that described by a quantile grouping of LSOAs based on green and blue space cover (Figure 12d).

4. Discussion

The methodology presented here succeeds in tackling some of the specific limitations of existing datasets on land use and land cover in a U.K. context through the combination and interpretation of available spatial data towards an integrated landscape approach. For example, the under-representation of green and blue space by the LCM 2015 and Urban Atlas 2012 is reflected in the distribution of percentage cover values per LSOA (Figure 5a–d), which were highly skewed and included many values close to or at zero. In the United Kingdom, the improvement on such data in terms of coverage made by the OS Mastermap Greenspace layer is clear from the much higher frequency of values at greater levels of green space cover for land use (Figure 5c). However, the distribution of land cover within the same dataset (Figure 5d) shows a similar pattern of under-representation as for the UA and LCM. Conversely, the ILM (Integrated Landscape Map) exhibited near-normal distribution for these values. Such differences in distribution highlight the shortcomings of currently available datasets for mapping city region-level green infrastructure, mainly a result of large minimum mapping units and spatial extent. In this paper, we have shown the improvements that can be made through the creation of composite datasets and their use to generate new landscape data, such as in the ILM.

Distinction between datasets in terms of the distribution of green and blue space cover that they report is important as it has implications for research on environmental justice and human well-being. For example, the distribution of percentage green and blue space cover described in Figure 5a–d and Figure 6 shows great variation between datasets. It follows, therefore, that the conclusions drawn from

such patterns, for example on inequalities in green space provision throughout an urban landscape, would likewise vary greatly depending on the data source used. Moreover, given the widespread use of both the LCM and Urban Atlas data programs in environmental research, the analysis developed here is of particular note and highlights the degree of uncertainty created when large minimum mapping units are employed.

Figure 7a–d highlight the inconsistencies that result in the variability of both mapping units and terminology employed by the UA 2012 and UK LCM 2015. The OS Mastermap Greenspace layer is a significant improvement in terms of detail and interpretability and, through its incorporation in the ILM, the latter is able to identify accurately small pockets of land such as allotments and community growing spaces and their land cover. Under the classification schemes of the UA and LCM, however, it is not possible to identify such sites as consisting of green and blue space at all. Such spaces provide important social [69–71] and ecological [71–73] benefits and present a pertinent example of how smaller but highly productive urban green spaces have hitherto been overlooked in urban mapping classification schemes. The ability to capture such spaces and their associated landscape features is a key improvement made possible through the mapping approach developed here.

The final classification scheme of the ILM into seven thematic land use types coupled with five land cover values revealed that individual landscape features exhibit significant and unique associations with both ecological and socioeconomic indicators (Table 2). The stronger correlation exhibited between the years of potential life lost indicator with individual landscape features (e.g., higher plants and shrubs in private gardens) over others (e.g., amenity trees), controlling for income, presents a landscape approach as a promising avenue for investigations into quality of life in urban areas. Therefore, the capture and classification of landscape features appears to be a valid approach to investigating social–ecological relationships and represents a key consideration in landscape assessments of both social and ecological dynamics in urban areas. The preliminary relationships explored herein suggest a significant improvement to mapping urban landscapes through the current study.

The results of the *k*-means clustering of LSOAs into landscape types demonstrated both visually (Figures 9–11) and statistically (Table 4, Figure 12) that combining data on land cover and land use, even when limited to a small number of categories, offers an effective means to describe urban environments using only a minimal amount of geoprocessing time. Such analyses can be conducted over large areas and more frequently than has been possible in the past. There are further datasets that can be used to replicate some of the local datasets used here, such as the U.K. National Tree Map produced via Lidar although, as in the case of the latter, not all of these are open-source. Table 4 shows the range of combinations of land use and land cover that can be observed for LSOAs in the landscape of Greater Manchester as an example of a large urban city region. The results illustrate the heterogeneity in urban landscapes, which can be captured and used in a data-driven delineation of neighbourhood types. Figure 12a–d demonstrate that classification of neighbourhoods according to these combinations may reveal greater levels of nuance in the associations between landscape configurations and social–ecological conditions. The simple stratification of the study area according to overall green cover was closely mirrored by an inverse trend in IMD score (Figure 12b). However, stratifying by a typology based on amount, use and cover revealed that IMD was sensitive to configurations of green space qualities as well as total cover. This suggests that a simple one dimensional metric such as overall percentage green space, as used in numerous social–ecological health and well-being studies to date, may fail to capture the true relationship between landscape and social–ecological conditions.

The ILM therefore provides a versatile mapping approach to evaluating the relationship between physical, socioeconomic, health and landscape characteristics. The nature of the final classification of Greater Manchester presented here, combining cover and a designation of use, offers the opportunity to explore a range of combinations reflecting urban form as well as investigating the cover and distribution of individual landscape features (e.g., residential trees). An assessment of their contribution to factors

such as landscape connectivity in urban environments may, thereby, be permitted, which offers greater interpretive power than coarse density metrics such as percentage green space alone. For example, the positive relationship between domestic green cover and both canopy connectivity and landscape cohesion seen in Table 3 presents the former as a potentially important structural component and a landscape feature worthy of further exploration and consideration in planning policy. Conversely, the ability of the ILM to delineate landscape features, combining data on use and cover reveals that individual cover types e.g., tree cover can exhibit contradictory relationships with landscape fragmentation depending on the land use in which they are situated (e.g., amenity versus private garden functions, Table 3).

Given the known relationship that exists between the natural environment, socioeconomic conditions and health, the use of composite datasets such as the Integrated Landscape Map presented here, and the analyses that are permitted, may contribute to sophisticated landscape-focused assessments of factors influencing urban well-being. For example, landscape types that exhibit local connectivity but consist of smaller patches of principally domestic green space (e.g., Leafy Residential) may, due to their distribution, provide important connectivity to larger open patches. Therefore, the creation of landscape types, and mapping of their spatial distribution may also facilitate studies across scales. Knowledge of the spatial contiguity of landscape features and types may open up analyses of spatially dependent relationships where non-linear approaches are required to understand social–ecological processes [74]. Moreover, the creation of landscape types could be tailored to particular research questions by including a range of variables of interest selected by the analyst. The method presented here represents a template for landscape explorations of social–ecological dynamics, the strength of which stems ostensibly from its ability to combine information on land use and land cover but may ultimately be applicable to a wide range of datasets and research agendas. The real merit of applying such an approach lies in the viewing of highly managed landscapes as lived environments. The consideration of land use, land cover and socio-geographic elements, in combination rather than exclusion, supports a social–ecological perspective that could be applied to the characterisation of city regions and their catchments around the world. In the coming years, the emergence of even finer sub-10 m spatial resolution imagery should allow even more refined assessments, both of landscape type and also of associated ecosystem and landscape characteristics. The integration of globally available, open-source and high-resolution imagery—such as that used here—with accurate land use data is therefore becoming increasingly viable. National land survey agencies provide land use data across the globe and, in a European context, for example, many datasets are freely available [75], further supporting the replication of the approach presented here.

5. Conclusions

The creation of a spatial dataset incorporating freely available remote sensing data and cartographic layers is a useful step towards a green infrastructure dataset for a wide range of uses for research, policy and practice. The work in this paper takes this dataset further through the development of a characterisation that encompasses elements of both land cover (form) and land use (function) culminating in a new urban landscape-oriented dataset. We have generated indicative labels based on our case study results. Labels can be modified to align with other country contexts, i.e., in line with the results for other cases study applications and to account for specific policy/practice perspectives, i.e., to give classifications local meaning and relevance. The landscape-oriented dataset provides insight into relationships between landscape features and social–ecological factors relevant to research into health and well-being and, moreover, does so in a way that goes beyond crude singular (i.e., percentage green/blue space or biomass measures, such as NDVI) or dichotomous (land use versus land cover) descriptions of landscape quality. In the case study city region, we have demonstrated that the use of high-resolution data was effective in capturing total green and blue cover in greater detail than other available sources (LCM 2015, Urban Atlas 2012 and OS Mastermap Greenspace 2017 datasets used for comparison). The associated methodology can be replicated in other urban areas, giving the potential

to generate urban landscape characteristics that are meaningful in the context of social–ecological systems and that help with consideration of the quality of the natural environment in analyses of health and well-being. To this end, the typology developed here, as described in Table 4, provides a promising point of departure that could be used as a template in city regions across the globe.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2073-445X/7/1/17/s1>.

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