USING THE URBAN LANDSCAPE MOSAIC TO DEVELOP AND VALIDATE METHODS FOR ASSESSING THE SPATIAL DISTRIBUTION OF URBAN ECOSYSTEM SERVICE POTENTIAL

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Contents

List of Figures

Chapter 2

Chapter 3

Chapter 4

Chapter 5

Chapter 6

Chapter 7

Chapter 8

Chapter 9

List of Tables

Chapter 6

Chapter 7

Chapter 8

Chapter 9

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Abbreviations

ANGSt	-	Accessible Natural Greenspace Standards
ANN	-	Artificial Neural Networks
ARIES	-	Artificial Intelligence for Ecosystem Services
CICES	-	Common International Classification of Ecosystem Services
DBH	-	Diameter at Breast Height
DEFRA	-	Department of Environment, Food and Rural Affairs
DN	-	Digital Number
DSM	-	Digital Surface Model
DTM	-	Digital Terrain Model
ED	-	Edge Density
ENN	-	Euclidean Nearest Neighbour
ETM+	-	Enhanced Thematic Mapper (Landsat)
GIS	-	Geographic Information Systems
GLUD	-	General Land Use Database
IBI	-	Index-based Built-up Index
IMD	-	Index of Multiple Deprivations
INVEST	-	INtegrated Valuation of Ecosystem Services and trade-offs
ITN	-	Integrated Transport Network
LiDAR	-	Light Detection And Ranging
LSI	-	Landscape Shape Index
LSOA	-	Lower Super Output Area
MA	-	Millennium Ecosystem Assessment
MLC	-	Maximum Likelihood Classification
MNDWI	-	Modified Normalised Difference Water Index
MPS	-	Mean Patch Size
MSAVI	-	Modified Soil Adjusted Vegetation Index
NDBI	-	Normalised Difference Built-up Index
NDBaI	-	Normalised Difference Bareness Index
NDVI	-	Normalised Difference Vegetation Index
NDWI	-	Normalised Difference Water Index
NIR	-	Near Infra Red
NLUD	-	National Land Use Database
NPPF	-	National Planning Policy Framework
OA	-	Output Area
OAC	-	Output Area Classification
OS	-	Ordnance Survey
OSMM	-	Ordnance Survey MasterMap
PD	-	Patch Density
PLAND	-	Percentage Land Cover
PR	-	Patch Richness
PSSD	-	Patch Size Standard Deviation
SAVI	-	Soil Adjusted Vegetation Index
SCC	-	Salford City Council
SHDI	-	Shannon's Index of Diversity
SIDI	-	Simpson's Index of Diversity
SMA	-	Spectral Mixture Analysis
STAR	-	Surface Temperature and Runoff (Tool)
TEEB	-	Economics of Ecosystems and Biodiversity

TM	-	Thematic Mapper (Landsat)
UI	-	Urban Index
UKNEA	-	United Kingdom National Ecosystem Assessment
UMT	-	Urban Morphology Types

Abstract

The benefits that humans receive from nature are not fully understood. The ecosystem service framework has been developed to improve understanding of the benefits, or ecosystem services, that humans receive from the natural environment. Although the ecosystem service framework is designed to provide insights into the state of ecosystem services, it has been criticised for its neglect of spatial analysis.

This thesis contains a critical discussion on the spatial relationships between ecosystem services and the urban landscape in Salford, Greater Manchester. An innovative approach has been devised for creating a landscape mosaic, which uses remotely-sensed spectral indices and land cover measurements. Five ecosystem services are considered: carbon storage, water flow mitigation, climate stress mitigation, aesthetics, and recreation. Analysis of ecosystem service generation uses the landscape mosaic, hotspot identification and measurements of spatial association. Ecosystem service consumption is evaluated via original perspectives of physical accessibility through a transport network, and greenspace visibility over a 3D surface.

Results suggest that the landscape mosaic accuracy compares favourably to a map created using traditional classification methods. Ecosystem service patterns are unevenly distributed across Salford. The regulating services draw from similar natural resource locations, while cultural services have more diverse sources. The accessibility and visibility analysis provides evidence for the importance of urban trees as mitigators of 'grey' views, and urban parks as accessible producers of multiple services. Comprehensive ecosystem service analysis requires integration of quantitative and qualitative approaches. Evaluation of spatial relationships between ecosystem services and the physical landscapes in this thesis provides a practical method for improved measurement and management of the natural environment in urban areas. These findings can be used by urban planners and decision makers to integrate ecological considerations into proposed development schemes.

1. Introduction

1.1. Context of research

According to United Nations statistics, the proportion of people residing in urban areas has exceeded 50% and is estimated to grow to 66% by 2050 (UN DESA, 2012). This trend of rising urbanisation is leading to increased population densities in urban areas across the world and is placing mounting pressure on already limited resources such as energy, water and food (The World Bank, 2012). Ecosystem services are defined by the Millennium Ecosystem Assessment (MA) as the direct benefits people obtain from ecosystems (MA, 2005). Urban greenspaces provide a range of ecosystem services and benefits vital for human physical, social and mental well-being (MA, 2005). However, these spaces are being sacrificed to build residential estates and associated commercial, industrial and infrastructure facilities (Pacione, 2003). This is resulting in an unsustainable degradation of quality of life and subsequent physical and mental health. Improved understanding of the ecosystem services that urban greenspaces contribute could improve this situation by increasing decision maker awareness of the magnitude and distribution of benefits produced by greenspaces across an urban landscape (MA, 2005).

Urban areas are key sites for evaluating ecosystem services as they represent the highest demand for ecosystem services through high urban densities, and the most fragmented and dynamic landscapes through intensive human activity (Bolund and Hunhammar, 1999). This thesis evaluates the practicalities of measuring ecosystem services using properties of the physical urban landscape mosaic of land cover and land use to pose new questions about how patterns of landscape features relate to benefits provided by the natural environment and their contribution to human well-being. Original methods have been derived to create a flexible and autonomous method of classifying and characterising the landscape. Further, the novel inclusion of 3D data and methods of spatial analysis have been introduced to provide new insights into the distribution of ecosystem services across an urban environment. In particular, this is used to provide new perspectives on how cultural ecosystem services such as aesthetic quality can be quantitatively measured across a landscape.

1.2. Ecosystem services in the urban environment

The ecosystem approach and the ecosystem services framework have emerged as a method for gaining a holistic perspective of underlying issues critical for management of greenspaces (Haines-Young and Potschin, 2008; Hubacek and Kronenberg, 2013; UKNEA, 2014). Ecosystem services represent a more sophisticated indicator than basic bio-physical landscape factors, as they are measured by landscape properties and by their subjective value to humans (Brown *et al.,* 2007; Burkhard *et al.,* 2012). This makes ecosystem services powerful, as they enable analysis of flows through a city, allowing a deeper understanding of greenspace evaluation (Bennett *et al.,* 2009). However, Eigenbrod *et al.,* (2011) state that this sophistication also produces challenges in developing and validating necessarily complex indicators. For example, the scientific community is still struggling to develop adequate spatial methods for ecosystem service assessment studies finer than national or regional scales (Fisher *et al.,* 2009; Potschin and Haines-Young, 2011). Further, Eigenbrod *et al., (*2010a) suggest that a lack of primary data for measurement often results in over-reliance and poor modelling of proxy data and consequent generalisation and extrapolation errors.

To address these shortfalls, this research develops a rapid, flexible landscape classification and characterisation from which to measure ecosystem services (Chapter 5). Remote sensing imagery, vector features and geodemographic datasets are used to integrate the three dimensional urban environment. To evaluate the suitability of ecosystem services for understanding the different qualities of urban greenspaces, indicators for the generation of five urban ecosystem services are developed and validated in Chapter 6, while spatial relationships between multiple ecosystem services and the landscape mosaic are evaluated through the novel use of spatial analysis drawn from other academic disciplines (Chapter 7). This is followed by evaluation of physical accessibility and visibility of urban greenspaces and ecological hotspots within a city as a proxy for measuring ecosystem service consumption (Chapter 8).

The proposed multidimensional landscape characterisation framework offers a uniquely spatial perspective on how key ecosystem services are generated and potentially consumed, accounting for spatial thresholds and external influences. This can be applied to measurement and mapping of potential ecosystem service provision hotspots across a range of urban areas to deepen our understanding and for comparison between and within cities to determine rankings of quality, identify areas in need of improvement and inform policy (Pacione, 2003). Additionally, further analysis could focus on inequalities of access by minority communities by studying how urban green spaces and ecosystems are being used and valued differently by different individuals and communities (Daw *et al.,* 2011).

1.3. Thesis structure

Chapter 2 contains a literature review and the objectives of research (Section 2.7). Chapter 3 contains a review of the methods used. Due to the complexity and diversity of methods used throughout this thesis, individual methodologies are included within each research chapter. Chapter 4 contains a detailed account of datasets and pre-processing. Chapters 5 to 8 are the research chapters containing four themes of research outlined above. Finally, Chapter 9 is a concluding chapter that discusses underlying themes, potential practical applications and directions for future research.

2. Literature Review

2.1. Introduction

This chapter contains a critical review of themes relevant to the issues highlighted in the previous chapter. The suitability of ecosystem services as a framework to measure benefits to humans is discussed in Section 2.2. Requirements for measuring ecosystem service generation across space are discussed in Section 2.3. This is followed by an evaluation on the potential for using accessibility as an indicator for ecosystem service consumer demand based on concepts of hedonic pricing (Section 2.4). Observer visibility is discussed as an approach to complement physical accessibility to better incorporate cultural service consumption. Based on these themes, relationships between ecosystem services and the physical landscape upon which they lie are evaluated before relevant land cover classification and landscape characterisation methods are critically reviewed (Section 2.5). Finally, gaps in knowledge and questions raised throughout the review are encapsulated into a research aim and subsequent research objectives (Section 2.6).

2.2. The ecosystem services framework

The ecosystem approach has emerged as a framework for elucidating measurements of natural resource generation based on a wider understanding of how nature works as a holistic system, valuation of ecosystem services and the inclusion of humans as consumers of ecosystem services and agents of ecosystem management (Potschin and Haines-Young, 2011). The ecosystem approach provides a holistic framework that considers wider ecosystems for a deeper understanding of the benefits provided by the natural environment (Defra, 2013). It has gained popularity in recent years as an anthropocentric framework that enables assessment of the surrounding environment (Seppelt *et al.,* 2011). The ecosystem service approach is based on twelve principles that cover four broad themes as demonstrated in Figure 2.1 (UKNEAFO, 2014).

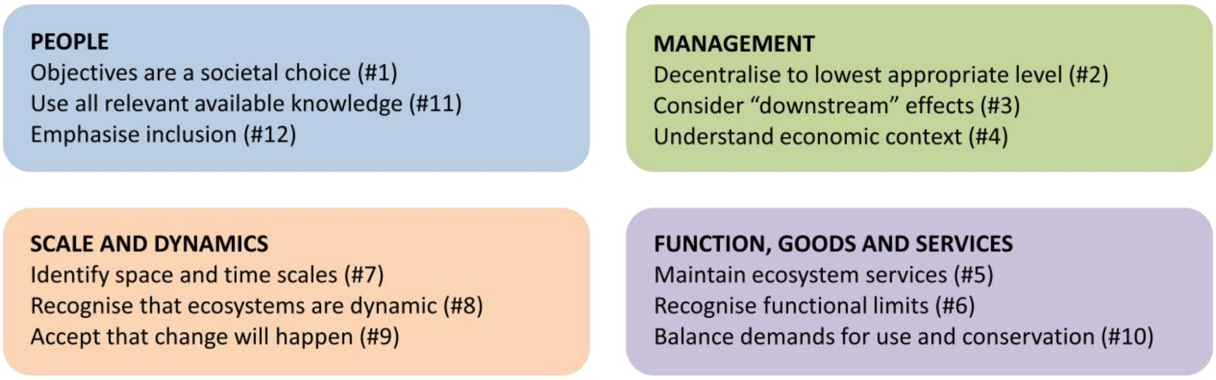

Figure 2.1. The twelve principles of the Ecosystem Approach grouped into four themes (adapted from UKNEAFO, 2014)

The UKNEAFO (21014) suggests that the ecosystem service framework can be used to operationalise the ecosystem approach. The ecosystem services framework provides a means to make measurements within the ecosystem approach and contributes towards principles of the ecosystem approach across each of the four themes outlined in Figure 2.1. The framework primarily contributes towards the theme of function, goods and services as it represents a method of measuring ecosystem production. These measurements influence the other three ecosystem approach themes of people, scale and dynamics, and management by providing a spatial framework for the management and prioritisation of ecosystem service production and consumption, and for monitoring change over time. The growing importance of the ecosystem service framework is reflected by its integration into the UK government's Natural Environment white paper (Defra, 2014) and National Planning Policy Framework (NPPF) (DCLG, 2012). However, ecosystem services are currently only briefly mentioned and have yet to play a central role in spatial planning and decision making. Conceptualised as a system, the components are inputs, outputs and processes within a wider complex system and the interactions between these components (Dale, 1970). In ecological terms, the inputs are biophysical and perceived psychological properties of the surrounding environment. Outputs are the ecosystem services, goods and benefits that ecosystems generate in contribution to human health and well-being (MA, 2005). By assessing inter-related flows of ecosystem services through a city, a deeper understanding of greenspace evaluation can be achieved (Bennett *et al.,* 2009). However, research into urban ecosystem services is still relatively young and there are current calls to improve the spatial aspect of ecosystem service research (Haines-Young and Potschin, 2009; Haase *et* *al.,* 2014a). The following sections contain an evaluation of the ecosystem service framework for measuring human well-being through the benefits that are produced by nature. This includes a discussion of ambiguities relating to the definition (Section 2.2.1) and classification (Section 2.2.2) of ecosystem services.

2.2.1. Ecosystem service definition

To date, Schroter *et al., (*2014) suggests that ecosystem service literature has been characterised by disputes over definition and classification. The holistic and multidisciplinary nature of ecosystem service research means that different definitions and frameworks have been recommended across a range of academic and practical disciplines to incorporate features such as efficient economic accounting (Boyd and Banzhaf, 2007; TEEB, 2010), spatial coverage (Bastian *et al.,*2012) and service exclusivity (Fisher *et al.,*2009). This is because the most commonly used definition, provided by the Millennium Ecosystem Assessment (MA) (2005) The MA broadly defines ecosystem services as the direct benefits people obtain from ecosystems, and that of Costanza *et al.,* (1997) were intentionally flexible and open to interpretation (Costanza, 2008). Seppelt *et al.,* (2011) suggest that this is problematic because it affects research decisions regarding data collection and methods of measurement and obstructs translation of results and discussion across scientific disciplines. Further, Nahlik *et al.,* (2010) argue that this has threatened the integrity of ecosystem services as a useful and valid concept. Despite this, the core concept of human benefit has remained constant and changes in definition have remained relatively subtle (Kline, 2009). Costanza (2008) further states that the evolution of definitions is characteristic of its immaturity as a concept, however there are concerns that without a conclusion common to wider audiences and available for practical use, the 'ecosystem services framework' may become obsolete (Sagoff, 2011).

Much of this confusion stems from the fact that ecosystem services are more complex ecological indicators than basic biophysical landscape factors. This is because they are also measured by their value to humans (Brown *et al.,* 2007; Burkhard *et al.,* 2012). This is evidenced by Costanza *et al.,* (1997) who in a seminal paper, define ecosystem services as "the products and benefits received by humanity", and distinguished them from ecosystem functions, defined as "intrinsic properties of host habitats and ecosystems" (Costanza *et al.,* 1997, p253). In making this distinction, they introduced the notion that ecosystem services were not only produced by ecosystem functions, but were also defined by human well-being through consumption or experience.

The cascade model from the Common International Classification of Ecosystem Services (CICES) is presented in Figure 2.2 (Haines-Young and Potschin, 2010). The model is designed to unify previous ecosystem service typology systems. CICES incorporates features from the MA, United Kingdom National Ecosystem Assessment (UKNEA) and The Economics of Ecosystems and Biodiversity initiative (TEEB). This provides a platform for ecosystem studies at a range of scales, but adding tiers to the hierarchy, which may blur distinctions between intermediate and final services. Further, Costanza (2008) suggests that this model still requires adaptation to include issues of scale, ownership and exclusivity. However, the cascade model in Figure 2.2 acts as a useful framework for the ecosystem service approach and as a tool for linking environmental assessment to economic valuations. The titles in the five cascading boxes follow a gradient from left to right, of factual and easily measureable quantities to subjective, value-led benefits. In particular, there is contention regarding the titles of the third and fourth columns: services and benefits. Costanza *et al.,* (1997) and Bastian *et al.,* (2012) consider ecosystem services to be the benefits to humans, produced by ecosystem functions, but the general consensus is that ecosystem benefits are the final outputs created from the necessary ecosystem services (Boyd and Banzhaf, 2007; Fisher *et al.,* 2009; CICES, 2013).

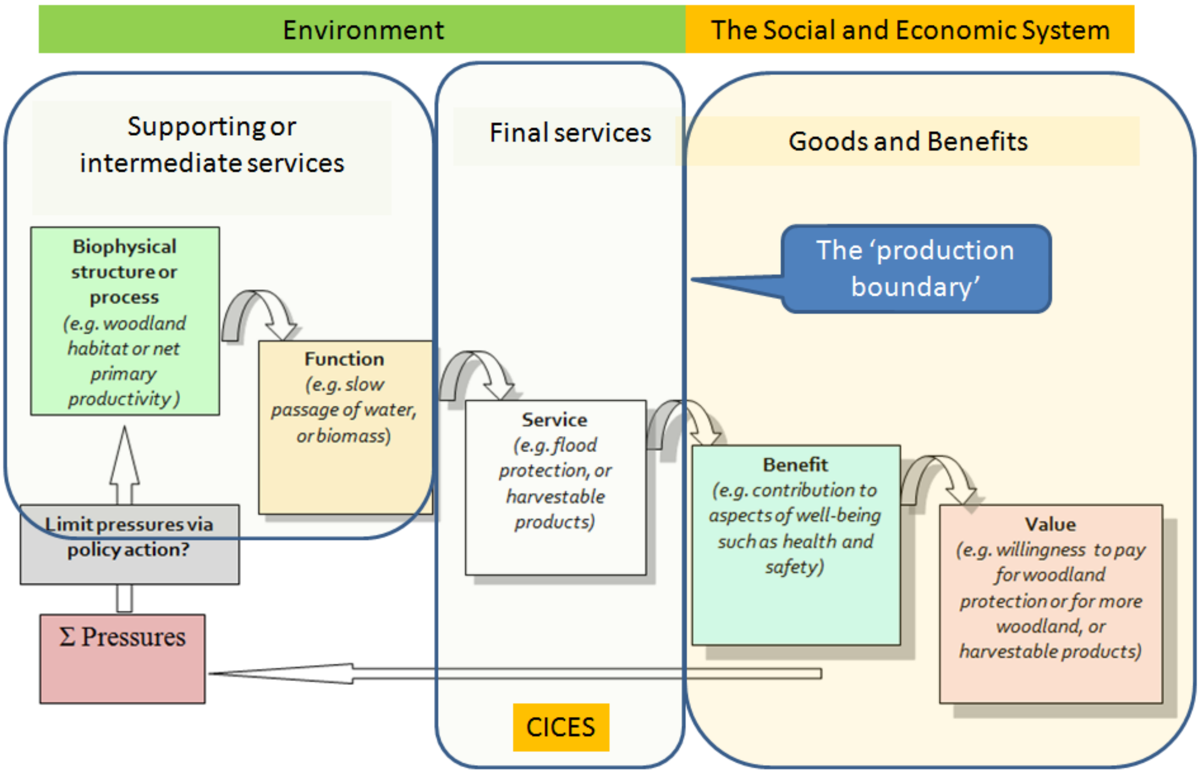

Figure 2.2. Ecosystem service cascade model (CICES, 2013).

Due to difficulties with collecting data for primary measurements of ecosystem service consumption, de Groot *et al.,* (2002, p394) suggest that emphasis should be placed on 'the capacity of natural processes and components to provide goods and services that satisfy human needs, directly or indirectly'. This implies that ecosystem services are actually potential benefits rather than actual measurements. In line with this, Haines-Young and Potschin (2010) separated ecosystem services and benefits by suggesting that ecosystem services maintain their connection with the functions that produce them, while ecosystem benefits do not necessarily. For example, Boyd and Banzhaf (2007) cite angling as a recreational ecosystem benefit, produced via ecosystem services such as a clean water body, aesthetically pleasing surroundings and a target fish population. Through their connection with the landscapes that create them, ecosystem services offer a more useful concept for scientific measurement than ecosystem benefits, which are heavily value-led and can be intangible in nature, relying on experiences and feelings Haines-Young and Potschin (2010). This also fits with critiques cited by TEEB (2010), who claim that separating intermediate and final services risks double counting of services. TEEB (2010) is an international initiative emphasising the economic costs of biodiversity loss, adopting purely economic valuations. TEEB acknowledge that cultural and spiritual valuations can be relevant, but they argue that economic valuation should be used as a tool to guide biodiversity management, stating easier interpretation and communication to decision makers (TEEB, 2010). This is further reinforced by Hölzinger *et al.* (2013) who prepared a comprehensive ecosystem service assessment for Birmingham City Council. Their assessment provided evidence for Birmingham's Green Living Spaces Plan, which seeks to value Birmingham's natural resources and features following UKNEA methodologies. Hölzinger *et al.* (2013) aimed to calculate the total economic value of as many ecosystem services as possible, citing that rather than being a price-tag for nature, the monetary value is better interpreted as a common denominator for measurement across ecosystem services. However, they also acknowledge difficulties in providing comparative measurements where economic value is not relevant.

The UKNEA (2011), classify ecosystem services by separating ecosystem processes (underlying ecological functions), intermediate services, and final services - Potschin and Haines-Young's (2011) 'benefits'. The UKNEA represents one of the first sub-global assessments after the MA and has been strongly influenced by research commissioned by the Department of Environment, Food and Rural Affairs (DEFRA) (UKNEA, 2011). The UKNEA suggests that the strict economic use of terms such as 'service' and 'goods' reinforces a bias towards economic measurements and cost-benefit analysis. Conversely, movement away from economics allows more flexibility in classification and definition. Fisher *et al.,* (2009) assert that ecosystem services are "aspects of ecosystems utilised (actively or passively) to produce human well-being" (Fisher *et al.,* 2009, p645). More recently, Bastian *et al.,* (2012, p9) have made this more explicit by defining ecosystem service as "the actually used or demanded contributions made by ecosystems and landscape for human benefit" to distinguish potential capacities from theoretical maxima. These potential services still need to be measured, but measurements can be made up to theoretical maxima. Bastian *et al.,* (2012) suggest that this enables direct relationships that are easier to quantitatively measure to be made with the ecosystem properties that produce these services. This allows analysis of more complex and subtle ecosystem services as well as non-monetary valuations, which better aligns with the underlying holistic principles of the ecosystems approach. Similarly, in tackling difficulties with defining and measuring less tangible ecosystem services, the UKNEAFO (2014) suggests that these services should instead be thought of as environmental settings where physical, social or mental states are changed through the cultural benefits that are consumed or experienced. Much of the debate around these nuances depends on the purpose of study.

2.2.2. Ecosystem service classification systems

Ecosystem service classification provides a structured framework for further scientific analysis (Costanza, 2008). These classification systems have evolved over the years as demonstrated in Figure 2.3.

Building on a list of seventeen services produced by Costanza *et al.,* (1997), subsequent authors have attempted to categorise ecosystem services into distinct classes: the provision of life-sustaining materials, the regulation of the surrounding ecological environment and the requirement for amenable social and psychological experiences with nature. Much research has been conducted into provisioning and regulating services (shaded in orange and green in Figure 2.3), but less has been completed for cultural services, due to challenges finding proxy indicators for measurement and validations (Norton *et al.,* 2012). Habitat services appear in the classifications of de Groot *et al.,* (2002) and TEEB (2010), but do not appear in other classifications. These services are key for consideration of biodiversity and sustainability (Jordan *et al.,* 2010), but within the ecosystem services framework, there are current debates on whether wildlife and biodiversity are services that directly benefit humans or not. In line with Figure 2.2, Bastian *et al.,* (2012) describe a supply/demand paradigm to demonstrate the relationships between the objective properties of the environment, the capacities to produce ecosystem services and the actual consumption or benefits gained. But the model does not acknowledge spatial inequalities.

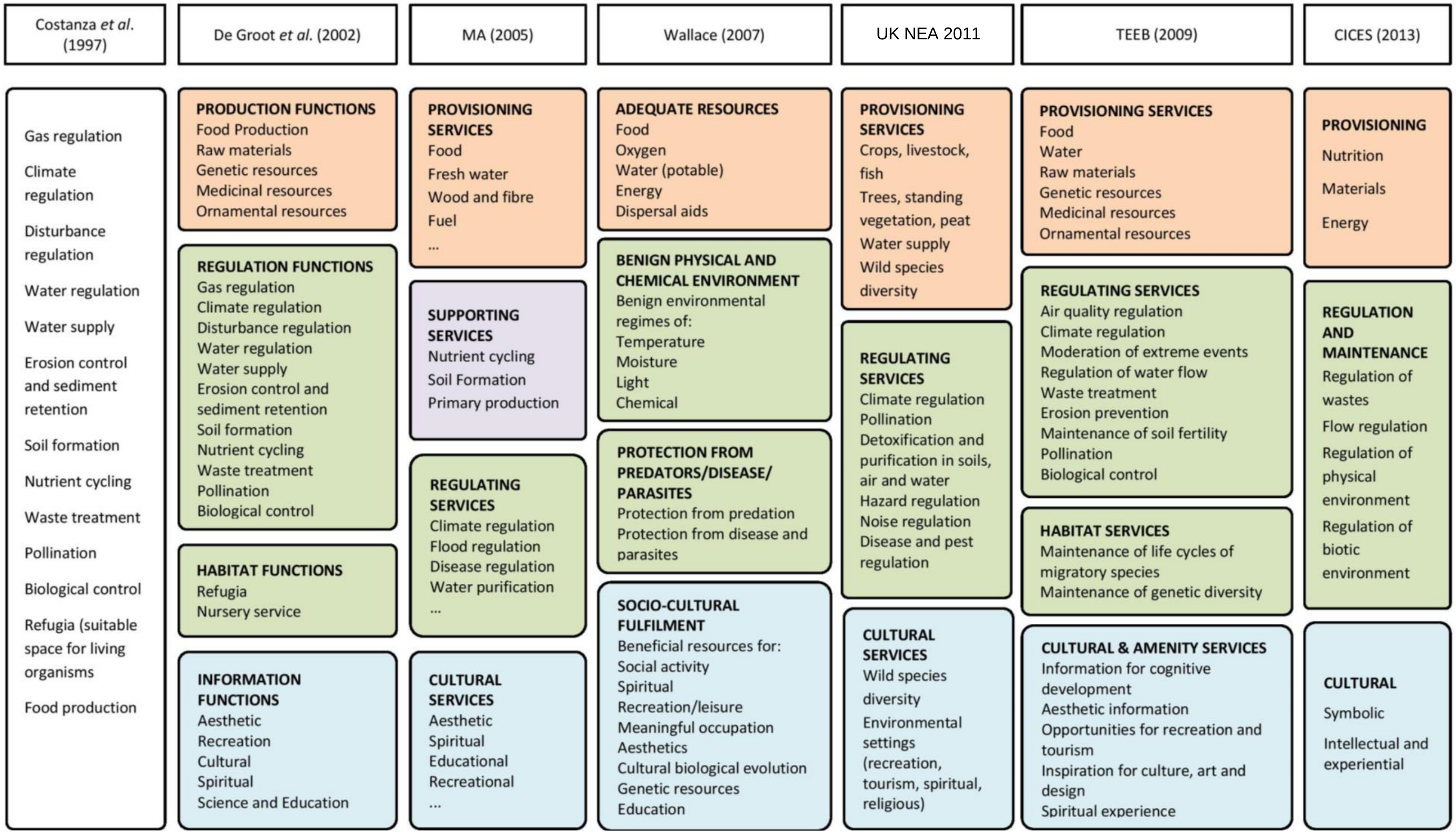

Figure 2.3. Evolution of ecosystem service classifications. The colours represent the evolutionary path of the supporting (purple), provisional (orange), regulation and maintenance (green) and cultural services (blue) and are taken from the CICES classification (Haines-Young and Potschin 2010).

Acknowledgement of an inequality in supply and demand across space allows for an amendment to the model produced by Bastian *et al.,* (2012) (Figure 2.4). This allows for a maximum demand or accessibility threshold for service consumption to match the current maximum capacity for service generation, which due to spatial patterns rarely overlaps perfectly. This provides balance to the model produced by Bastian *et al.,* (2012), and emphasises the potential value in approaching ecosystem service research from a value-led direction rather than the more traditional ecosystem property-based measurements. However, Alessa *et al.,* (2008) state that measurements of demand, usage or value as perceived by humans is societal and subject to change between communities, stakeholders and individuals. This is a challenge when ecosystem services cannot explicitly be measured and boundaries between columns are blurred further (Burkhard *et al.,* 2012). The two 'potential' columns provide a relevant, balanced framework for scientific study as data collection and modelling becomes easier when dealing with theoretical capacities than actual human-valued consumption.

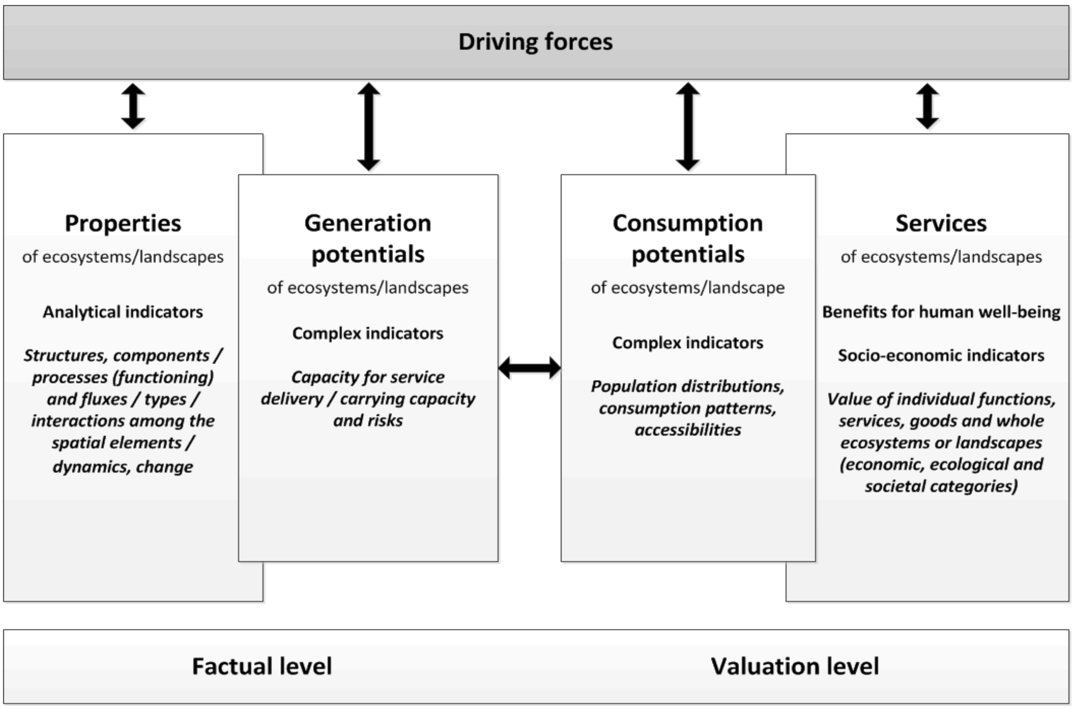

Figure 2.4. Revised ecosystem service framework (Author's own - amended from Bastian et al., *2012).*

Current debates still surround the definitions and classifications of ecosystem services. A number of perspectives and frameworks have arisen to create ordered systems for analysis and measurement of the generation and consumption of different ecosystem services. However, there is an emerging consensus, which is reflected in the fact that differences between later evolutions of classification are becoming more subtle (Figure 2.3). Due to its national relevance and holistic approach, the UKNEA ecosystem services framework will be followed within this research. This section has demonstrated that primary data collection remains a challenge as the spatial scales of research often cover wide areas. Consequently, measurements of proxy indicators provide more appropriate assessments of the potential capacities available for consumption. This thesis considers potential capacities rather than actual generation of ecosystem services as a more appropriate measurement. This provides the maximum levels of generation possible. This approach allows easier comparison between different cities and regions, and also resolves issues of landscape management and human activity that may differ across space.

2.3. Ecosystem service measurement

The section contains a critical review of different approaches to measure the generation of ecosystem services. The importance of currently neglected spatial analysis is discussed and some of the methodological requirements are revealed (Section 2.3.1). The section closes with a critical review of the current state of multiple ecosystem service generation (Section 2.3.2).

2.3.1. Ecosystem service generation

Ecosystem service assessments measure patterns of generation for specific ecosystem services or groups of services to determine locations of high ecosystem service generation (known as ecosystem service hotspots) (Egoh *et al.,* 2008); assess impact of land use; (Koschke *et al.,* 2012) or evaluate how ecosystem service levels change over time (Zhang *et al.,* 2011). This information can inform land planning decisions based on supply/demand relationships and concepts of sustainability (Blaschke 2006; Burkhard *et al.,* 2012). However, due to the complex nature of ecosystem service generation and consequent primary data collection, ecological indicators based on properties of the earth's surface are commonly used in their place as proxies for measurement (Muller and Burkhard, 2012). In urban areas, Hölzinger *et al.,* (2014) stress the importance of improving information at local and regional scales, where most planning and policy decisions affect ecosystem services. In their assessment of ecosystem services in Birmingham, they conclude that while there is sufficient data available to conduct a satisfactory desktop-based urban ecosystem services assessment, they acknowledge that much baseline data is missing or incomplete. Furthermore, Crossman *et al.,* (2013) state that inconsistencies in indicator development across the field of research challenge robust valuations and validations of ecosystem services. This makes research difficult to translate across space and through time. Bockstaller and Girardin (2003) stress the importance of developing indicators which meet with scientific standards. This implies a requirement to validate indicators using alternatively collected primary or secondary data (Muller and Burkhard (2012). While this is critical for developing robust methods of ecosystem service assessment, Seppelt *et al., (*2011) found that a high percentage of studies published include no validation information at all.

Potschin and Haines-Young (2011) suggest that earth surface processes reflect some ecosystem services better than others, which has led to an increase in the analysis of some ecosystem services over others. For example they cite that regulation and provisioning services such as crop production, water flow mitigation and carbon storage generation have been better developed than cultural services such as spirituality or aesthetics, or measurements of service consumption. Examples of ecosystem service generation mapping include efforts by both Kreuter *et al.,* (2001) and Liu *et al.,* (2010), which are based exclusively on assigning service generation levels to specific land cover types. Alternatively, Hölzinger *et al.,* (2014) consider the ecosystem services generated by defined habitat types. Frank *et al.,* (2012) develop this, via use of spatial algorithms called landscape metrics, to measure changes in aesthetic value and ecological functioning through spatial changes in land cover patterns. Potschin and Haines-Young (2013) label this the habitat approach, where ecosystems are assumed to be composed of distinct habitat patches and ecosystem service generation is an output of the biophysical properties of that habitat (Potschin and Haines-Young, 2013). The habitat approach is the most common within the literature and has been adopted by the MA and UKNEA. This approach lends itself to quantitative methods available today and data such as satellite imagery and digital boundaries. However it is dependent on the quality of information provided and is bias towards ecosystem service generation. This is an important limitation as Hölzinger *et al.,* (2014) note that required data quality and coverage is not always adequate for robust research.

Reginster and Goffette-Nagot (2005) warn that errors in measurement of ecosystem service generation may arise from neglect of neighbouring spaces. For example, Koschke *et al.,* (2012) directly linked ecosystem service provision with CORINE land cover data in Saxony, East Germany and found that this proxy land cover data often does not consider variability within land cover classes or the impacts of different land management. They also discovered that aggregating areas into larger homogenous units exaggerated the influence of urban areas and undermined that of arable farming. Zhang *et al.,* (2011) also cite issues with mismatch in land use composition and heterogeneity and related ecosystem service value estimations. This is particularly true for cultural services (Plieninger *et al.,* 2013).

Willemen *et al.,* (2014) cite a requirement to improve measures of uncertainty based on simple land cover data. For example, Eigenbrod *et al.,* (2010a) evaluated generalising errors arising from heterogeneous provision of ecosystem services within single land cover classes. They created three proxy land cover-based service data sets from primary data to explore errors of uniformity, sampling and regionality. They highlight that simple land cover-based mapping of ecosystem services is a poor fit. Chan *et al.,* (2006) corrected for this to an extent by introducing a system of weighting in their evaluation of ecosystem service generation against biodiversity conservation. However, Koschke *et al.,* (2012) found that weighting services using a prioritisation survey was too challenging for most stakeholders, particularly when asked to rate similar services. Further, many stakeholders did not want to disclose personal demographic information, which meant that analysis of social patterns was frustrated. Consequently, Wu *et al.,* (2013) stress the importance of using appropriate data to build suitable proxies and Rounsevell *et al.,* (2013) highlight the importance of integrating observations and synthetic models. Alternatively, Reginster and Goffette-Nagot (2005) suggest that landscapes have features and processes that have unique spheres of spatial influence with discrete or graduated boundaries signifying influence thresholds. For example, a football pitch, supplying the environmental settings and opportunity for recreation has defined boundaries, but Bastian *et al.,* (2012) note that noise and heat mitigation have blurred boundaries of different sizes.

This section has highlighted the importance of the habitat approach, but has also emphasised the need to build robust indicators that are based on more sophisticated measurements than simple direct relationships with the underlying landscape (Eigenbrod *et al.,* 2010a). Muller and Burkhard (2012) suggest that as indicators, ecosystem services can be placed within an Impact component of the Drivers Pressures State Impact Response (DPSIR) framework. This position is most appropriate because it places ecosystem services between the biophysical measurements of the landscape (State) and the human-well being benefits generated (Response). Measurement of ecosystem service generation provides a picture of how different ecosystem services are distributed across a landscape. Potschin and Haines-Young, (2013) state that the use of indicators based on landscape features is a common approach because ecosystem service generation can be characterised by biophysical properties. However, the review highlights that indicators of measurement need be more sophisticated than simple land cover maps because ecosystem services are fundamentally related to human activity as well as ecological processes (Muller and Burkhard, 2012). Pleasant *et al.* (2014) highlight the fact that challenges remain for cultural service measurement due to their non-market value and intangible nature, but frameworks have been altered to allow indicators that incorporate spatial criteria to these services (e.g. UKNEAFO, 2014). For example, by making measurements of environmental settings that provide the potential to produce a service rather than the specific service itself. Crossman *et al.* (2014) have also shown that there is demand for better attempts at validation of ecosystem service indicators to provide a measure of confidence that can be used to place research into a more scientific context.

2.3.2. Holistic analysis - multiple ecosystem services

A principal issue in ecosystem service research is the evaluation of relationships between ecosystem services (Rodriguez *et al.,* 2006; Bennett *et al.,* 2009). In their study, Seppelt *et al.,* (2011) note that half of the ecosystem service studies identified, focus on isolated services such as carbon sequestration in urban trees (Davies *et al*., 2011), or proximity to attractive spaces and amenities (Hamilton and Morgan, 2010). Even the MA assessed its services in isolation (Bennett *et al.,* 2009). There is growing recognition that ecosystems produce multiple services and ecosystem services are produced by multiple ecosystems (Fisher, *et al.,* 2009; Dobbs *et al.,* 2011; Koschke *et al.,* 2012). For example, Andersson *et al.,* (2014) consider the use of Service Producing Units (SPUs) as defined spatial entities that can facilitate analysis of the interaction of groups of ecosystem services. They cite trees as an SPU, which can potentially generate services such as air quality regulation, food provision and a range of cultural benefits. Alternatively, crop fields, orchards and gardens can all produce food. Brown *et al.,* (2007) suggests that according to the ecosystem approach, these services react and relate to each other and the landscape from which they are all created. But Gret-Regamey *et al.,* (2014) state that interactions between spatial and temporal scales must be considered to facilitate more relevant ecosystem service generation maps.

Rodriguez *et al.,* (2006) state that ecosystem service relationships can be conflicting or supportive, resulting in service trade-offs or synergies, which are often dynamic over time and space. Bagstad *et al.* (2013) demonstrate that these relationships depend on how different services exploit required natural resources for generation and also the nature of service consumption by humans. They identify provisioning benefits where the ecosystem service provides the benefit, and preventative benefits, where the ecosystem service mitigates an otherwise harmful process. These require ecosystem services to be modelled in different ways. Alcamo *et al.* (2005) provide a further example by suggesting that provisioning services are typically destructive in their consumption as they generate products that are eaten as food, or burnt as fuel. Conversely, cultural services may be produced simply by a landscape feature existing and consumption can potentially be shared with others without diminishing the service for future consumption (Bolund and Hunhammar, 1999).

Bennett *et al.,* (2009) state the importance of ecosystem services that commonly appear together into clusters as a way to consider the relationships between multiple services. This approach emphasises the importance of ecosystem service synergy and promotes the concept of multifunctional landscapes (Plieninger *et al.,* 2013). The majority of research uses ecological units such as land cover or land use (Chan *et al.,* 2006; Nelson *et al.,* 2009; Koschke *et al.,* 2012). However, Raudsepp-Hearne *et al.,* (2010) suggest that the delimitation of clusters into administrative spatial units provides a link to present socio-ecological systems. They claim that use of these administrative units echoes social pressures that influence the flows of ecosystem services. Improvements to this approach could be made by creating bespoke spatial units representing homogenous landscape features, such as Homogenous Urban Patches developed by Herold *et al.,* (2002), which can then be overlaid with existing land use units. This has not yet been done in ecosystem service assessment. However, methods from other disciplines, such as object based image analysis (Blaschke, 2006) and statistical approaches to hotspot analysis currently applied in crime mapping do exist and can contribute to this analysis (Zhu *et al.,* 2010).

Raudsepp-Hearne *et al.,* (2010) and Ericksen *et al.,* (2012) have both used ecosystem service clusters to analyse trade-offs between provisioning and regulating services, and provisioning and cultural services. However, both studies use negative correlations of service values across a landscape as evidence of trade-offs. This relationship is not necessarily due to service trade-off, but may be due to different landscape conditions and processes producing different ecosystem services, even standardising trade-off measurements to economic cost simplifies relationships that do not consider underlying drivers of change (Ruiijs *et al.,* 2014). Martin-Lopez *et al.,* (2012) derive three distinct ecosystem service clusters: services demanded by urban residents, such as cultural services, air purification and microclimate mitigation, services demanded by rural residents including provisioning services, regulation of soils and water and cultural forestry services, and finally services relating to agricultural activities. Alternatively, Wu *et al.,* (2013) found trade-offs across North East China, between a natural service cluster composed of soil retention, habitat services and carbon sequestration, and an artificial service cluster composed of material production and population support. However, their choice of ecosystem services highlights the issue of typological inconsistency across the discipline. On the other hand, Van der Biest *et al.,* (2014) applied a Bayesian belief approach to develop an ecosystem service cluster index incorporating biophysical and socio-economic properties. Based on these inputs and current land use patterns, the index was calculated with current land use patterns and optimal land use patterns to determine a value of difference indicating potential for improvement. However, they cite weighting in the belief network and validation as issues to be overcome.

To operationalise the ecosystem approach, the UKNEAFO (2014) have developed a suite of tools for use by decision makers (Scott *et al.,* 2014). These tools serve to assist in matters of planning regulation, land management incentives, engagement with local communities, valuations and trade-offs, and future predictions of ecosystems and their services. Geographic Information Systems (GIS) and remotely sensed digital data play an important role in some of these tools; particularly in the development of multi-service mapping frameworks to manage challenges with differing scales, examine trade-offs and consider stakeholder involvement and landscape management (Petz and Oudenhoven; 2012; Jackson *et al.*, 2013). In particular, the capability to store, manipulate and analyse vast quantities of data in different formats is highly valued (Troy and Wilson, 2006). Digital models have been developed at national scales, such as the INtegrated Valuation of Ecosystem Services and trade-offs (INVEST) and the Artificial Intelligence for Ecosystem Services (ARIES). These models are now commonly used in research studies to value ecosystem services at a national level (e.g. Nelson *et al.,* 2009; Villa *et al.,* 2009; Kareiva *et al.,* 2011). These models are highly sophisticated, but often require significant levels of expertise, data acquisition and processing times. Further, Vigerstol and Aukema (2011) note that fundamental mechanisms behind the programmes are different: INVEST is deterministic and based on simplifications of current models, while ARIES is based on probabilistic models. This means that inputting the same variables into these models is likely to produce different results and to-date, no comparison or verification has been made between them. Computer models have also started to incorporate 3D elements, although generally only for visual purposes so far (Gret-Regamey *et al.,* 2013). This review section highlights the requirement to develop the integration of 3D data into ecosystem service models as an approach to improve mapping and produce new questions on the impact that the 3D urban form may have on ecosystem service distribution, connectivity and flow.

Potschin and Haines Young (2013) recommend a place-based approach to perceiving the ecosystem service framework, which considers how different clusters of ecosystem services have different social values dependent on their location. This approach as applied by Sherouse *et al.,* (2011) involves a focus on participatory data collection and engagement with local communities to discern how services and clusters are differently viewed. Raymond *et al.,* (2009) suggest that this is potentially the most important for determining perceptions of ecosystem service values and indeed may be the only method of truly capturing cultural service valuations at the local scale as it engages with local communities. But, a major drawback of the place-based approach is the lack of transferability, even to alternative locations very close by (Alessa *et al.,* 2008). As each research site is unique, so too are the values placed on service clusters. This raises questions about the feasibility of generating ecosystem service indicators that satisfy the place-based approach.

This review section has highlighted the requirement to improve on clustering of multiple ecosystem services over space (Raudsepp-Hearne *et al.* 2010). Pre-constructed administrative areas are useful for the other data they can integrate into analysis, but principles behind their design may conflict with ecosystem service measurements, which are largely bio-physical. Consequently, there is a suggestion that producing bespoke spatial units may improve characterisation of ecosystem service generation patterns over a city to better manage and maintain acceptable levels (Potschin and Haines-Young, 2013). GIS and remote sensing technologies have proven to be a useful platform for such research (Jackson *et al.*, 2013). However, there is a demand for models that can accurately reflect patterns of ecosystem service generation across a diverse urban landscape (Bagstad *et al.,* 2013). The next section considers the left-hand side of Figure 2.1 and Figure 2.3, which focus on how accessibility to services can be used as a measurement of potential ecosystem service consumption.

2.4. Ecosystem service accessibility

2.4.1. Ecosystem service accessibility as a measure of ecosystem service consumption

Ecosystem service consumption is less well understood than ecosystem service generation (Bastian *et al* 2012). This is because it is more challenging to measure as it deals with human values rather than objective measurements. Ecosystem service consumption occupies the right hand side of Haines-Young and Potschin's cascade model in Figure 2.1 (CICES, 2013). The review in this section evaluates the application of accessibility to ecosystem services as a proxy for potential ecosystem service consumption. Physical accessibility and observer visibility studies are evaluated for their potential to provide different perspectives and raise new questions on ecosystem service consumption.

Valuation of ecosystem services is a key outcome of many ecosystem service assessments. This determines the level of demand and provides justification for management actions (Boyd and Banzhaf, 2007; TEEB, 2010). Economic measurements are the most common, based on cost per unit. These provide simple comparative results for non-specialist decision makers (Brown *et al.,* 2007). However, Sagoff (2011) criticises these methods as being blunt and simplistic. Liu *et al.,* (2010) and Brown *et al.,* (2007) continue, stating that different valuations arise from dynamic market conditions and economic data quality and coverage. Sherrouse *et al.,* (2011) suggest that economic measurements ignore relationships between people and place, where bequest or existence values may be valued more highly. These focus on experiential cultural services and less tangible regulatory services that are traditionally ignored (Raymond *et al.,* 2009). Local qualitative knowledge is important and adds a dimension that cannot be collected through analysis of land cover mapping, making quantification and generalisations challenging (Vizzari, 2011). Moreover, local knowledge is often incomplete, only focussing on issues of subjective importance to local stakeholders, potentially neglecting influential underlying issues (Raymond *et al.,* 2009). There is a drive towards developing non-monetary quantification based on physical service units (Boyd and Banzhaf, 2007; Burkhard *et al.,* 2012).

A solution to this presents itself through analysis of accessibility to ecosystem services. Schroter *et al.,* (2014) suggest that access to greenspaces provides the opportunity for humans to consume or experience the services and benefits produced by in an ecosystem. Without this mechanism, there are no ecosystem services as there no stakeholders to benefit (Burkhard *et al.,* 2012). Hedonic pricing analysis has emerged as a common method of determining access to ecosystem services, relating the Euclidean proximity of amenities and attractions (ecosystem services) to house prices (Wu *et al.,* 2004; Ready and Abdaller, 2005; Sander and Polasky, 2009). Sander and Haight (2012) consider hedonic pricing analysis of cultural ecosystem services in relation to property prices in Dakota County, USA. They found that access to recreational spaces and the proximity of trees increased prices, but they only considered Euclidean distances. Kovacs (2012) also emphasises the importance of the ecosystem service clusters in urban parks on property prices. He suggests that the optimum percentage of parkland within a half mile neighbourhood around a property is 20%, although he also find that homes in immediate proximity to parks have lower values, due to higher levels of noise and a higher risk of crime. Klaiber and Phaneuf (2010) state that the quality of parks may reduce house prices if they are not maintained. While this work focuses on economic valuation in relation to open space proximity, accessibility is also linked to health. Reyes *et al.,* (2014) find that accessibility to parks is higher in suburban areas and generally supports previous theories that lower socio-economic classes have lower access and are affected adversely as a result (Lucas and Jones, 2012). That said, Witten *et al.,* (2008) and Timperio *et al.,* (2007) found no relationships between park access and socio-economic status, while Cradock *et al.,* (2005) and Ellaway *et al.,* (2007) found that more deprived members of society had higher access to parks. Comber *et al.,* (2008) and Byrne (2012) found that ethnic minorities in Leicester, UK and Los Angeles, USA were less likely to use park facilities than the majority white population, but both studies use methods that concentrate residential neighbourhoods into single points representing the centres of administrative areas. This preserves confidentiality within the data, but does not present the population distribution across the area, assuming all residents live in the same space and have the same accessibilities.

Alternatively, Kroll *et al.,* (2012) consider ecosystem service provision of food, fresh water, and energy across the wider Leipzig-Halle region of Germany. Demand was calculated through determining the ratio between the amount supplied and the average need of a household. They use concentric circles to apply an urban-rural transect to analysis, but this does not account for local geographic features such as rivers or mountains that can deviate the growth of cities from the circular ideals (Wolfe and Mennis, 2012). Further, they do not consider distances between areas of supply and areas of demand or methods of transport of services or consumers. They find that through migration of residents and industry out of urban centres and into suburbs, demand for services decreased in urban areas and increased in suburbs, flattening urban-rural differences. Similarly, Nedkov and Burkhard, (2012) focus on flood regulation, dividing a catchment into regions to determine differing levels of service supply and demand. Here, demand is measured by the population density and is highest in urban areas, but it assumes that levels of demand are equal. Elsewhere, Schroter *et al.,* (2014) identify the difference between capacity as the potential supply and flow as actual consumption of ecosystem services. They differentiate flow from demand by suggesting that demand is the subjective consideration of an individual or community, whereas flow considers the actual consumption. In considering these catchments together, measurements of sustainability can be made (Burkhard *et al.,* 2012). However, flow is challenging to measure because it requires knowledge of resource consumption and waste patterns as well as efficiency of generation. This is likely to be measured using different datasets, accuracies, collection methods and temporal currencies, making robust comparisons challenging.

2.4.2. Accessibility in a UK context

In the UK, the Accessible Natural Greenspace Standards (ANGSt) proposed by Natural England have informed local government green space strategies (Natural

England, 2010). ANGSt recommends that everyone, wherever they live, should have accessible natural greenspace:

- of at least 2 hectares in size, no more than 300 metres (5 minute walk) from home;
- at least one accessible 20 hectare site within two kilometre of home;
- one accessible 100 hectare site within five kilometres of home

Comber *et al.,* (2008) use ANGSt guidelines and network analysis to determine accessibility to local parks of ethnic minorities in Leicester, UK, while Barbosa *et al.,* (2007) use the ANGSt guidelines to determine accessibility to greenspaces in Sheffield. They find that the absence of private gardens from the guidelines reduces the apparent accessibility of residents who have larger gardens and may not need to access municipal space. However, ANGSt standards neglect the contribution that informal urban green spaces and street trees make for enhancing wildlife connectivity and recreational opportunities (Jim, 2013; Rupprecht *et al.,* 2014). They also do not consider the importance of visual line-of-sight for reducing stress and maintaining contact with nature (Hauru *et al.,* 2012). This is particularly true of urban forests, which function as green barriers that increase perceived distance from urban disturbance (van Herzele and Wiedemann, 2003; Yang *et al.,* 2009).

The UK's National Planning Policy Framework (NPPF) published in March 2012 highlights the importance of safe and accessible community spaces to encourage different members of society to integrate (DCLG, 2012). Greenspaces of particular importance to a community can be designated as Local Green Spaces, but proof must be provided of the importance of the greenspace, either via historical or cultural significance or outstanding natural beauty (DCLG, 2012). Further, emphasis on locally derived standards suggests that national standards may not be necessary, even though building regulations are centrally derived. In a revision made in 2014, clarification suggests that designations can only be made where suitable alternative land has been identified to meet local development plans and where planning permission has not already been granted (DCLG, 2014 paras 75 – 76). Carmichael *et al.,* (2013) note that sustainable development is a key principle behind the NPPF, but they have been sceptical regarding the lack of definitions or measurements outlined to quantify.

At local authority scale, greenspace standards are variable. Recommended accessibility standards for households in each of the ten local authorities that make up Greater Manchester along with the ANGSt guidelines are contained in Table 2.1. Distances relate to neighbourhood or district parks that are 2 ha or larger in size. Trafford Council does not use this measurement, instead it uses accessibility to the nearest 2 ha woodland. The information in the table demonstrates that the ANGSt guidelines are the smallest standards. Where local authorities have large distance thresholds, above one kilometre (Salford, Wigan, Bolton, Stockport), this is due to additional smaller standards to smaller greenspaces. They were not included here as not all authorities have included them.

Table 2.1. Open space accessibility standards for households to their closest neighbourhood/district park (2 ha +) for each of the ten local authorities that make up Greater Manchester and Natural England's ANGSt guidelines for 2 ha + greenspaces.

Local Authority	Open space accessibility standard (m)	Source
Manchester	480	Manchester City Council (2009)
Salford	1200	Salford City Council (2006)
Wigan	600	Wigan Council (2007)
Trafford	500 (2 ha woodland)	Trafford Council (2012)
Bolton	1200	Bolton Council (2007)
Bury	800	Bury Council (2015)
Oldham	720	Oldham Council (2015)
Rochdale	400	Rochdale Council (2008)
Tameside	440	Tameside Council (2010)
Stockport	1000	Stockport Council (2011)
ANGSt	300	Natural England (2006)

Less research has been done on an observer's view of urban spaces with regard to experience of ecosystem services. The majority of this research lies in rural locations such as national parks, where analysis of view composition is related to popularity for tourism studies (Baerenklau *et al.,* 2010; Brabyn and Mark, 2011). There is an emphasis on recreational spaces, but with a consideration of the aesthetic qualities of either the composition and makeup of the landscape or the landscape as a whole. In particular, attention is paid to the psychological health contributions that urban forests make (Velarde *et al.,* 2007; Lee *et al.,* 2009), the fragmentation of the landscape (Standish *et al.,* 2013), and the scale at which certain landscape features appear (Yang *et al.,* 2009). There is clear emphasis on the benefits of wide, open green spaces, which promote accessibility and safety (van Herzele and Wiedemann, 2003). Further, Hauru *et al.,* (2012) and Dobbs *et al.,* (2011) revealed a perceived lack of safety in wooded areas, sparking the debate for how to properly manage these spaces in terms of providing adequate lighting or reducing canopy cover. Alternatively, Wolfe and Mennis (2012) suggest that by encouraging local communities to use urban greenspaces more frequently, a virtuous circle is formed, whereby increased use makes the area feel safer, which in turn promotes more interaction.

This section of the review has highlighted that current measures of ecosystem service consumption are not suitable for all services and in particular, most do not measure cultural ecosystem services very well, particularly across a landscape. Measures of physical accessibility have been suggested as an explicitly spatial measure of the ease of access to various cultural services. Further, analysis of observer view has not yet been considered in ecosystem service research, but can offer a different perspective into the accessibility of different urban greenspaces, and the patterns of ecosystem services available to those can observe these spaces. Consequently, there is potential for the twinned approaches of physical accessibility and observer visibility to provide new insights into how cultural services may be accessed in different ways by different people. Ecosystem service generation largely relies on the properties and configuration of the underlying landscape mosaic, while accessibility is fundamentally tied to landscape features such as land use, topography and visibility. Relationships between ecosystem services and landscape properties and current approaches to landscape analysis are critically reviewed in the next section for their relevance for use in this thesis.

2.5. Ecosystem services and landscape

Simple land cover classification do not supply enough raw information for ecosystem service research (Sections 2.2 to 2.4), and a requirement for better appreciation of the underlying landscape via more sophisticated spatial analysis has been identified. The relationship between ecosystem services and landscapes is critically reviewed in this section by evaluating the practicalities of using physical landscapes as a context for measuring ecosystem service generation. Landscapes defined by their physical classification are discussed as a foundation for more sophisticated conceptualisations, each that can provide a contribution to this thesis (Section 2.5.2). Landscapes characterised by their uses are discussed as a way of producing broader homogenous regions that still contain information on underlying landscape variation (Section 2.5.3).

2.5.1. Relating ecosystems to landscape

Ecosystems describe interactions between biological entities and the abiotic environment they are set in (Colin *et al.,* 2008). Their changing physical and functional boundaries make them difficult to measure and spatially define (Post *et al.,* 2007). On the other hand, Forman (1995) defines a landscape as a space, at least a few kilometres in area, perceived by people. The Council of Europe (2000) add that a landscape is the result of the action and interaction of natural and/or human factors. Although perceptions of a landscape may differ, these definitions tie landscapes to physical boundaries more easily than ecosystems, which have more blurred edges. This is more practical for measurement of ecosystem service indicators (Haines-Young and Potschin, 2008). Landscapes provide a setting for day-to-day human life as they represent the social and psychological relationships that people have with a place (Swanwick, 2002). The suggestion made by Termorshuizen and Opdam (2009), and Burkhard *et al.,* (2012) that ecosystems services are measures of biophysical properties of the landscape, implies a spatial component that few studies have adequately addressed. Haines-Young and Potschin (2008, p26) voice this concern through a call to develop a spatially explicit assessment of ecosystem services as “an effective way of making the ecosystem services approach operational”. Introducing a landscape context would allow further evaluation of spatial interactions and relationships between people and the environment. Gobster *et al.,* (2007) state that while ecological processes occur at different spatial scales, humans interact with these processes at a particular scale: the human experience of the surrounding landscape. Among other things, this includes aesthetic experiences.

The Natural Environments White Paper (Defra, 2014) emphasises the importance of using landscapes within the ecosystem approach to integrate benefits, costs and management as well as land management. Landscape ecology has been prominent as a framework for landscape characterisations and relating ecological processes to the physical landscape. It states that landscapes are natural or man-made mosaics composed of patches and corridors that share common land covers (Forman, 1995).

This framework can provide insights into the changing flows of energy and matter within a landscape, making it perfect for ecosystem service research (Palang *et al.,* 2000; Potschin and Haines-Young, 2013). For example, land use patches shrink as urbanisation increases (Alberti, 2005). This fragments natural habitats increasing their vulnerability and reducing their capacity to sustain ecological networks (Angold *et al.,* 2006). This means higher demand for space and for natural resources as the patches that generate them shrink and fragment (Wu *et al.,* 2006). However, issues arise where the boundaries between patches blur (Kong and Nakagoshi, 2006), or when changing research scale means that patches of homogeneous land cover either are merged together or segregated into new categories (Willemen *et al.,* 2012).

Wentz *et al.,* (2014) suggest that mapping urban land cover drives further research into the development of more complex urban indices and models as well as being a key input for applications such as mapping urban extents and compositions, surface temperatures and air quality. The relationships are demonstrated in Figure 2.5. The model emphasises the foundation of simple land cover maps based on landscape ecology concepts of land cover patches (Theme 1). The arrows represent increasing levels of interpretation, from raw data to land cover mapping to indices and models. Each layer includes additional assumptions, but in doing so present further information that is often more meaningful (Comber *et al.,* 2005).

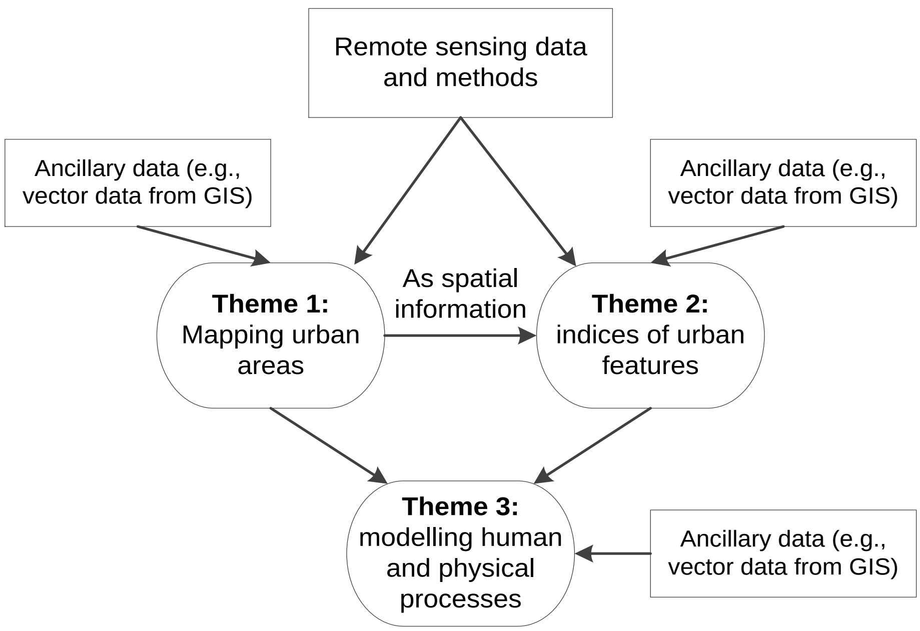

Figure 2.5. Three interrelated themes describing how remote sensing data and methods support research in global environmental change (from Wentz et al., 2014).

2.5.2. Mapping land cover in the urban environment

Classification and characterisation of land cover and land use is vital for creating a systematic order from raw data. As discussed in Section 2.3, land cover maps are commonly used in ecosystem service research. Land cover relates to the physical composition of the earth's surface, purely descriptive of the present material (Stefanov *et al.,* 2001 and Aplin, 2004). However, Comber *et al.,* (2005) identifies a difference between land cover data and land cover information. They state that land cover data is the result of objective measurements, but land cover information relies on some form of interpretation, or classification of the data. For example, elevation measurements are land cover data, but can be converted to information through classification as mountains, valleys or hills dependent on context. Boots and Csillag (2006) provide evidence for this through a virtual workshop they ran with a number of experts from spatial information and landscape ecology backgrounds to compare two maps. They found that differences in comparisons arose due to the map characteristics and scale considered, the units of measurement and nature of comparison and tests of significance.

Land cover types can be used to model ecological processes, which in turn are commonly used as indicators for more complex ecosystem services (Chan *et al.,* 2006). Traditional land cover mapping relied on work-intensive and time consuming field surveys and interpretation of aerial photography (Matikainen *et al.,* 2012). Interpretation of remote sensing imagery acquired from airplanes and satellites has provided a quicker, cheaper and more easily repeatable alternative for urban environmental analysis since the 1950s (Patino and Duque, 2013). Maps can be produced at scales that range from local neighbourhoods to coverage of the entire globe and can be collected with daily frequency (Wentz *et al.,* 2006), although indicators derived from this data need to be created with care to be relevant proxies (Eigenbrod *et al.,* 2010b). The timely acquisition of spatial information for land cover mapping has proven to be valuable for gaining a deeper understanding of how the process of urbanisation influences global environmental change (Weng, 2012).

Land cover classes provide useful information for observers, but may change as perspectives change (Mather and Koch, 2011). This is particularly important in urban landscapes that are characterised by high levels of land use change and highly fragmented patterns of land use inferring low levels of environmental sustainability

(Alberti, 2005). Fragmentation and diversity of land cover in small areas leads to a compromise between land cover distinction and breadth of classification (Epstein *et al.,* 2002). Further, due to the multitude of urban land covers present, many may look similar in the data, but in reality have very different properties. This can include different building materials, chimneys on roofs, and automobiles on roads (Wentz *et al.,* 2014). Haines-Young and Potschin (2008) caution that while current mapping standards are suitable for regional exercises; urban environments contain more challenging, highly fragmented patterns of land covers and land uses, which are not currently catered for. Further, some land cover types are more transient than others. For example, bare earth and soils are an integral part of urban and rural landscapes and can represent a seasonal phase of agriculture, an unused brownfield, or the development of a new urban infrastructure (Zhao and Chen, 2005)

Previous ecosystem service studies applied land cover categories provided by pre-constructed land cover/land use maps such as LCM2000 or CORINE (Eigenbrod *et al,* 2011; Burkhard *et al.,* 2012). These maps provide a good, wide coverage, but may only be suitable at specific scales and only present a single point in time with updates being time-consuming, work-intensive and expensive. Figure 2.4 emphasises the use of ancillary datasets to augment remote sensing imagery. This is especially important for more complex models that require more information than surface cover. Examples include analysis of flood risk (Weng, 2001), urban heat islands (Memon *et al.,* 2007) and provision of urban greenspaces (Pacione, 2003).

Consideration of research scale is a key concept highlighted by Haines-Young and Potschin (2008). Hein *et al.,* (2006) find that stakeholders are more likely to benefits from provisioning and regulation services at a regional or national scale, whereas cultural services are more locally valued. Further, Burkhard *et al.,* (2012) find that scale can change within a single service. For example, fuel is supplied locally, but demanded globally. This makes defining the scale of the research site challenging, but Turner (2005) argues that application of different scales offer further levels of analysis. This is particularly important as ecosystem services commonly cross different political and administrative boundaries (Goldman *et al.,* 2007). Consequently, Potschin and Haines-Young (2013) suggest considering ecosystems as a series of functional relationships, which is more in line with the ecosystem approach. This approach considers how different drivers and pressures affect the flows of ecosystem services. This dynamic spatial approach has piqued an interest in geographers and there have been a number of attempts to measure supply and demand for ecosystem services across a region (Burkhard *et al.,* 2012; Syrbe and Walz, 2012). This approach creates ratios which can provide measures of environmental carrying capacities and sustainability for urban metabolism (Zhang *et al.,* 2006) or create matrices relating service indicators against land cover types for ecosystem service budgeting (Burkhard *et al.,* 2012). Together, these studies provide a platform for further research through their recognition that ecosystem services are often generated in one location, before being transported and consumed in another. This platform poses interesting questions regarding how distance can affect service 'values', relates indicators of ecosystem service generation to indicators of ecosystem service accessibility suggested in Section 2.4, and provides directions for tackling the 'spatial issue' by producing overlaying areas of interest for supply and demand (Haines-Young and Potschin, 2008).

2.5.3. Characterising land use

Translating land cover to land use (Figure 2.5, Theme 2) is required for measuring complex processes such as characterisation of urban areas (Swanwick, 2002), climate change analysis (Gill *et al.,* 2008) and monitoring change in urban environments (Vanderhaegen and Canters, 2010). However, mapping land use is problematic because it describes a function or human activity occurring on the landscape rather than the physical form described by land cover (Barnsley and Barr 1997, Weng, 2012). For example, a landscape completely covered by impervious land cover may include land uses such as industrial estates, residential housing and transport networks. Herold *et al.,* (2002) and Gill *et al.,* (2008) argue that additional streams of auxiliary data should be included to landscape classifications to characterise the landscape into forms more meaningful to humans as demonstrated in Figure 2.5. This represents a further step in interpretation of the data. This means that land use characterisation must also acknowledge the assumptions and perspectives of the land cover classification on which it was based (Comber *et al.,* 2005). For example, Urban Morphology Types (UMTs), derived through interpretation of aerial photography, recognise relationships between the physical environment and human activity providing a richer description and allowing deeper analysis (Wilson *et al.,* 2003; Gill *et al.,* 2008). UMTs are a powerful method of landscape characterisation and have been successfully used in climate change research and evapo-transpirational modelling (Gill *et al.,* 2007). The additional information land use provides more meaning to landscapes, which helps drive decision making (Verburg *et al.,* 2006).

Early attempts at classifying UK land use were found to be patchy, un-standardised and underfunded (Harrison and Garland, 2001). They were also criticised for lack of attention in urban areas (Cassettari, 2003). In the 1990s, The National Land Use Database (NLUD), developed by the Ordnance Survey (OS) and the Office of the Deputy Prime Minister, attempted to create a unifying framework for naming and identifying groups of land covers and land uses. However, the overall concept was abandoned in favour of a focus on previously developed land (NLUD, 2000). The NLUD classification system is still commonly used and forms the basis of the most recent National Land Use Map, created by the Geoinformation Group (Jones, 2012). This map focuses on land use to properly acknowledge urban areas using different sources of data and provide regular annual updates. However a common critique with national mapping programmes is slow temporal updates (Cassettari, 2003). This is important when considering the transient nature of urban areas and in particular, vacant brownfield sites (Nassauer and Raskin, 2014).

However, there are issues with land cover classifications for ecosystem service research. They often lack the detail necessary for appropriate measurements and make no allowances for neighbouring influences or the impacts of different human activities. Following Figure 2.5, higher levels of interpretation provide potential solutions. For example, characterisation of land uses based on land cover composition provides a broader scale of analysis, which better incorporates ecosystems and ecological processes. Through their description of human activities, they also tie objective landscapes to human social and ecological systems. These are often subjective in their description, but this means that they are more meaningful spatial units for structuring analysis and informing decision making.

The importance of integrating topographical information in urban characterisation is emphasised by Brennan and Webster (2006) and Guan *et al.,* (2013) who used detailed height data collected from airborne laser scanning data to enhance classification. This has proven successful in the extraction of features such as buildings from roads, which have similar spectral characteristics (Miliaresis and Kokkas, 2007) and improving land use classifications (Brennan and Webster, 2006). Further, Hermosilla *et al.,* (2012) characterise six urban land uses in Sagunto, Spain, using LiDAR data to include height data and graph theory to measure adjacency between buildings. They find that vegetation covered ratio, building covered ratio and mean building volume were key variables. However, none of these studies considers the vertical structure of vegetation in characterising the urban landscape. Cionco and Ellefsen (1998) and Nichol and Wong (2005) evaluate the impact of street trees in mitigating high velocity wind and urban heat islands and van Herzele and Wiedemann (2003) consider the influence of trees as barriers to distance observers from urban disturbance. Hauru *et al.,* (2012) and Beil and Hanes (2013) provide additional evidence for the positive psychological effects of viewing trees in urban areas. However, fear of safety may lead residents to prefer open or semi-open views rather than those completely closed from the urban matrix (Hauru *et al.,* 2012). Elsewhere, Grove *et al.,* (2006) found that lifestyle behaviour derived through census data, and median house age dictated the coverage of vegetation on private land and public land respectively. The influence of the third dimension is therefore an important component of urban land use mapping programmes and should be considered, in the built environment, and in the structure of urban vegetation.

Land cover maps are adequate for mapping simple ecological processes, but this section of the review has highlighted a requirement for more complex interpretation of land cover data to develop suitable indictors that reflect the increasing sophistication of ecosystem services and their components. Landscapes have been revealed as a useful framework for developing indicators to measure ecosystem services. They have ties to physical surroundings, which enable research sites to be defined and scientific method to replicate measurements. In line with the ecosystem services framework, landscapes also incorporate the impact and perception of human beings, which means that research at the landscape scale can accommodate appropriate measurements of ecosystem service generation and consumption. Following Figure 2.5, Themes 2 and 3 become more useful as they present an interpretation of land cover that can include human impacts. This evolves interpretation of the underlying landscape mosaic from objective land cover to a more subjective land use dataset.

2.6. Research aim and objectives

The ecosystem services framework has emerged as a popular and relevant approach for academic and professional use due to its focus on integrating humans into ecological analysis (Haines-Young and Potschin, 2011). However, the concept has been characterised by confusion and debate over definitions and typologies (Section 2.2.1). From the review in Section 2.2, this research follows Haines-Young and Potschin (2011) by defining ‘ecosystem services’ as the outputs of ecosystems that most directly affect the well-being of people. Due to the relevance of its UK context, its recent update and its development for integration into policy and decision making, the UKNEA ecosystem service structure will be adopted in this research (UKNEA, 2011). Of particular interest, the UKNEA framework considers measurement of cultural services to be (at least partly) based on environmental settings, which enables easier use of physical landscape as inputs.

Addressing the spatial issues measuring ecosystem services, the literature review provides evidence that current methods of spatial analysis are too basic and too rigid for ecosystem service assessment (Section 2.5). Following Comber *et al.,* (2005) and Figure 2.5, it is apparent that different interpretations of the landscape should be used for different components of ecosystem service analysis. For example, surface land cover has direct relationships with many environmental phenomena making it a useful input for proxy indicators. However, no research has yet developed landscape models appropriate for different stages of ecosystem service analysis. In particular, no research has yet developed physical characterisations of land use that can be assessed against characterisations of ecosystem services (Section 2.5.3). Further, there has currently been no consideration of variation within land use units or the impact of surrounding areas. This suggests that there is potential for research to contribute knowledge to an anthropocentric perspective of spatial influences in ecosystem service assessment, using Haines-Young and Potschin’s (2013) habitat and functional approaches to perceiving ecosystems (Section 2.3.1).

Ecosystem services are challenging to measure in terms of actual consumption or generation, so this research follows Bastian *et al.,* (2012) in taking the first step of measuring the potential ecosystem service generation and provision. The measurement of potential generation is logical as it provides the opportunity to measure concepts of ecosystem service generation efficiency and wastage, which may provide new, useful insights for urban planning. However, the review in Section 2.2 and Section 2.3 has identified a requirement to develop or adopt spatial methods that reflect the complexity and sophistication of ecosystem services. To develop these indicators, sophisticated tools and measurements are needed to properly evaluate the multi-functionality of urban green spaces. These exist (Sections 2.3 and 2.4), but have not been used in ecosystem service research. This will provide new insights into how the wider landscape affects the generation of ecosystem services.

Based on the outcomes of the critical review in this chapter, the overarching aim of this research is to develop a new body of knowledge that focuses on how multiple ecosystem services are generated and consumed within a complex three dimensional urban landscape mosaic. This aim will be achieved through completion of four research objectives as outlined below and described in Figure 2.6. The objectives are described in more detail in the following sections.

2.6.1. Objective 1: Characterising the physical 3D urban environment

Ecosystem service assessment in cities is complicated by the diverse array of land covers and land uses present. Development of ecosystem service indicators in an urban environment has not yet been fully addressed (Section 2.5.2). The review in Section 2.5 has highlighted relationships and similarities between ecosystem services and patterns in the landscape mosaic including bio-physical properties, spatial scales and the underlying impact of human activities and perceptions on both concepts. Following the UKNEA approach to ecosystem service assessment, landscapes can also tie cultural ecosystem services into the physical framework. This makes landscapes a relevant platform for situating ecosystem service research (Seppelt *et al.,* 2011).

This research objective applies a classification process involving use of spectral indices to increase classification efficiency as well as decision tree classifications to incorporate original detail from 3D tree and building feature heights (Section 2.3.2). The land cover model lies in concert with a detailed digital surface model that allows evaluation of topography as an additional dataset for characterising and visualising the landscape. An urban land use characterisation builds on this land cover map and is a key component of ecosystem service assessment that has not been previously researched (Section 2.5.3). By developing the interpretation of the landscape, this characterisation applies a wider spatial context providing a basis for more complex ecosystem service research at a more meaningful human scale. This will allow integration of previously neglected neighbourhood impacts and a broader characterisation of land uses. This approach can provide new insights via characterisations of ecosystem service generation and consumption.

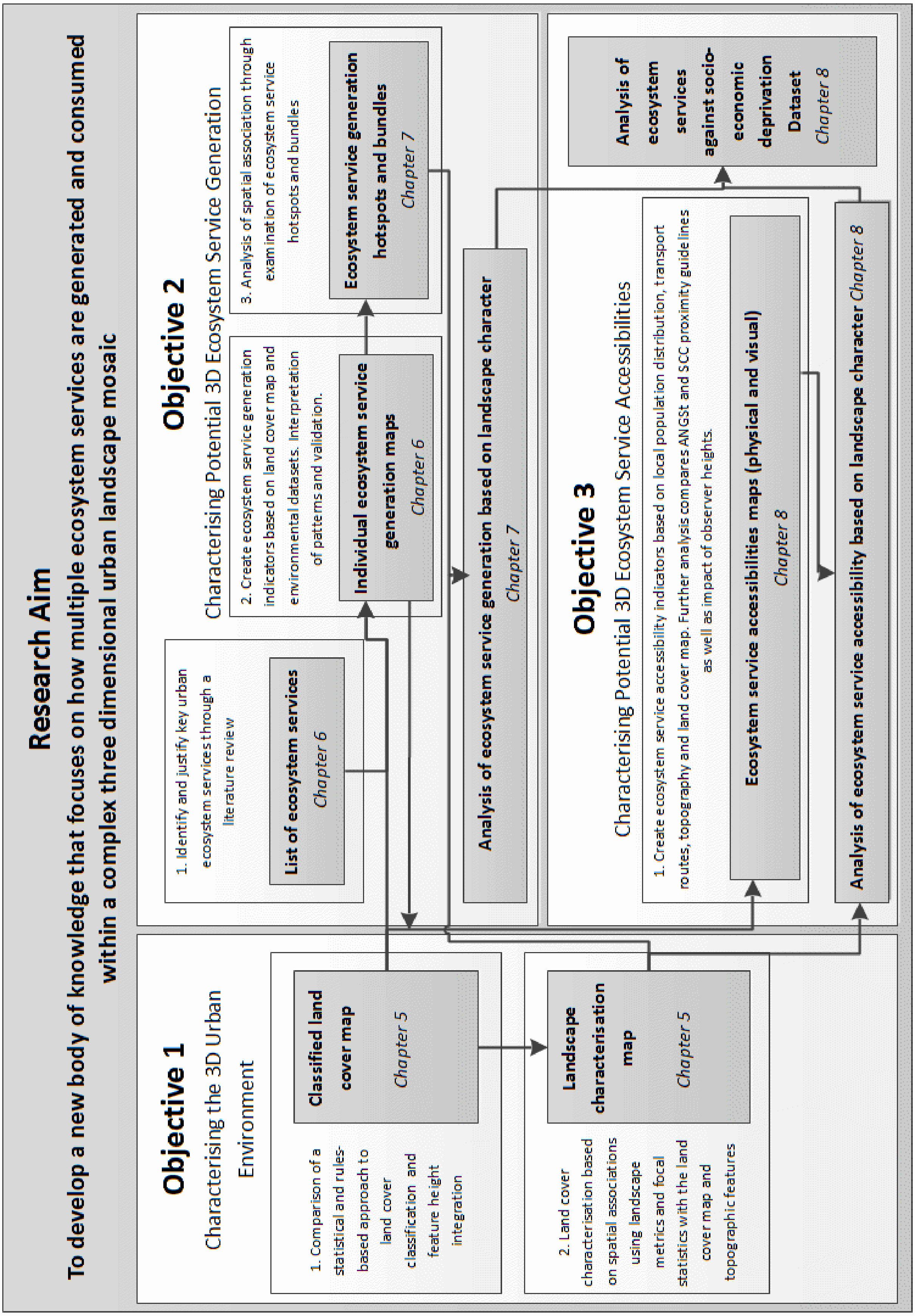

Figure 2.6. Flow diagram of overall thesis structure

2.6.2. Objective 2: Characterising ecosystem service generation

The review in Section 2.3.2 has provided evidence that there are gaps in the literature surrounding how multiple services flow and interact over an urban area. Authors such as Raudsepp-Hearne *et al.,* (2010) have bluntly related service clusters to administrative areas, but no studies have attempted to characterise ecosystem service clusters purely on the composition of the landscape mosaic through bespoke spatial units. This is important because the clusters currently being created in the literature are largely of potential service generation, which is related more to the landscape more than the surrounding consumers. Through measurements of actual and potential, and generation and consumption, analyses can be drawn out that explore features such as efficiency, wastage, deprivation and overuse, which develops research from a mapping exercise to one with a more scientific basis.

This research objective tackles the neglected issue of spatial analysis of ecosystem service generation highlighted in Sections 2.2 and 2.3. Building on concepts of supply and demand units, this research explores where service resources come from and the spatial nature of the service source itself in terms of size, shape and distribution across the landscape mosaic. A systematic literature review is conducted in Chapter 3, to determine ecosystem services deemed to be of importance in urban areas. Environmental datasets will be collected and combined to reflect ecosystem service generation for each service individually. Specifically, there will also be a novel focus on the city scale and the level of detail within as well as 3D influences and impacts that such indicators make by integration of feature heights to more accurately model the urban landscape. These datasets will be validated against other secondary datasets and field survey work in Chapter 6. Consideration of the previously neglected spatial analysis of multiple overlapping ecosystem services is addressed in Chapter 7 though evaluation and characterisation of hotspots and clusters.

2.6.3. Objective 3: Evaluating physical and visual access to aesthetics and recreational ecosystem services

Ecosystem service consumption is a subjective value-led concept, which makes full assessment of ecosystem services challenging. However, the review in Section 2.4 highlights that measurement of ecosystem service generation on its own is only half of the ecosystem service picture, but is still where the majority of research finishes.

The review in Section 2.4.1 also suggests that no research has attempted to integrate concepts of physical and visual accessibility to service hotspots and urban green spaces as a method of predicting potential consumption and demand for ecosystem services. This is particularly relevant to cultural services that have been identified as being valued most highly by local communities (Hein *et al.,* 2006). There are also gaps in the knowledge in the consideration of 3D datasets for the modelling of landscapes and mapping of ecosystem service flows, particularly for urban vegetation structures (Section 2.5.2). This would be useful for acknowledging the multifunctional impacts that urban green spaces make, especially as they are in urban landscapes that carry the highest population densities and offer higher potential values of ecosystem services (Gomez-Baggethun and Barton, 2013). To enhance this research and bring it closer to the real world, this thesis recognises that cities are complex three dimensional structures that challenge simple land cover mapping as a method of representing urban surfaces (Section 2.3.2). Local knowledge is important in this context, but remains challenging to integrate with the spatially holistic landscape approach and will consequently be neglected from this thesis.

The final research objective, addressed in Chapter 8, analyses ecosystem service consumption using a local population's potential accessibility to ecosystem services as a functional proxy indicator. This objective quantitatively deals with the nature of turning ecosystem functions into ecosystem services via the potential for consumptions by humans, taking into account distances from local populations. The originality of this research lies in the focus on physical and visual as twinned concepts, both of which explore accessibility in different ways. In particular, observer views are currently neglected in ecosystem service research and may provide new insights for cultural services that are more difficult to measure using traditional methods. These accessibilities will be evaluated against a 2D transport route network, 3D viewsheds and population data (ecosystem service consumers) to explore different types of accessibilities. These results will then be compared against current standards promoted by Natural England and Salford City Council. Finally, patterns of inequalities in population ecosystem service accessibility will be analysed in terms of the social and economic deprivation through spatial analysis of, patterns and distributions within the Index of Multiple Deprivations (IMD) (Daw *et al.,* 2011).

3. Methods

3.1. Introduction

Methods for satisfying the requirements of the research objectives (Sections 2.6.1, 2.6.2 and 2.6.3) are discussed in this chapter. Figure 3.1 presents a re-iteration of the thesis structure diagram (Figure 2.6), including annotations stating the section in this chapter that address each component. Further clarification is provided in Table 3.1, which lists the main processes and methods used in the thesis.

The first three sections (3.2 – 3.4) provide information that is relevant to the whole thesis. Section 3.2 contains a discussion justifying the city of Salford as a case study representing an urban area composed of typical land covers and land uses. Section 3.3 contains review of current literature to derive a list of ecosystem services important in urban settings, and appropriate measurement methods. This provides a context for the whole thesis, and directly contributes to objectives 2 and 3. The review in Section 3.4 discusses what form landscape information needs to take in order to fulfil the requirements for research objective 1. Categorising the landscape into land covers of homogeneous biophysical profiles is important for measuring ecosystem service generation. Equally, integration of human impacts into the landscape information provides a more sophisticated dataset more suitable for further analysis and reporting of results.

Based on the information provided in Sections 3.3 and 3.4, Sections 3.5 and 3.6 provide information on methods relevant to satisfying specific objectives. Objective 2 requires methods of measuring the spatial association of individual and multiple ecosystem service generation levels as well as methods to characterise multiple overlaying ecosystem service generation. This is discussed in Section 3.5. Objective 3 requires methods for measuring accessibility to ecosystem services. This is discussed in Section 3.6. This includes consideration of what is required to properly assess physical and visual accessibility in a 3D urban environment. A summary of final methods chosen for each research objective is detailed in Section 3.7.

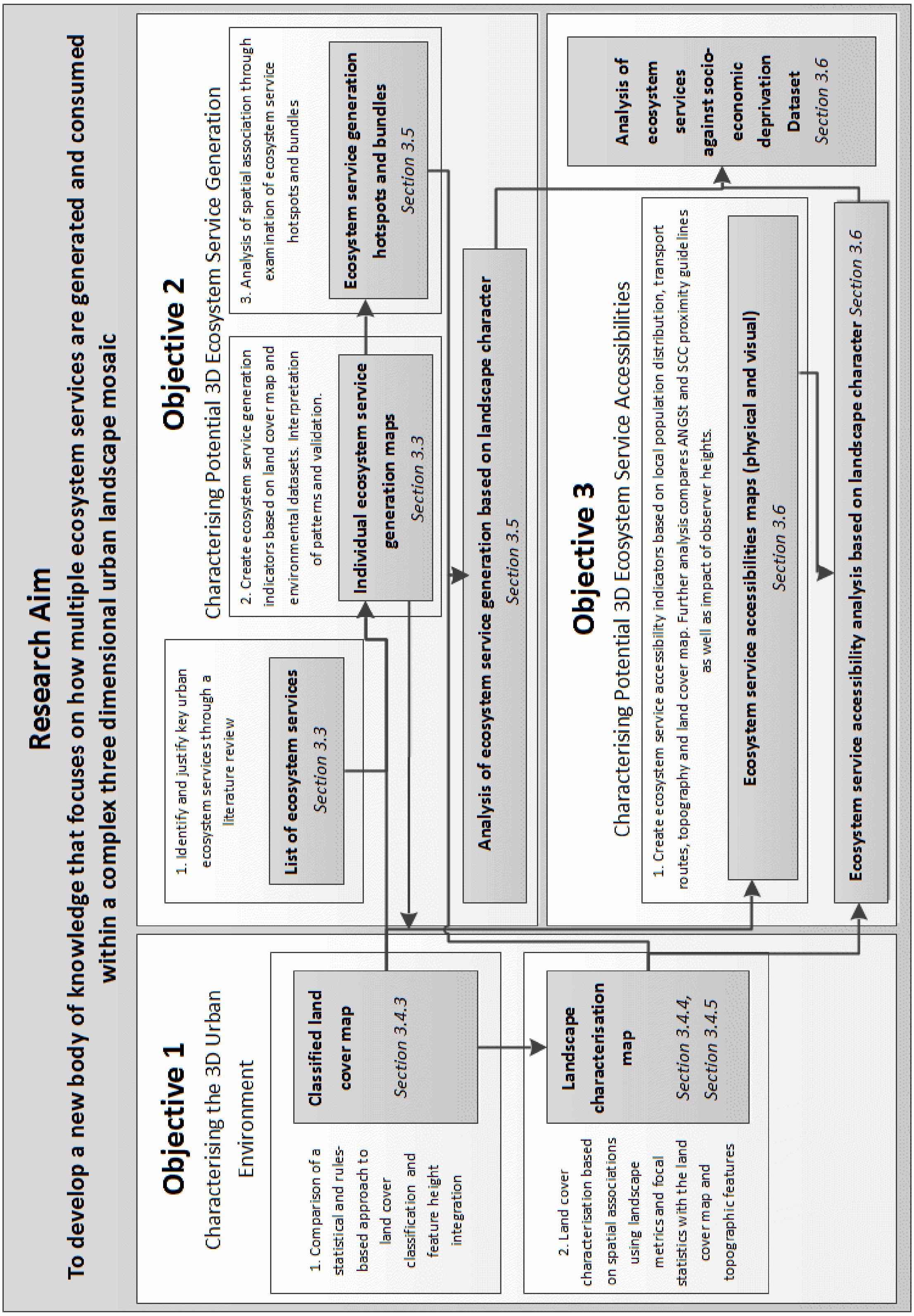

Figure 3.1. Overall thesis structure.

Table 3.1. Methods used in the thesis. Numbers within the table refer to thesis chapters and sections.

Method	Methods section	Implementation			
		Chapter 5 - Characterising the physical urban landscape	Chapter 6 - Characterising ecosystem service Generation	Chapter 7 - Spatial patterns of ecosystem service generation	Chapter 8 - Evaluating ecosystem service accessibility and visibility
Decision Tree Classification	3.4.3	5.4			
Spectral Indices	3.4.3	5.3			
Landscape Metrics	3.4.5	5.9.1			
Ecosystem service generation methods	3.3		6.2.2		
Hotspot analysis by value thresholding	3.5.1		6.2.4		
Hotspot analysis using Getis-Ord Gi*	3.5.1		6.2.4		
Overlap analysis	3.5.1			7.2.2	
k-mean clustering	3.5.2	5.9.2		7.2.3	
Object-based segmentation	3.4.6			7.2.4	
Network analysis	3.6.1				8.2.1
Viewshed analysis	3.6.2				8.2.2

3.2. Case study site

The introduction and literature review has outlined the importance of studying ecosystem services in urban environments (Sections, 2.3, 2.4 and 2.5). To model and test spatial relationships between ecosystem services and the urban landscape, the research in this thesis is applied to the city of Salford. This section describes features of Salford that have been highlighted in Chapter 2 as important for ecosystem service assessment: the location and physical composition of Salford, the socio-economic patterns present in Salford and the distribution of greenspaces across Salford.

Salford is a city and a metropolitan borough located in Greater Manchester, England (latitude, 53°30'N, longitude 2°18'W). Salford has an area of approximately 97 km^2 and contains a range of land cover and land use types including several urban centres (Figure 3.2) (SCC, 2006). Salford contains residential suburbs, a large commercial and industrial area near Salford Quays to the East and large areas of agricultural land to the West, which is appropriate for urban ecosystem service research.

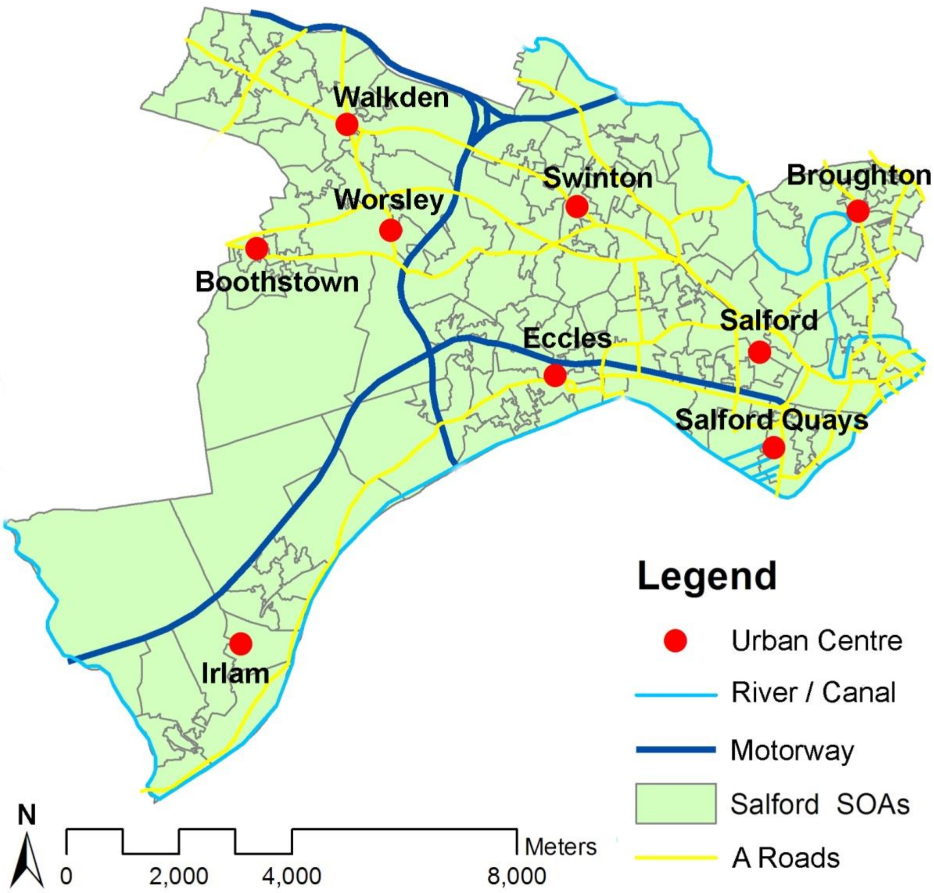

Figure 3.2: Map of Salford. This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown (2015).

The selection of Salford also provides potential for future work to look at how the ecosystem services generated and consumed in Salford contribute to the larger urban system of Greater Manchester (Figure 3.3). Comprising ten boroughs including the cities of Salford and Manchester, Greater Manchester is widely regarded as one of the drivers of the industrial revolution at the turn of the century (Douglas *et al.,* 2002). However, despite decline in manufacturing which led to increasing economic and social depression, recent creative investment is attempting to transform Salford and Greater Manchester into the economic hub of the North (Craggs and Schofield, 2011). In particular, the relocation of the BBC's operations to Salford Quays in Salford has promoted large scale investment and regeneration as well as an influx of highly skilled, creative workers (Noonan, 2012). The benefits of this economic shift are still being realised and data from the 2011 census shows that Salford is still experiencing higher levels of economic and social deprivation compared to the rest of England (ONS, 2015).

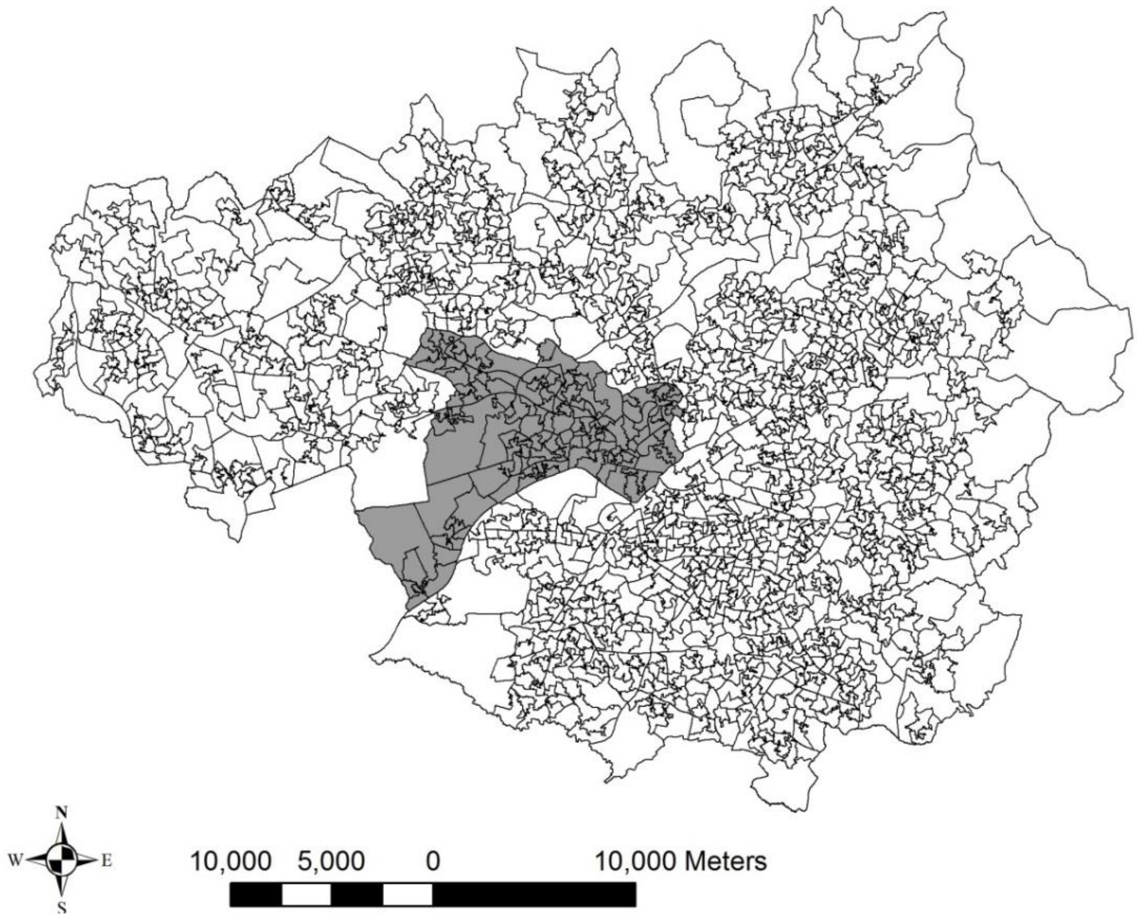

Figure 3.3. Salford (shaded in grey) as part of Greater Manchester (white). Black outlines represent Administrative Lower Super Output Areas. This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown (2015).

The Index of Multiple Deprivations (IMD) 2010 provides further information on patterns of deprivation across Salford (Figure 3.4). Out of 32482 administrative Lower Super Output Areas (LSOAs) across England, Salford has ten LSOAs in the top 1% least deprived (included in the white shaded areas of Figure 3.4). These are situated towards the West, around Worsley village (Figure 3.2). On the other hand, there are many LSOAs of very low deprivation, including two LSOAs in the bottom 5% nationally, i.e. the most deprived areas. These LSOAs are located in Weaste and Langworthy, towards the East of Salford, near the point marked ‘Salford’ in Figure

3.2. This demonstrates a diverse range of residents that facilitates analysis into potential inequalities of ecosystem service provision and accessibility.

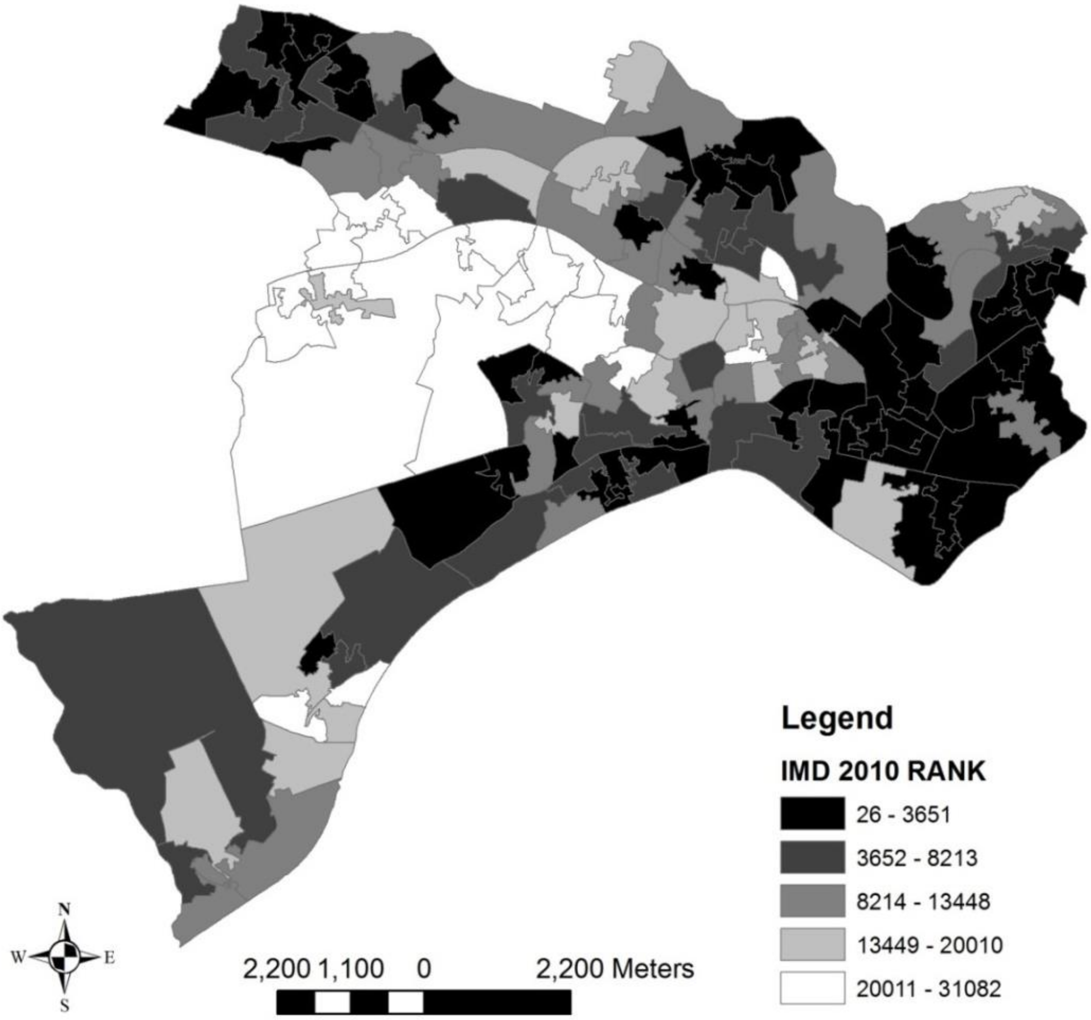

Figure 3.4. The ranked index of Multiple Deprivations (IMD) 2010. Black outlines represent Administrative Lower Super Output Areas. Low values indicated by darker shading represent the most deprived areas, while higher values shaded in lighter greys represent the least deprived nationally. Values are ranked such that 1 is the most deprived. This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown.

The previous chapter highlighted relationships between ecosystem services and physical urban greenspaces. Consequently, urban greenspaces is a relevant focus for this research. Almost 20% of Salford is covered by greenspace audited by Salford City Council (SCC) (Figure 3.5, Table 3.2). There is a relatively even division of land use between local and natural green spaces, district and neighbourhood parks, sports pitches and golf courses, which each occupy approximately 3% of Salford.

Woodlands occupy over 5% of Salford, and appear to be well distributed across the city apart from the South East (Figure 3.5). Consequently, management and monitoring of this development and the whole city would be valuable in ensuring that provision of ecosystem services is available to both workers and local populations. However, this data does not include unaudited greenspaces like grass verges along transport routes, brownfield sites or large expanses of agricultural land to the South and West of Salford

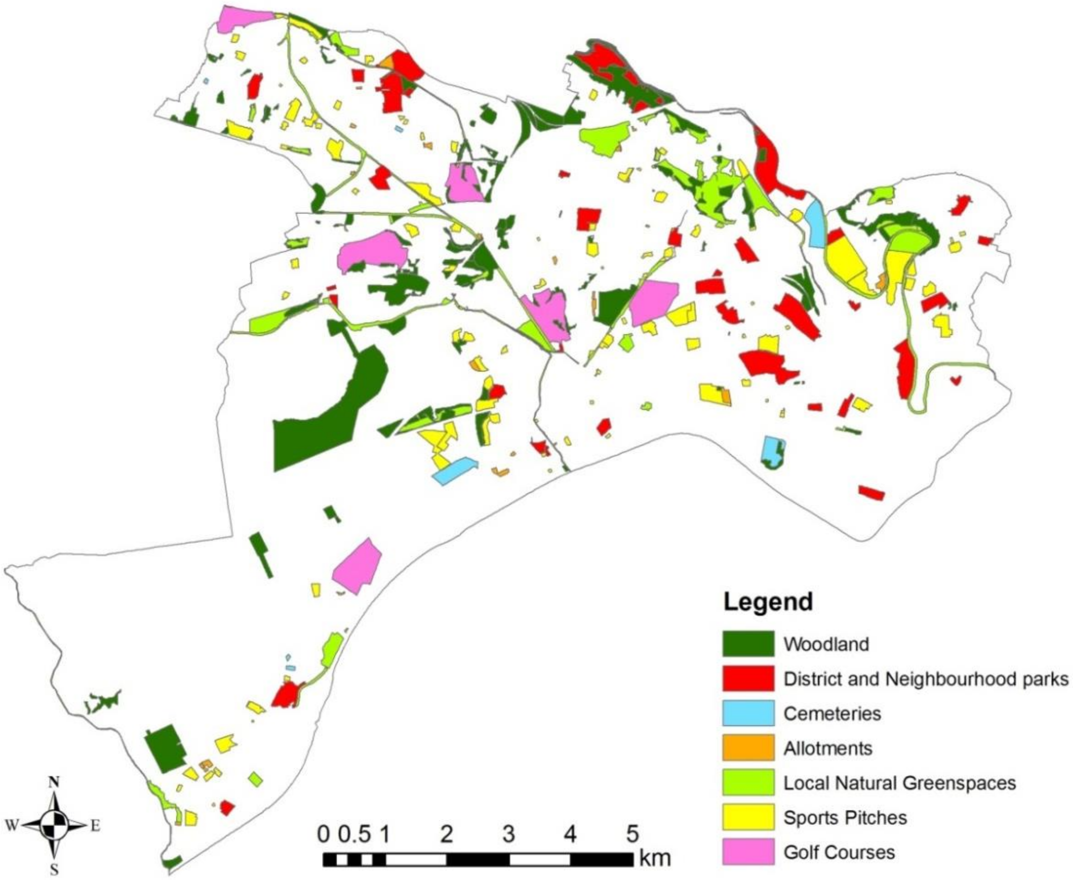

Figure 3.5. Greenspaces audited by Salford City Council. (SCC, 2006)

Table 3.2. Area of greenspace by type over Salford (data from SCC Greenspace Audit, 2006)

Greenspace type	Area (m^2)	Percentage of Salford
Woodland	5690952	5.9%
Local Natural Greenspaces	3484967	3.6%
Sports Pitches	3113346	3.2%
District and Neighbourhood Parks	3032800	3.1%
Golf Courses	2147438	2.2%
Cemeteries	467449	0.5%
Allotments	184217	0.2%
Total	18121169	18.7%

This section has presented requirements for defining a suitable urban case study and identified Salford as a typical urban area, appropriate for research. The social and economic background of Salford provides a backdrop of historic industrial development linked to economic and social depression, while the more recent history shows signs of increasing prosperity. Despite this, there are still stark spatial patterns in deprivation that overlay land cover patterns characterised by a widely distributed network of municipal greenspaces. Using Salford as a case study also provides opportunities for assessing its performance in generating and consuming ecosystem services against other boroughs of Greater Manchester as one of the UK's largest urban conurbations.

3.3. Selecting and measuring ecosystem services

Selection of ecosystem services is essential to satisfy research objectives 2 and 3, but also to set a context for the entire thesis. Potschin and Haines-Young's (2013) acknowledgement of a place-based approach states that different cities and neighbourhoods have different priorities and these may change for communities within the neighbourhood. However, there are a series of underlying ecosystem services that are important for human health and security (Gomez-Baggethun and Barton, 2013). Ecosystem services considered in previous urban ecosystem assessments are presented in Table 3.3, with services broadly categorised into rows. Regulating and cultural services in particular are prevalent and will be the focus for this thesis. For example, water and air regulation are critical for maintaining physical health (Gomez-Baggethun and Barton, 2013), while recreational and aesthetic services encourage exercise and formation of social networks through shared use of space (Alessa *et al.,* 2008). These trends have been reinforced by Haase *et al.,* (2014b) in a recent meta-analysis of urban ecosystem service assessments. Provisioning services such as energy and food production are important, but are typically generated outside urban boundaries. Further, apart from smaller urban agricultural projects spatial relationships for provisioning food at a city scale are not easy to map (Koschke *et al.,* 2012). Noise buffering is removed from the selection due to difficulties with city-wide data collection, modelling and validation of data, although this would be a useful variable to consider for future research.

Table 3.3. Important ecosystem services in urban areas.

Previous ecosystem service studies			Ecosystem services chosen for Chapter 5
Bolund and Hunhammar (1999)	**Haines-Young and Potschin (2008)**	**Dobbs *et al.*, (2011)**	
Air regulation	Air quality	Air quality	Carbon storage
Micro-climate regulation	Climate regulation	Climate regulation	Climate stress mitigation
Noise reduction	Noise buffering		
Water regulation Waste treatment	Water flow regulation Water quality regulation	Drainage Storm Protection	Water flow regulation
Recreational/cultural values	Aesthetics Spirituality Recreation	Aesthetics Recreation	Aesthetics Recreation
	Genetic/biodiversity conservation Pollination	Genetic/biodiversity conservation Soil quality Productivity (Trees)	

3.3.1. Regulating services

Carbon storage and sequestration have demanded the most interest at local, national and global scales as an important feature in climate change mitigation policies (e.g. Chisholm, 2010; Davies et al., 2011; Eigenbrod *et al.,* 2011). Hein *et al.,* (2006) found that carbon storage was considered most important, although the nature of the service means that benefits are experienced globally. Carbon storage is not directly mentioned in the table above, but Petz and van Oudenhoven (2012) identified the key role that vegetation quantity plays in air quality regulation through capture of fine particular matter. They estimated that the 31% vegetation cover in the Groene Wood near Eindhoven, Netherlands contributes to a 10-15% reduction in local particulate matter concentration. Additionally, Whitford *et al.,* (2001) note that tree cover can also be linked to aesthetics, noise buffering, and temperature regulation. Direct measurement of trees therefore contributes to a range of ecosystem service measures. Methods of carbon storage measurement assume a direct correlation between vegetation quantity and stored carbon. This is usually determined through equations based on allometric tables of derived equations, (Davies et al., 2011; Strohbach and Haase, 2012), estimates from the Centre of Ecology and Hydrology (Eigenbrod *et al.,* 2011) or use of the Normalised Difference Vegetation Index (NDVI) (Nagendra, 2001). Sewtnam *et al.,* (2011) demonstrated that carbon sinks other than trees (e.g. soils, grasses, litter) were negligible in comparison to carbon stored in trees. Carbon storage will be measured using allometric equations, following a methodology proposed by Davies et al., (2011).

The second most commonly measured service in urban areas is climate stress mitigation, which measures ambient temperatures and permeability. This is related to the urban heat island effect, where urban areas are hotter due to increased pollution and a lack of mitigating vegetation (Memon *et al.,* 2009). Nichol and Wong, (2005) state that the urban heat island effect is considered more serious in warmer climates, but rising temperatures in urban areas are still of concern across temperate climates (Bolund and Hunhammar, 1999; Tomlinson *et al.,* 2011). Measurements typically use land cover-related evapotranspiration rate equations (Whitford *et al.,* 2001; Pauleit *et al.,* 2005; Tratalos *et al.,* 2007). These surface temperature maps are actually maps of ecosystem properties rather than ecosystem services. Few studies actually measure an ecosystem service in terms of mitigating factors (Schwarz *et al.,* 2011). Climate stress mitigation will be measured using land cover-based surface temperatures taken from remotely sensed imagery.

Flood risk and water flow management have been key issues in urban research due to increasing densification of urban land covers, which exceed drainage capacities (Swan, 2010). Kazmierczak and Cavan (2011) stress the vulnerability of poorer communities living in marginal, higher risk areas. Water flow mitigation measurements have commonly featured in models attempting to map multiple ecosystems services (e.g. Jackson *et al.,* 2013; Vigerstol and Aukema 2013). Measurements are typically made via land cover permeability equations (Whitford *et al.,* 2001; Tratalos *et al,* 2007; Eigenbrod *et al.,* 2011). Whitford *et al.,* (2001) use two equations to determine run off based on storage capacity utilising curve numbers to determine infiltration and interception rates. This requires only land cover types and assumes a flat 2D landscape, which does not properly reflect the landscape. Alternatively Nedkov and Burkhard (2012) include topography in their model to map supply and demand for flood risk. Jackson *et al.,* (2013) use cost-distance analysis across a Digital Surface Model (DSM) to determine mitigators to water flow through the use of a novel hydrological model. Cost-distance analysis builds friction surfaces, where each pixel or spatial unit infers an impedance value or cost to traverse it. In its simplest form, their model adjusts flow accumulation through a catchment based on infiltration properties of land cover and will be the conceptual basis for the methodology used in this thesis. Although water quality is an important ecosystem service, this thesis only focuses on water flow and subsequent flood risk as being more critical in urban areas. Water flow mitigation will be modelled using cost-distance analysis over a DSM (Nedkov and Burkhard, 2012, Jackson *et al.,* 2013).

3.3.2. Cultural services

Aesthetics and recreation along with other cultural services are more challenging to measure due to their ephemeral and interpretive nature (Fisher *et al.,* 2009). Consequently, methods are more diverse. Norton *et al.,* (2012) related eight cultural services to national habitat types based on biophysical characteristics and focus groups. They found that woodland, water and coastal habitats held the highest potential for service provision. Alessa *et al.,* (2008) relate survey results to biophysical properties of the landscape using kernel density estimation. The national scale of study to be too coarse, but the focus on physical characteristics is useful for measurements of potential service generation. Raudsepp-Hearne *et al.,* (2010) quantitatively mapped a count of observations of rare and endangered species for tourism estimates and instances of deer killed for hunting as an ecosystem service across Canada.

Qualitative methods are more commonly found in literature for cultural service measurement. For example, Raymond *et al.,* (2009) conduct interviews and mapping workshops to derive surfaces of cultural ecosystem service values and threats. Photo analysis has also gained in popularity De la fuente de Val *et al.,* (2006) ranked photos of two Mediterranean landscapes by eleven visual qualities before, reporting that complexity and diversity of vegetation to be of highest regard. Alternatively, Qiu *et al.,* (2013) collected visitor photography along a guided walk to relate biodiversity to aesthetics and recreation. More recently, web-based methods have arisen through social media photography sites such as Flickr or Panoramio, which exploits geo-tagged information from volunteered photos to derive perceived tourist attractions (Jiang *et al.,* 2013; Lee *et al.,* 2014). This method negates the requirement for conducting field surveys across potentially huge landscapes, instead producing estimation from points that individuals have chosen themselves as of importance (Wood *et al.,* 2013). Moreover, specialist programmes have recently been developed to make use of this new information. For example Salesses *et al.,* (2013) developed *Place Pulse*, a website that compares Google Street View images by criteria including uniqueness, safety, beauty and wealthiness in order to determine perceived inequalities in urban areas.

Qualitative methods focus on user preference through collection of local knowledge of the landscape. These methods capture local character, but they are difficult to validate and scale up (De la Fuente de Val *et al.,* 2006; Fagerholm *et al.,* 2012), and local knowledge is often incomplete or biased (Alessa *et al.,* 2008; Norton *et al.,* 2012; Zielstra *et al.,* 2012). This thesis adopts the UKNEA definition of cultural services as the environmental settings that enable provision of services. This explicitly links cultural services to the landscape. Recreational values and aesthetics values will be measured using a land cover-based approach. Aesthetics potential is further augmented with a density surface, mapping a count of scenic photos from a web-based programme, over the research site. The importance of cultural ecosystem services concerns the requirement of human contact with nature for the maintenance of physical and mental health (Pacione, 2003; Tzoulas *et al.,* 2007) This is linked to the landscape via connectivity of urban design to increase health related activities such as walkability (Lwin and Murayama, 2011; Hankey *et al.,* 2012). Chiesura (2004) points to the specific importance of urban parks as spaces that incorporate ecological and environmental services as well as being designed for social and psychological benefits.

Based on the above review, this research will use the following ecosystem services: Climate stress mitigation, Water flow mitigation, Carbon storage, Aesthetic value and Recreational value.

3.4. Landscapes

Requirements for the first research objective are addressed in this section by considering characterisation of the physical landscape as a basis for research. The section discusses different approaches and interpretations of landscape data based on a remote sensing approach. Remote sensing is established in the literature as a primary source of data for land cover and land use mapping, due to its synoptic perspective, wide coverage and diversity of available sensors (Burkhard *et al.,* 2009; Weng, 2012; Wentz *et al.,* 2014). Implementation is conducted in Chapter 5.

The structure of this section follows the urban remote sensing structure supplied by Wentz *et al.,* (2014) in Figure 3.6. Figure 3.6 is adapted from Figure 2.5 to include characteristics specific to this research. The figure demonstrates how urban remote sensing will be used to support the landscape analysis throughout this thesis. Theme 1 of Figure 3.6 describes the mapping of urban land areas. This is discussed in Sections 3.4.1 - 3.4.3 which include a justification for the land cover and land use types used in the thesis, and methodologies and parameters for land cover classifications and land use characterisations. Theme 2 of Figure 3.6 describes the creation of urban indices. This is discussed in Section 3.4.4 and 3.4.5 and implemented in Chapter 5. Theme 3 describes the modelling of human and physical processes. The research completed in Chapters 5, 6 and 7 maps onto Theme 3 and is discussed in Section 3.5 and Section 3.6.

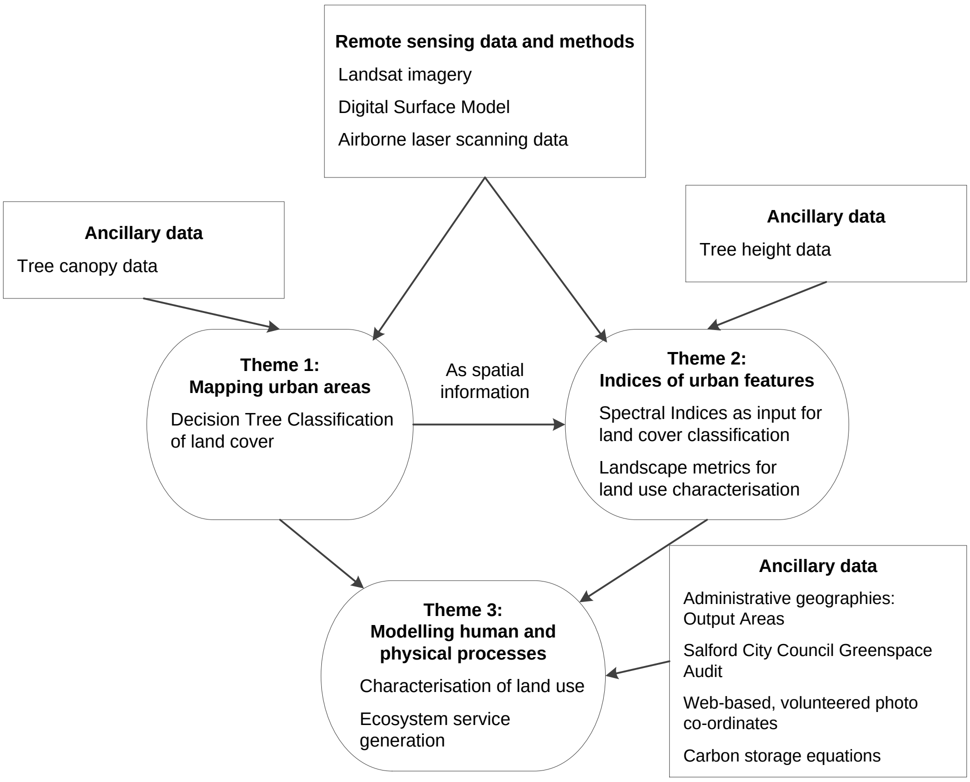

Figure 3.6. Remote sensing structure adapted from Wentz et al., (2014) to include features specific to this research.

3.4.1. Land cover typologies

Based on the review in Section 3.3, it would be useful to classify vegetation and impervious surfaces as key drivers in the promotion or obstruction of ecosystem service generation (Gaston *et al.,* 2013). Classification of water is useful for establishing sources and sinks for hydrological modelling (Xu, 2007), and classification of bare earth is useful to identify brownfield sites and other transitional areas (Zhao and Chen, 2005). In addition, preliminary experimentation suggested a requirement for a mixed pixel, particularly in suburban areas where there was a mixture of impervious, bare earth and vegetation within a single pixel (Epstein *et al.,* 2002). Further, the existence of large exposed wet peat bogs to the south west of Salford were misclassified as impervious due to high water content. A Peat land cover was included as a subset of the Bare Earth classification.

3.4.2. Land use typologies

To represent ecosystem service generation at the landscape level, a broad measurement of the physical environment is required. The review in Section 2.5.2 discussed the importance of characterising more descriptive land uses and concludes that characterisations based on urbanisation and residential neighbourhoods would be useful for representing and analysing ecosystem services. Urban land use models have traditionally applied core land use categories including a central business district, industrial estates and residential areas, greener hinterlands (Park and Burgess, 1925, Hoyt 1939). These land uses have distinct spatial patterns. They have been retained by more recent studies (e.g. Tratalos *et al.,* 2007; Herold *et al.,* 2004), and UK national land use datasets (Bibby, 2009). The National Land Use Database (NLUD), was developed as a series of records geographically referenced to Ordnance Survey (OS) Mastermap data using Easting and Northing co-ordinates (NLUD, 2004), and pre-defined land use classifications. The full NLUD was eventually abandoned in 2005 in favour of a simplified General Land Use Database (GLUD) (Bibby, 2009). NLUD and GLUD provide land use information at a scale that is too fine for the purposes of this research (e.g. gardens, roads, and rail) (Table 3.4), which is to provide each OA with a character type. However, the main categories of GLUD are still relevant.

Alternative methods use typologies relevant to the scale of their research. Kroll *et al.,* (2012) used seven broad land use categories from CORINE to determine ecosystem service supply and demand in the Leipzig-Halle region of Germany, while at a finer city-block scale, Hermosilla *et al.,* (2012) used *historical, urban, open urban, detached housing, terraced housing* and *industrial land use types from* the Land-Cover and Use Information System of Spain (SIOSES) for their characterisation of Sagunto, Spain. As a further example, Vanderhaegen and Canters (2010) used ten distinctive urban morphologies in Brussels, Belgium, while Yoshida and Omae (2005) characterised city blocks in Shibuya, Japan, using a LiDAR dataset into only three categories - residential, commercial and mixed. Alternative measures of development (rural/suburban/urban) have been classified using impervious surface cover (Magura *et al.,* 2008) or vegetation proportion (Dimoudi and Nikolopoulou, 2003) to derive more general fractions of urbanisation, but this provides no information on actual or perceived land use.

Table 3.4. General Land Use Database (GLUD), National Land Use Database (NLUD) land use classifications and Land use types selected for this research.

GLUD	NLUD	Thesis land uses
Domestic Buildings	Residential	Terraced Semi-detached Detached
Non-Domestic Buildings	Retail Industry and Business Utilities and Infrastructure Community services	Non-Domestic
Roads Paths Rail	Utilities and Infrastructure Transport	
Domestic Gardens		
Green	Recreation and Leisure	Green and blue
Water		
Other	Agriculture and Fisheries Forestry Minerals Vacant and Derelict Defence Unused Land	Agriculture Woodland

Based on the relevant UK context of the NLUD and GLUD, the final column of Table 3.4 lists the land uses used in this thesis. Categories have been primarily derived from both the NLUD and GLUD, but draw from the other studies reviewed. Separate residential land uses will be defined due to their dominance of the urban landscape. Non domestic land uses are aggregated from NLUD due to challenges in separation. This is discussed in further detail in Chapter 5. Network based infrastructure is not included as land use types as they are primarily represented as lines, rather than polygons and therefore not useful for mapping ecosystem services. Green and water are grouped together to better map open urban greenspaces, which may include water bodies. Finally, Agriculture and Woodland are extracted as important land uses from the SCC Greenspace Audit (SCC, 2006) (Figure 3.5) and Section 3.2.

Characterising urban structures is an important application for land use mapping, which can be used to readily distinguish residential, commercial and industrial land uses (Gil *et al.,* 2012; Heiden *et al.,* 2012; Hermosilla *et al.,* 2012). Characterisation is usually derived from analysis of the distribution and shape of features on the earth's surface (Herold et al., 2004). Building dimensions are significant in urban characterisation (Gupta *et al.,* 2012). Hussain *et al.,* (2007) were able to characterise different types of residential buildings in Manchester, UK based on a building footprint dataset, using immediate adjacency and total neighbours. However, the heights of buildings were not considered. Alternatively, Vanderhaegen and Canters, (2010) considered spatial metrics within city blocks in Brussels, Belgium. They used a detailed vector-building footprint layer, including number of floors. They found that building density, street-side pattern, footprint size and building heights accounted for 86.8% of the total variance. However, Yoshida and Omae, (2005) stress the importance of general morphology rather than specific architecture when they characterise residential, commercial and mixed city blocks in Shibuya, Japan.

Non-domestic buildings will remain as a single land use as in GLUD, as it is unlikely that a single type of non-domestic building will be present throughout an OA. Conversely, the term 'domestic building' (GLUD), or 'residential' (NLUD) is too vague because the majority of Salford is residential and application of a single character type would make the characterisation largely irrelevant. Consequently, this research will follow the Output Area Classification (OAC) variables (Vickers and Rees, 2007), who use housing stock as a method of separating residential land uses, and Hussain *et al.,* (2007) who used five classes of building: Detached, semi-detached, terraced and end terrace, with an additional complex category for other building types to characterise land use in Manchester, UK. Features such as minerals and fisheries are not relevant to this research and it is unlikely that whole OAs will be categorised as 'vacant and derelict', so these have been removed. However, agriculture is maintained due to large areas of activity to the west of Salford. Finally, the importance of urban green space, as emphasised throughout Chapter 2, will be separated into two categories to emphasise the importance of urban trees as evidenced in the literature (Yang *et al.,* 2009, Escobedo *et al.,* 2011, Hauru *et al.,* 2012, Dobbs *et al.,* 2014). Splitting green space into Woodland and other vegetation provides wider scope to disaggregate ecosystem services. This research uses the land uses outlined in the final column of Table 3.4, derived from currently used land use categories and based on the known composition of the research site.

3.4.3. Land cover classification method

Research objective 1 (Section 2.6.1) outlines the importance of classifying land cover, within the context of measuring ecosystem service generation (Section 3.3). The challenges of land cover mapping for ecosystem service research detailed in Section 2.5.2 suggest a requirement to develop rapid, autonomous methods for deriving urban land cover. Ecosystem service generation measurements are based on physical properties of the landscape, but are also characterised by their dynamic nature. The importance of ecosystem services spans the globe and it is important to be able to measure the generation of these services across a myriad of urban environments using a series of standard rules in to achieve results that can be translated and compared. Burkhard *et al.,* (2009) state that datasets like CORINE are suitable for initial analysis, but more detailed land cover classifications are required for local and regional studies. In particular, Burkhard *et al.,* (2009) suggest that spatial resolutions need to be finer, additional feature details need to be added and a methodology that allows easy repetition for temporal studies. The following paragraphs discuss current methods used to classify land cover from remote sensing imagery.

Land cover classification typically relies on deriving land cover types through interpretation of remotely sensed data. This involves direct analysis of reflectance values across the electromagnetic spectrum, or analysis of the textural patterns of these reflectance values. Pal and Mather (2003) identify three main types of land cover classification: Logic-based approaches, statistical approaches and neural approaches. Logic-based classifications apply a set of rules to reflectance values or textures to classify pixels into land cover types. Logic-based decision trees recursively separate data into smaller subclasses based on a series of decisions or tests at each node in the tree (Figure 3.7). Each leaf in the tree represents a different class member (land cover type) (Friedl and Brodley, 1997).

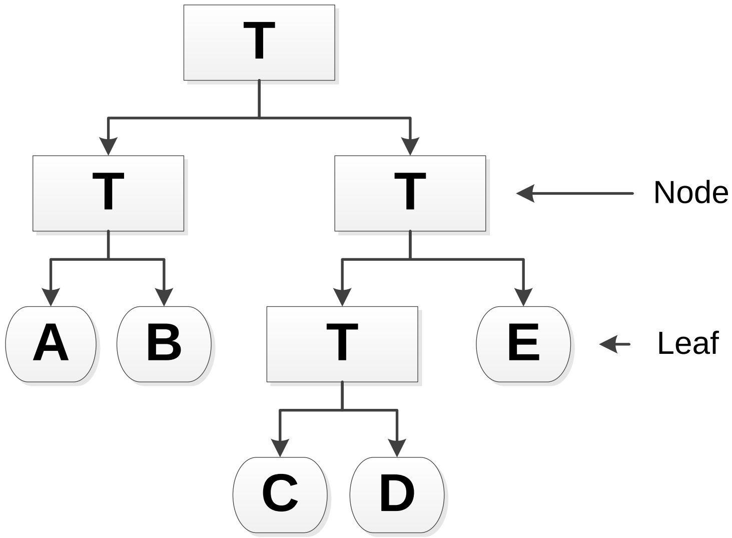

Figure 3.7. Representation of a Decision Tree Classification system. T represents the test or criteria that determines which branch is taken. Letters A-E represent final classification members (land cover types) (from Friedl and Brodley, 1997)

Statistical classifications assign land cover types to pixels based on probabilities. An initial library of known land cover types is created, which relies on data taken from areas in the image that contain only one land cover type. The record for each land cover type includes information on the pattern of reflectance that it produces. Statistical classifications compare all other pixels in the image to this library of 'pure' land cover data and assign a land cover type based on a chosen statistical algorithm. Examples include Maximum Likelihood Classification (MLC), where pixels are assigned the land cover that they are most likely to belong to (Lillesand *et al.,* 2008), and support vector machines (SVM). SVMs are statistical regression models that differ from tradition statistical models in that they focus on the values that define class boundaries rather than statistical properties such as mean and variance.

Neural classifications such as artificial neural networks (ANN) are designed to simulate the human learning process. Similar to statistical classifications, neural classifications rely on a set of data on known land cover types. A network of neurons (functions) is created to convert input pixels to output land cover types. Weights are added to each neuron. The classification is then 'trained' to learn which route through the network should be taken for each input to reach the correct output. This is done through iteration of classification, with the weights being amended to strengthen or weaken connections as necessary each time (Campbell and Wynne, 2011).

In their evaluation of classification approaches on Landsat ETM+ data, Pal and Mather (2003) report that decision tree classifications are more appropriate than either statistical or neural methods. Decision trees have advantages over statistical methods because they make no assumptions of the frequency distribution of data and are able to use multi-scalar inputs although performance tends to drop with high dimensional (i.e. hyperspectral) data (Pal and Mather, 2003). Decision trees do not out perform ANN, but Foody and Arora, (1997) and Huang *et al.,* (2002) found that training times for neural methods and SVMs can extend to days. On the other hand, decision trees are easier to train, quicker to implement and provide a completely transparent methodology for deeper interpretation of results (Tooke *et al.,* 2009). A further advantage of decision trees is the facility to aggregate multiple decision trees into random forests (Breiman, 2001). As well as improving accuracies, the random forest algorithm also produces error estimations for each variable allowing measurement of variable influence. This is useful for complex data, but Walton (2009) found that random forests were out-performed by SVM, for urban land cover classification. A decision tree approach was applied to classify the land cover classification. The classification also uses ancillary datasets as highlighted in Figure 3.6 to incorporate tree canopies and building footprints that are smaller than Landsat pixels.

Hard classifications assume that pixels can only belong to one class or another (Walton, 2009). Alternatively, soft classification algorithms can improve accuracy by allowing individual pixels membership to more than one class. This is typically based on two approaches: splitting pixels into a number of different land cover types (sub-pixel approaches) (Ridd, 1995) or producing probabilities into the classification (fuzzy classification) (Zhang and Foody, 2001).

Sub-pixel approaches such as Spectral Mixture Analysis (SMA) estimate the fraction of each land cover type or ‘endmember’ within a pixel (Small and Lu, 2006). This is based on comparison of the data in that pixel against known land cover types. Separate maps are produced for each endmember, displaying the fraction expected within each pixel. However, Weng (2012) found that impervious surfaces are often over represented in low impervious areas and under-represented in high impervious areas.

In fuzzy classification, a pixel is assigned probability values dependent on how close the spectral signature is to that of pure training areas (Jensen, 2005). This means that pixels may have partial membership to several classes (Foody, 1999). Fuzziness has been incorporated into all methods outlined in the previous paragraphs, including object-based analysis (Hu and Weng, 2009), decision trees (Myint, 2006) and neural networks (Chen *et al.,* 2009). Hu and Weng (2009) find that fuzzy methods outperform SMA in their comparative classification of impervious surfaces in Marion County, Indiana. Fuzzy methods have also been used to improve SMA classifications (Tang *et al.,* 2007) and have also shown a higher accuracy when compared against them (Hu and Weng, 2011). However, accuracy assessment is complex as fractional land cover ‘ground truthing’ is required. This is difficult to define and difficult to implement, and conventional confusion matrices used for hard classification are not suitable (Tang *et al.,* 2007). This thesis uses a hard classification approach because the complexity of soft classifications and data at the sub-pixel level is not required.

Validation of a land cover classification is the final step before it can be used with any confidence. This process produces information on how close to reality the classification is (based on reference data). Confusion matrices are a common method of accuracy assessment (Lillesand *et al.,* 2008). They produce an overall accuracy for the whole classified image, a producer’s accuracy and user’s accuracy for individual classes and a kappa statistic. The producer’s accuracy measures how good the classification has been based on dividing the total number of correctly classified pixels for each class by the number of observed points taken for that class. The user’s accuracy indicates the probability that a pixel with this class will actually be the correct land cover. This is measured by dividing the total number of sampling points classified as that class by the total number of correctly classified pixels in each class (Lillesand *et al.,* 2008). Kappa is a statistical measure of difference between the actual agreement between reference data and an automated classifier and the chance agreement between reference and a random classifier (Congleton and Green, 1999). A value of 1 indicates full true classification and that everything classified is the same in reality. A value of 0 indicates pure random chance of agreement. Any value above 0.6 is deemed acceptable (Landis and Koch, 1977). Comber *et al.,* (2012) critique the confusion matrix for neglecting the spatial distribution of error. They address this by presenting a method that incorporates Geographically Weighted Regression (GWR) approach, which incorporates local spatial associations between points. However, there are significant issues with determining how distance weights are produced or how they might change in different locations (Chen and Yang, 2012). Consequently, accuracies will be assessed using traditional confusion matrices, which are standard practice in academia (Lillesand *et al.,* 2008).

3.4.4. Land cover classification parameters

Based on a requirement for an autonomous method suggested in Sections 2.6.1 and 3.4.3, it would be relevant to incorporate spectral indices into the classification approach. This is because indices are mathematical algorithms based on sensor band combinations and they do not require any prior knowledge of the research site or land cover types (Chen *et al.,* 2006). Created using ratios of spectral bands, indices are commonly thresholded to extract specific land cover types (Masek *et al.,* 2000; Zha *et al.,* 2003; Xu, 2007). Impervious surface measurement has traditionally used vegetation indices and inferred impervious surface patterns from vegetation quantity estimations (Bauer *et al.,* 2007). Spectral indices commonly used or designed for use in urban areas are listed in Table 3.5.

Despite the fact that the Normalised Difference Vegetation Index (NDVI) is still the most widely used index in terrestrial remote sensing for rural and urban studies (Carlson, 2004), its use has been criticised in less vegetated urban areas. Indices that consider soil reflectances such as Soil Adjusted Vegetation Index (SAVI) and Modified SAVI (MSAVI) have shown increased accuracies compared to NDVI (Huete, 1988; Baret *et al.,* 1991). Further, modern building materials made of glass and metal have higher reflectivity than traditional brick and stone buildings. This means higher reflectances in the Red and NIR, which contributes to NDVI scores saturating. However, Kawamura *et al.,* (1997) argue that using vegetation indices assumes anything that is not vegetation is impervious. This means land covers such as soils are not considered. Furthermore, vegetation quantities fluctuate seasonally, affecting seasonal impervious estimates (Weng, 2012). The use of spectral indices reduces data redundancy and band correlation. This significantly reduces confusion between land cover identification (Xu, 2007). Therefore, spectral indices have been chosen as an autonomous, standardised and simple method for rapidly classifying landscapes.

Table 3.5. Spectral indices commonly used or created for use in urban areas. Data based on articles found through a Web Of Science™ search of five leading remote sensing journals from 2003 to 2013 that include the terms "urban", "built" or "impervious" and the index abbreviation in the article title.

Full spectral index name	Abbr.	Original purpose of index	Equation	Articles using index
Normalised Difference Vegetation Index	NDVI	Vegetation	$\frac{B_4 - B_3}{B_4 + B_3}$	90
Normalised Difference Built-up Index	NDBI	Impervious	$\frac{B_5 - B_4}{B_5 + B_4}$	18
Normalised Difference Water Index	NDWI	Water	$\frac{B_2 - B_4}{B_2 + B_4}$	16
Soil Adjusted Vegetation Index	SAVI	Vegetation	$\frac{B_4 - B_3}{B_4 + B_3 + L}(1 + L)$	12
Modified Normalised Difference Water Index	MNDWI	Water	$\frac{B_2 - B_5}{B_2 + B_5}$	5
Modified Soil Adjusted Vegetation Index	MSAVI	Vegetation	$\frac{2B_4 + 1 - \sqrt{(2B_4 + 1)^2 - 8(B_4 - B_3)}}{2}$	3
Index-based Built-up Index	IBI	Impervious	$\frac{\frac{2B_5}{B_5 + B_4} - \left[\frac{B_4}{B_4 + B_3} + \frac{B_2}{B_2 + B_5}\right]}{\frac{2B_5}{B_5 + B_4} + \left[\frac{B_4}{B_4 + B_3} + \frac{B_2}{B_2 + B_5}\right]}$	3
Urban Index	UI	Impervious	$\left(\frac{B_7 - B_4}{B_7 + B_4} + 1\right) \times 100$	2
Normalised Difference Bareness Index	NDBaI	Bare Earth	$\frac{B_5 - B_6}{B_5 + B_6}$	2

Table 3.5 lists four indices that have been designed to extract impervious surfaces. These use a wider range of the electromagnetic spectrum than vegetation indices. This highlights the more challenging heterogeneous nature of impervious surfaces, compared to vegetation. However, the first Urban Index (UI) created by Kawamura *et al.,* (1997) and the Normalised Difference Built-up Index (NDBI) created by Zha *et al.,* (2003) were only used in conjunction with the NDVI. This was because the impervious indices could not separate out areas of drier vegetation (Xu *et al.,* 2013). NDBI is further criticised for its inability to differentiate between impervious and bare earth (Stathakis *et al.,* 2013). As an alternative approach to extracting bare earth pixels, Zhao and Chen (2005) propose the Normalised Difference Bareness Index

(NDBaI), which makes unique use of thermal infra-red reflectance, although Huang and Cai (2009) suggest that use of this band can have consequences in suburban areas, where its larger spatial resolution (pixel sizes) can reduce precision.

3.4.5. Land use characterisation

Characterising land uses relies on broader interpretation of the surface of the earth than per-pixel land cover measurements. Chapter 5 uses landscape metrics to measure patterns in the land cover map to characterise land uses. This allows analysis of land cover proportions, or arrangement /density of specific land cover types, which could represent open vegetation, buildings or trees. Originating from landscape ecology-based vegetation studies, landscape metrics are algorithms that quantify spatial characteristics of patches, classes of patches, or entire landscape mosaics (McGarigal and Marks, 1994). Metrics operate on different spatial levels including individual patches, patch classes and landscape level (McGarigal and Marks, 1994; Syrbe and Walz, 2012). Metrics can be separated into categories (Herold *et al.,* 2004). Patch size and shape metrics, such as Mean Patch Size (MPS), Patch Size Standard Deviation (PSSD), Patch Density (PD), Edge Density (ED), and Landscape shape index (LSI) are useful for analysis of building size and complexity, allowing categorisation of land use (commercial, industrial, residential) (Herold *et al.,* 2006). Landscape diversity metrics such as Percentage of Land cover (PLAND), Shannon's index of diversity (SHDI) Simpson's index of diversity (SIDI) or Patch Richness (PR) describe the complexity and can indicate levels of fragmentation due to urbanisation (Luck and Wu, 2002; Kong and Nakagoshi, 2006). Finally, spatial association metrics such as Euclidean Nearest Neighbour (ENN), Aggregation metrics and Connectivity metrics describe how clustered or dispersed particular land cover classes are and can provide insight into patterns of impervious or vegetated areas (Kong and Nakagoshi, 2006). However, Herold *et al.,* (2002) acknowledge that most metrics do not consider the three dimensional structure of the built environment. Further, Luck and Wu (2002) note difficulties in generalising results due to local geographic features that impact on the rate and direction of urbanisation. Finally, Kong and Nakagoshi (2006) emphasise the importance of relating pattern to process to assist determination of the underlying causes or drivers of these patterns and changes. This research uses landscape metrics to provide indicators for characterisation of the landscape mosaic into land uses.

This study uses the nine metrics listed in Table 3.6, based on k-means clustering (discussed in section 3.5.2) of OAs to provide information on shape, size and distribution of land cover patches in Salford. Simpson's Diversity Index was selected from 'Landscape Metrics/Diversity' to provide information on landscape fragmentation (Zhang *et al.,* 2013). Percentage Land, Edge Density, Mean Patch Size, and Patch Size Standard Deviation were selected from 'Class Metrics/Area – Edge' to provide information on the size, and uniformity of land cover classes (Herold *et al.,* 2002). In addition to these landscape metrics, the mean and standard deviation of tree heights and building heights were included to provide information on the three dimensional form of impervious and vegetated surfaces.

Table 3.6. Landscape metrics used in the landscape characterisation. From McGarigal and Marks, (1994).

Landscape Metric	Description
PLAND (Class)	The sum of all patch areas of a given class divided by the total landscape area, expressed as a percentage.
Mean Patch Size (Class)	The mean patch size of a given class within an area.
Patch Size Standard Deviation (Class)	The standard deviation of patch sizes of a given class within an area.
Edge Density (Class)	The sum of edge segments of a given class (ha).
Simpson's Diversity Index (SIDI) (Landscape)	The value of SIDI represents the probability that two pixels chosen at random from the landscape will be of a different class. Range = $0 \leq SIDI < 1$. Values closer to 1 indicate high landscape diversity.
Building and Tree heights (mean)	Descriptive statistics from datasets derived in chapter 4.
Building and Tree heights (standard deviation)	

3.4.6. Spatial units

Measurement of ecological functions is based largely on environmental information, which has little or no bearing on human impacts or land uses. Consequently, it is relevant to use uniform square pixels that relate to raw datasets and are not changed by human impacts. Conversely, development of ecosystem services requires a spatial unit that is related to human activities. Land use characterisation studies commonly use local administrative units (Owen *et al.,* 2006; Li and Weng, 2007;

Rozenstein and Karnieli, 2011; Raudsepp-Hearne *et al.,* 2010). In the UK, census data collected by the Office of National Statistics (ONS) was collated into a series of hierarchical spatial units. The smallest of these are Output Areas (OAs), which have a minimum size of 40 households and 100 residents (ONS, 2013). OAs have been the basis for studies evaluating accessibility to facilities and services (Comber *et al.,* 2012; Higgs and Langford, 2013) and measurement of urban form for biodiversity potential (Tratalos *et al.,* 2007). However, they hide internal variation and are subject to change over time (Deas *et al.,* 2003; Gale and Longley, 2013). Consequently, some authors have created irregular spatial units based on landscape properties. For example, Hussain *et al.,* (2007) and Hermosilla *et al.,* (2012) used block geography to characterise buildings enclosed by road networks and Herold *et al.,* (2006) who manually derive 'Homogenous Urban Patches', based on a series of criteria such as incorporation of single land uses or following natural boundaries and being of adequate size for further analysis. Jellema *et al.,* (2009) adopted an object-based approach, where homogeneous regions are grown around seed pixels (Blaschke, 2010). These methods create 'objects' from spatially, spectrally or texturally similar areas. This reduces 'salt and pepper' noise from pixel-based classifications (Benz *et al.,* 2004).

Guan *et al.,* (2013) integrated height data from airborne laser scanning and hyperspectral data using object-based landscape segmentation to increase accuracies by highlighting specific urban features. They found that accuracies between object and pixel-based classifications were similar but suggest that a more robust segmentation algorithm is required to enhance results. Blaschke (2010) noted that segmentation issues may be due to the heterogeneous nature of vegetation growth, which can confuse classifications. Gupta *et al.,* (2012) continue to suggest that object-based analysis encounters difficulties in dense urban areas, where land cover types with similar spectral properties are commonly aggregated together. Sebari and He (2013) suggest this may be resolved using fuzzy thresholds in the segmentation process. Jellema *et al.,* (2009) find accuracy levels to be satisfactory, but they note that subjectivity is introduced through human interpretation of segmentation and aggregation.

Vanderhaegen and Canters (2010) critique regular spatial units as being unsuitable for modelling landscape units, preferring irregular landscape units, which they claim are more meaningful. However Nichol and Wong (2009) suggest that uniform pixels are more suited to environmental variables. Consequently, uniform pixels were used to create ecosystem service generation maps as these are uniform, unchanging spatial units. OAs were compared against object-based homogenous units for characterisation of ecosystem service generation to explore the relevance of administrative versus environmental boundaries. This research used OAs for landscape characterisation because they are the current standard for collection of socio-economic data easing comparative analysis and potential transition into current planning models (Deas *et al.,* 2003).

3.5. Multiple ecosystem services

The previous chapters have considered methods appropriate for measuring and mapping single ecosystem services. The following section reviews methods suitable for measuring the spatial distribution of ecosystem services and the spatial association between ecosystem services. These are mechanisms to satisfy research objective 2 outlined in Section 2.6.2 and Figure 3.1. The methods chosen will be implemented in Chapters 6 and 7

3.5.1. Spatial association

Methods of overlap analysis have been used to make measurements of spatial association between paired ecosystem service layers to determine trade-off and synergy patterns (Swallow *et al.,* 2009; Wu *et al.,* 2013). At the most basic, spatial association is based on percentage of shared area. Alternatively, phi analysis measures the spatial association of two overlaying coverages, where a value of 1 indicates total overlap and a value of -1 represents no association (Brown and Raymond, 2014). Neither of these solutions produces information on how equal the overlap is. For example similar percentages may be achieved by two equally sized coverages sharing a portion of their area or a small coverage completely subsumed by a large coverage. Consequently, the method used in this research follows the approach taken by Chan *et al*. (2006) and Bai *et al.,* (2011). The method uses pairwise correlation and two functions of overlap analysis: the ratio of observed to expected numbers of overlapping cells, O_e (Equation 3.1, from Table 3.7) and the number of overlapping cells as a fraction of the number of cells in the smaller hotspot.

Equation 3.1 $$O_e = \frac{C1C4}{(C1 + C2 + C3 + C4)}$$

Table 3.7. Contingency table for equation 3.1

		Ecosystem service Hotspot A	
		Absent	**Present**
Ecosystem service Hotspot B	**Absent**	C1	C2
	Present	C3	C4

The ratio of observed to expected overlap provides a measure of overlap strength, while high percentages of overlap in the smaller coverage overlap demonstrate that paired services are generated from similar areas, identifying potential tradeoffs or synergies. Low overlap percentages show that services are produced in different areas. This means they may be produced by different processes and may not share or compete for the same natural resources (Chan, *et al.,* 2006).

3.5.2. Clustering

Cluster analysis aggregates single and multi-variate data into groups that contain similar characteristics. Clustering has three main purposes: To gain insight into data, to identify a degree of similarity among members and as a method for organising and summarising datasets (Jain, 2009).

K-means cluster analysis aims to minimise within-cluster variability in k clusters to produce clusters that are as distinct from each other as possible (Everitt *et al.,* 2001; Vickers *et al.,* 2007). It iteratively relocates individuals into different clusters to minimise the sum of squared standard deviations within each cluster. A new iteration begins when all cases (pixels/areas) have been processed (Aldenderfer and Blashfield, 1984). Clusters are identified using proximity measurements across each of the variables, where cases that are very close to the cluster have very small distance values and cases far from the cluster have large values (Vickers *et al.,* 2007). (Raudsepp-Hearne *et al.,* 2010) used k-means clustering to characterise ecosystem service clusters across Quebec, while Soto and Pinto (2010) used k-means to characterise landscape units in Costa Rica. Reger *et al.,* (2007) found k-means to be a simple and workable method for landscape characterisation in Germany.

Alternatively, Owen *et al.,* (2012) used hierarchical clustering to characterise the landscape, while Martin-Lopez *et al.,* (2012) used it to derive ecosystem service clusters based on social values in USA. Hierarchical clustering assumes that each case is initially considered its own cluster. In the first step, the two cases closest together join to form a single cluster. Following steps repeat this process until all cases are joined into a single cluster. Final cluster numbers rely on interpretation of an accompanying dendrogram, which presents information regarding when clusters are formed. This provides a neater method for identifying cluster numbers than k-means, but once cases are joined together, they cannot be moved to other clusters, as during the iterations of k-means (Vickers *et al.,* 2007). Owen *et al.* (2012) tackled this by introducing probability into cluster membership.

At a more basic level, ecosystem service research has used simple GIS overlay to normalise and sum overlapping layers. Sheate *et al.,* (2005) summed five separate ecosystem services to produce aggregated hotspots. However, they acknowledge that this does not reflect reality as interrelationships between services are not considered and areas may be double-counted. Gimona and van der Horst (2007) assessed the multifunctionality of afforested agricultural land in Scotland, by weighting and overlaying potential recreation, visual amenity and biodiversity in wooded areas. However, their landscape-based approach is awkward as they only focus on woodlands as benefit producing sites. Alternatively, methods have been derived to cluster together ecosystem services by land use. Ericksen *et al.,* (2012) used expert knowledge and land cover characteristics to attribute crude service levels to different land use types in northern Kenya, while Burkhard *et al.,* (2012) developed capacity and demand matrices based on land use properties, but Eigenbrod *et al*. (2011) suggest that using direct relationships from land use produces inaccurate proxies for estimation. Troy and Wilson (2007) converted service levels to dollar values by land cover in USA. This works well for regulating and provisioning ecosystem services that are largely defined by bio-physical functions, but works less well for less tangible cultural services (Norton *et al.,* 2012).

3.5.3. Hotspot mapping

Modelling ecological hotspots is a useful tool for combining multiple service generation or service consumption spaces to highlight areas which provide the largest or most diverse range of services (Crossman and Bryan, 2009; Sheate *et al.,* 2005). Hotspot modelling was used in Chapter 6 (Figure 3.1). Egoh *et al.,* (2009, p554) define ecosystem service hotspots as "areas which provide large components of a particular service". However, there are inherent challenges involved in determining service generation thresholds. In ecosystem service research, this has traditionally been tackled by defining a basic value threshold such as the top 5% or 10% of values. (Anderson *et al.,* 2009; Bai *et al*; 2011, Wu *et al.,* 2013), or where possible, values drawn from literature (Egoh *et al.,* 2009). This is based purely on numerical values and does not consider the spatial distribution of values at all.

Recently, there has been more recognition of spatial influences. For example, Raudsepp-Hearne *et al.,* (2010) measured the spatial autocorrelation of services using Moran's I statistic as a means to determine how clustered they are. Spatial autocorrelation suggests that points closer together have more similar characteristics than those further away. The Getis-Ord Gi* statistic, adopted from crime and epidemiology mapping has also gained in popularity (Getis and Ord, 1992). Getis-Ord Gi* defines hotspots as areas where values are higher than would be expected (ESRI, 2008). The spatial methodology employs the Getis-Ord Gi* statistic within the Spatial statistics toolkit in ESRI's ArcGIS 9.3, which follows Equations 3.2, 3.3 and 3.4, where x_j = the attribute value for feature *j*, $w_{i,j}$ = the spatial weight between features *i* and *j* (calculated using inverse distance weighting) and *n* = the number of features.

Equation 3.2.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

Equation 3.3.

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

Equation 3.4.

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$$

This is quantified through the production of z-scores. High z-scores indicate that high value points are clustered and low scores indicate low value points are clustered. McPhearson *et al.,* (2013) used Getis-Ord Gi*, separating points with z-scores with significances $p < 0.01$ to investigate ecological and social needs at the neighbourhood level in New York, USA, while Dobbs *et al.,* (2014) used Getis-Ord

Gi* to focus on the benefits provided by urban forests. Zhu *et al.,* (2010) found improved results with Getis-Ord Gi* over simple density mapping, But Brown and Raymond (2014) found that both approaches were highly associated.

3.6. Accessibility and visibility

The following section considers the methods and parameters to be used to satisfy objective 3 (Section 2.6.3). Methods to measure physical access and observer visibility are discussed in the following subsections. These will be implemented in Chapter 8.

3.6.1. Physical accessibility

Accessibility studies are increasing being incorporated into measures of deprivation (Langford *et al.,* 2008). Based on the discussion in Section 2.4, this research adopts an accessibility approach to the consumption of ecosystem services, which will contribute to studies of access inequalities. Transport networks offer a suitable platform to model the flow of movement from an origin to a destination as they most accurately model how people or traffic are travelling across a landscape (Comber *et al.,* 2012). With regard to transport systems, edges represent road sections, while nodes represent junctions or destinations. By attaching a value (e.g. edge length or time-to-travel), distances between can be easily calculated by summing edge sections. In comparison, traditional methods apply straight line distances from points of origin to points of destination (Jordan *et al.,* 2004). Although Apparicio *et al.,* (2008) found high correlations between the two approaches, but the results were not uniform across Montreal, Canada. Comber *et al.,* (2008) state that network analysis operates with more accuracy than more traditional point-to-point and buffering straight line distances, which do not account for actual routes of passage (roads, paths) or obstructions (rivers, one-way systems). Oh and Jeong (2007) compared network analysis, finding service areas of urban green spaces were half the estimated area when using buffer analysis. Services areas are described as the spatial catchment within which residents have access.

Current methodologies applied by local councils use uniform service areas around green spaces to define access. The current consensus for council methodologies is to decrease the straight line distance by 40% of the desired distance threshold to account for barriers and obstructions (e.g. a 300 m straight line distance to represent a 500 m distance) (SCC, 2006). However, Higgs *et al.,* (2012) state that using straight line distances almost always underestimates transport routes. This is because straight line distances do not consider the geography of a location, or features that must be detoured around. Using a multiplier (as above) can only provide a rough estimate of journey times and actual distances. Therefore, in this research (Chapter 8), distances are modelled using road network data from Ordnance Survey. Network analysis was used to determine physical accessibility. Porta *et al.,* (2006) describe networks as a pattern of nodes connected together with edges. To improve network analysis in Chapter 8, Barbosa *et al.,* (2007) and Comber *et al.,* (2008) measured accessibility from OA centroids to known access points rather than park centroids or park boundaries that may not be accessible. This is a useful method, but individual households are not considered as origin points and more sparsely populated OAs may be much larger than densely populated OAs. This research follows Higgs *et al.,* (2012) identification of using individual buildings and park access points as the gold standard, though they recognise that this is complex and time-consuming to complete, current computing algorithms in GIS are developing technology to deal with large amounts of data.

Langford *et al.,* (2008) highlight the rising popularity of accessibility-based measurements, but warn that the methods used to create populations require greater attention. They compared dasymetric mapping and mailing lists to spatially weight population estimates in grid squares against an even population distribution. They report significant differences between the two approaches that increase with distance from urban centres, with dasymetric mapping tending to produce lower accessibility scores. Alternatively, Van Herzele and Wiedemann (2003) constructed ‘access possibility areas’ using an accessibility map derived from cost-distance analysis over a raster map. By summing pixel values between origins and destinations, a thresholded area can be derived. However, urban transport networks are currently best represented in vector form as lines and nodes (points). Elsewhere, social sciences have focussed on perceived accessibility to urban green spaces. Bonaiuto *et al.,* (2003) correlated higher perceived proximities to green spaces with increasing neighbourhood attachment related to attractive surroundings. Stronegger *et al.,* (2010) reported higher levels of physical exercise for residents who perceived their neighbourhood to have more ‘greener’ spaces, While Kondo *et al.,* (2009) compared objective neighbourhood environmental characteristics against a perceptual questionnaire, finding gender difference in physical activity when related to local knowledge levels, aesthetic value and public amenities. However, Maddison *et al.,* (2010) found poor correlation between perceived and objective distances to local recreational facilities for adolescents. Further, Pacione (2003) states that perceptions change dependent on local geographies and demographics between and within neighbourhoods.

3.6.2. Visibility

Viewsheds represent all the points on a 3D surface that are visible by line-of-sight from a single observation point (Llobera, 2003). Viewsheds are typically represented in a GIS as a binary raster grid, where pixels are either visible or invisible. When using multiple observation points in cumulative viewsheds, the value of each cell represents the number of observers that can see the cell (Fisher *et al.,* 1997). Llobera (2003) states that interpretation of viewshed analysis is reliant on the quality of the DSM used to apply the analysis. DSMs are now commonly derived using airborne laser scanning data, which can achieve spatial resolutions of less than 1 m^2 (Hamilton and Morgan, 2010). Viewshed algorithms operate by checking were observation points are obstructed by topography, so the DSM must incorporate surface features such as buildings and trees to maintain validity. In particular, vegetation remains an issue for visibility studies. Sander and Haight (2012) created a viewshed analysis to determine the aesthetic views around sample houses for hedonic pricing analysis, primarily focussed on the presence of green space. However, due to data quality constraints, they were unable to include trees as obstructions and had to crudely estimate building heights. Alternatively, Bartie *et al.,* (2011) used a DSM, with urban features extruded to determine initial visibility, with an ancillary weighted vegetation map overlaid in a second step to make amended assessment of line of sight. This has been improved by Murgoito *et al.,* (2013) through the use of airborne laser scanning to model obstructing tree trunks. However, the utility of this application is only serviceable for local research sites. Yasumoto *et al.,* (2011) created a virtual city model from 5000 sampled houses and a series of cumulative viewsheds of various amenities. They found spatial and demographic inequalities across Kyoto, Japan. In particular, older communities had less visible green space and water bodies, but also less visible industry, while richer communities had more visible access to greenspace, and historical buildings, although they assume the quality of amenities is equal. Further the patterns may be a result of specific local geographies and not necessarily due to consumer demands (Wolfe and Mennis, 2012).

In rural areas, observer height is typically considered as eye-height of an average person above the ground (Baerenklau *et al.,* 2010). However, in urban areas, views can be obtained from different heights in a building. Typically this is a given height below a derived building height (Bin *et al.,* 2008). Hamilton and Morgan (2003) used observer heights as the highest floor in a building derived from laser scanner data, using a value of 1.5 m below the mean roof height in their hedonic pricing analysis of beach views. Bishop *et al.,* (2004) augmented their viewshed analysis of city centres through the use of altered imagery for public interpretation. They found that vegetation and water were positive, while urban and industry was negative. Yang *et al.,* (2009) created the green view index using field surveys and photo interpretation for evaluating the visibility of urban forests. They reported good correlations with actual visibility, but note that interpretation is subject to personal taste and the method is time-consuming to repeat or scale up (Jim and Chen, 2010). Viewshed analysis was used to determine visible accessibility using a range of observer heights to represent the top floor of typical urban buildings including two storey residential accommodation and tower blocks.

3.7. Conclusions

This chapter has provided justification for each of the typologies and methods used in the rest of this research. A summary of the ecosystem services selected and typologies used for the land cover and use categories are presented in Table 3.8 and the key methods used throughout the thesis are listed in Table 3.1.

Table 3.8. Land cover, land use and ecosystem service typologies used in this research.

Ecosystem services	Land cover types	Land use types
Carbon storage Climate stress mitigation Water flow mitigation Aesthetics Recreation	Vegetation Impervious Water Bare Earth Trees Buildings Peat Mixed	Detached housing Semi-detached housing Terraced housing Non-domestic Agricultural Green and blue spaces Woodland

Decision tree classification and spectral indices have been chosen to map land cover. This provides an easily autonomous and transparent approach utilising sophisticated input parameters that allow simple adjustment where required if necessary. Developing a landscape approach throughout the research continues through the use of landscape metrics and k-means clustering to characterise the land cover mosaic into land use categories. This is implemented in Chapter 5.

The ecosystem services selected in Table 3.8 will be measured in Chapter 6. This is followed by hotspot analysis using thresholded values and the Getis-Ord Gi* statistic will be used in Chapter 6 to analyse the association of services with a view to exploring the relationships between services. Following Chan *et al.,* (2006) two measures of overlap analysis will be used in Chapter 7 to determine spatial association: the ratio between observed and estimated hotspot overlap, and the number of overlapping cells as a fraction of the number of cells in the smaller. This is followed by k-means clustering, which is used to characterise ecosystem service generation layers into clusters. Finally, network analysis and viewshed analysis will be applied in Chapter 8 to explore physical and vertical accessibility to services and to provide new insights into how cultural services might be evaluated. Datasets required to complete the research are explored and justified in the next chapter. These are based on the methods chosen in this chapter and the theoretical background posed in Chapter 2.

4. Datasets and Pre-processing

4.1. Introduction

This chapter is structured around Figure 4.1 and considers firstly justification and identification of suitable datasets and secondly the processing steps required to use the data. Figure 4.1 presents a further reworking of Figure 2.6 to outline the key datasets used within each research objective. Together with Figure 4.1, a list of datasets used is supplied in Table 4.1. The columns in Table 4.1 also show how the objectives are linked to Chapters 5 – 8, where the data is applied..

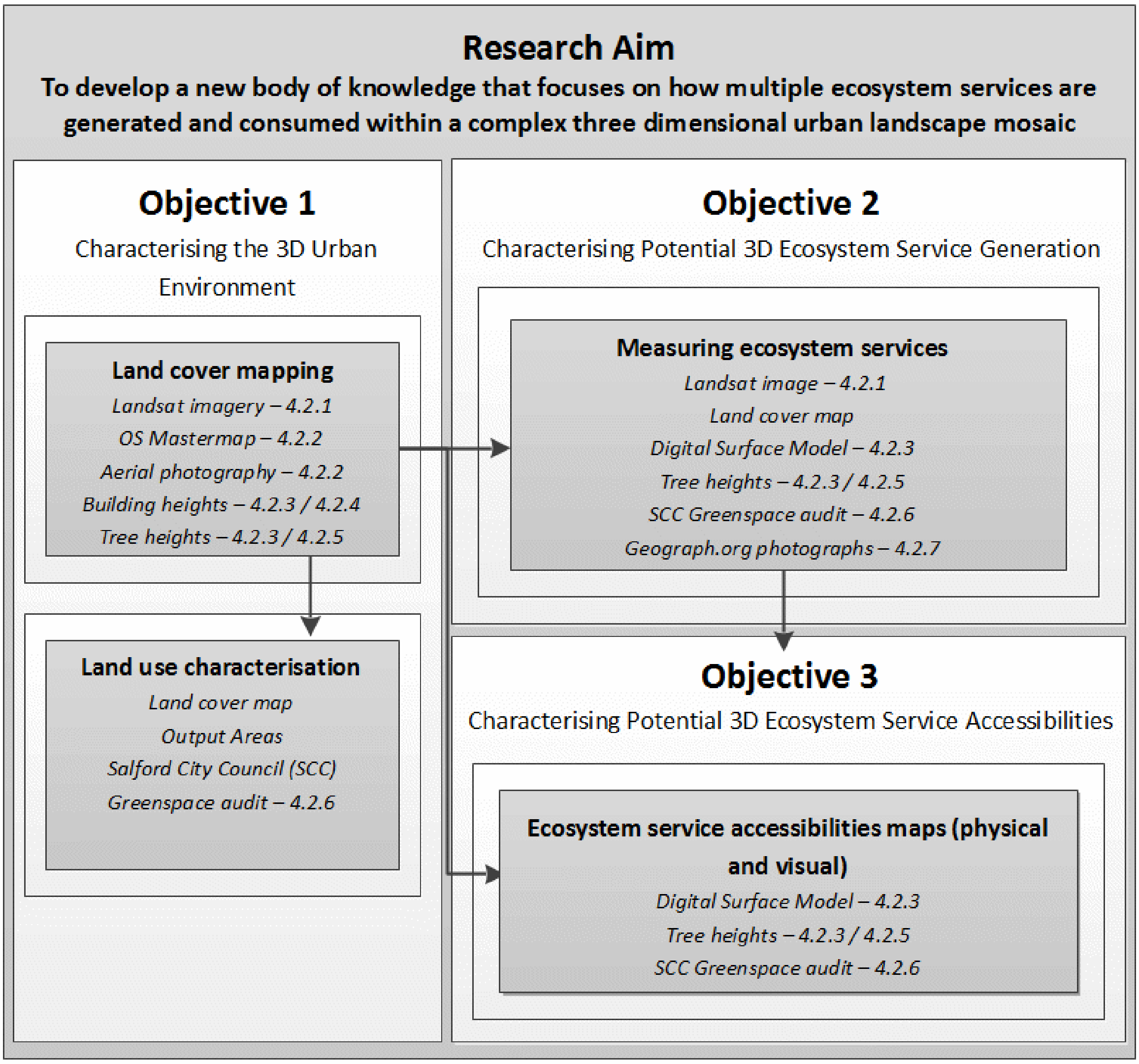

Figure 4.1: Datasets used within each component of the thesis.

Table 4.1. Raw datasets used in this thesis and the research outputs they were used to develop.

Dataset	Outputs			
	Objective 1 (Chapter 5)	**Objective 2 (Chapter 6)**	**Objective 2 (Chapter 7)**	**Objective 3 (Chapter 8)**
Landsat Image, June 2006	Land cover map	Climate stress mitigation		
Laser scanning topography (DSM)	Land cover map	Water flow mitigation		Viewshed analysis
Building Heights	Land cover map Land use characterisation			Viewshed analysis
Tree Height Survey	Land cover map	Carbon storage		Viewshed analysis
Ordnance Survey MasterMap	Land cover map validation - accuracy assessment			
Salford City Council Greenspace Audit	Land use characterisation	Aesthetics Recreation		2 ha audited greenspaces
Output Area Boundaries	Land use characterisation		Ecosystem service clusters	
Aerial Photography	Land cover map Accuracy assessment			Greenspace access points
Geograph.org geotagged photo co-ordinates		Aesthetics		
Ordnance Survey AddressBase				Network analysis Viewshed analysis
Ordnance Survey Integrated Transport Network				Network analysis Viewshed analysis
Ordnance Survey 1:25000 Map				Greenspace access points
Index of Multiple Deprivations 2010				Socio-economic analysis of ecosystem service accessibility

4.2. Datasets

4.2.1. Remote sensing imagery for base land cover mapping

The land cover classification that underpins objectives 1 and 2 (Sections 2.6.1 and 2.6.2) requires remotely sensed data as an input. This data will be used to create the land cover map in Chapter 5 and as an input for the climate stress mitigation layer in Chapter 6 (Table 4.1). Suitable input remote sensing data must have appropriate spatial and spectral resolutions for capturing features and classifying the land covers listed in Table 3.8.

The pixel size of an image is its spatial resolution. This defines the smallest features that can be identified in the image (i.e. an object the size of a single pixel) (Weng, 2012). Landsat Thematic Mapper (TM) produces 30 m x 30 m pixel images, which are categorised as medium resolution - between 10 m x 10 m and 100 m x 100 m pixels (Li and Weng, 2007; Weng and Hu, 2008; Gao *et al.,* 2012). Landsat data has been used to monitor the growth of mega cities (Taubenbock *et al.,* 2012), derive biophysical indices to monitor urban vegetation mapping and related temperatures in urban areas (Chen *et al.,* 2006), and calculate impervious cover to estimate population size (Wu and Murray, 2005). Images with higher spatial resolution (pixel size < 1 m^2) are more suitable for identifying urban features than Landsat and can mitigate misclassification (Lu *et al.,* 2011), but they cannot match Landsat's spectral resolution (Weng, 2012; Xu, 2013). High levels of misclassification from use of Landsat in urban areas have been mitigated through either data fusion with laser scanning data (Gao *et al.,* 2012), higher resolution imagery (Lu *et al.,* 2011), or development of fuzzy or sub-pixel algorithms discussed in Section 3.4.3.

The spectral resolution of an image represents the number and width of bands within the electromagnetic spectrum that a sensor is able to record (Weng, 2012). Landsat records seven bands including three visible light bands, three infra-red bands and one thermal infra-red band. In contrast, satellites with a higher spatial resolution usually have fewer bands. For example, IKONOS (4 x 4 m) and Quickbird (5.76 m^2) only record four bands including three in visible light and one in infra-red (Patino and Duque, 2013). Forestier *et al.,* (2013) found that Landsat outperformed higher spatial resolution sensors in discriminating urban surface cover types due to the additional infra-red bands improving identification of man-made surfaces (Herold *et al.,* 2002). Hyperspectral sensors capable of recording hundreds of spectral bands are better at distinguishing features with similar spectral features (Heiden *et al.,* 2012; Shafri *et al.,* 2012), but spatial and temporal coverage is lacking (image size and repetition of data capture), which means that images only partially cover cities. A Landsat TM image is approximately 170 km x 183 km in size, which is more than adequate to cover a city. The repeat rate for data is 16 days (USGS, 2012). Consequently, a Landsat TM image was chosen for this research.

The Landsat TM satellite was chosen over the more recent Landsat Enhanced Thematic Mapper Plus (ETM+) satellite due to the latter's scan line corrector failure, which has caused areas of the image to remain uncaptured. Masks are provided to remove vacant pixels from analysis and algorithms have been developed to fill in gaps (e.g. see Storey *et al.,* 2005), but most rely on previously collected data or information from neighbouring pixels. In either case, these solutions are not useful when dealing with heterogeneous urban areas. This is further exacerbated because the case study is situated in one of the corners of the image where the error is at its highest.

The Landsat image used in this research was taken on a day clear of cloud cover on 10th June 2006, (path 203, row 23) and was captured at 10:56 am. A shadow classification is often used with high resolution sensors (Xu, 2013), but use of a summer image minimises this issue because the full sun is almost directly overhead. An image was chosen from 2006, because ancillary datasets: the tree survey, building heights and aerial photography were also collected at a similar time. All seven spectral bands were used, with band 6 – the thermal infra-red band (10.40-12.50 µm), processed separately as it has a coarser resolution (120 m re-sampled to 30 m). Table 4.2 outlines the bandwidths for each wavelength. The image was radiometrically corrected before use to remove the influence of atmospheric haze.

Table 4.2. Landsat TM spectral information

Band Number	Description	Wavelength (micrometres)
Band 1	Visible (Blue)	0.45-0.52
Band 2	Visible (Green)	0.52-0.60
Band 3	Visible (Red)	0.63-0.69
Band 4	Near Infra-Red	0.76-0.90
Band 5	Mid Infra-Red	1.55-1.75
Band 6	Thermal Infra-Red	10.40-12.50
Band 7	Short Wave Infra-Red	2.08-2.35

Radiometric correction removes the affects of light scattered from atmospheric haze, and converts pixels from raw digital numbers to surface reflectance values. The first step involves converting digital numbers (DN) to units of radiance using a standard methodology derived by Chander and Markham (2003) and amended by Chander *et al.,* (2009) and calibration values taken from the header file of the image. Atmospheric correction was applied to radiance values following the darkest object subtraction method as implemented by Song *et al.,* (2001) and Hadjimitsis *et al.,* (2010), although Xu (2013) found no significant difference in classification results when comparing an image with raw values against an image with radiometrically adjusted values. Darkest object subtraction assumes that the darkest pixel in an image does not reflect any light at all back to the sensor (typically deep water or steep slopes in shadow). Therefore, the difference in reflectance in these pixels is a result of light scattering from atmospheric haze rather than the properties of the Earth's surface (Chavez, 1988). The image is atmospherically corrected by subtracting this reflectance value from all pixels in the image. This process must be done separately for each sensor band in the image. For this research, the process was completed in ERDAS IMAGINE, based on minimum and maximum values for each sensor band. Finally, radiance values were converted to reflectance values in ERDAS IMAGINE using standard methods (Chander and Markham, 2003).

Processing for input into the climate stress mitigation layer (Table 4.1) requires the thermal band of Landsat to be converted to temperature. Landsat TM band 6 is the thermal infra-red band (Table 4.3) and is used to calculate atmospheric and terrestrial temperatures. After converting DN values into radiance, Equation 4.1 converts radiance to temperature (°K) (Chander and Markham, 2003; Weng *et al.,* 2008). Where T = at-satellite temperature °K, $K2$ = calibration constant 2 (= 1260.56) , $K1$ = calibration constant 1 (= 607.76), λ = Spectral radiance at sensor aperture. ($K1$ and $K2$ taken from a look up table, see Chander and Markham, (2003)).

Equation 4.1:

$$T = \frac{K2}{\ln(K1/\lambda + 1)}$$

Due to the higher spatial resolution of the building and tree feature datasets, which had a spatial resolution of 5 m x 5 m pixels, all bands in the Landsat image were resampled to a matching resolution.

4.2.2. Detailed topographic data

Validation of the land cover classification is required in Chapter 5 (Table 4.1). This is traditionally completed through accuracy matrices. This relies on training points collected in the field from large uniform land cover types. However, the 30 m resolution of Landsat is likely to produce a number of mixed pixels (Epstein *et al.,* 2002). Therefore, selection of training points in dense, heterogeneous urban areas is challenging (Zhou *et al.,* 2010). As an alternative approach, Ordnance Survey MasterMap topographical data (OSMM) was chosen because it has been used to develop previous land cover models and is a well validated and robust dataset (Smith *et al.,* 2007). The OSMM topography layer was obtained from Digimap for the entire coverage of Salford (Edina, 2013,). It is based on previous 1:1250 mapping and achieves a positional accuracy of 1 m in urban areas (Ordnance Survey, 2015a). OSMM is a highly detailed, digital boundary dataset, which distinguishes objects and features on the Earth's surface and includes a range of attributes, primarily categorised into themes of feature type. However, these themes are broad and there is only one theme per polygon (Schubert *et al.,* 2009). Despite this, OSMM is still suitable for discerning the composition of mixed pixels within coarser 30 m x 30 m pixels that align with Landsat. OS 1:25000 raster data was also collected to identify urban greenspace access points for research objective 3.

The OSMM topographical layer was intersected with a grid of squares 30 m x 30 m to correspond with the Landsat imagery pixel resolution. The images in Figure 4.2 demonstrate how the pixel samples relate to aerial photography, comparing both a pure and mixed pixel. Figure 4.2 (A) presents the Landsat data, while Figure 4.2 (B) shows how ordnance survey data overlaps. A sample of 375 pixels were randomly selected for the land cover types selected in Table 3.8 as demonstrated in Figure 4.2, C (50 pixels for each of seven land cover classes, 25 for peat due to low representation in the case study), as Foody's (2002) recommendations. This sample was compared to aerial photography taken in 2006 to validate land cover categorisation, assuming that sample pixels were unlikely to have changed over the time difference (Figure 4.2, D). A new 'landcover' attribute was added to the sample of pixels and the land cover for each polygon was input as 'vegetation', 'trees', 'urban', 'bare earth' or 'water'. The sample of pixels was then used to develop the decision tree classification rules outlined in Chapter 5.

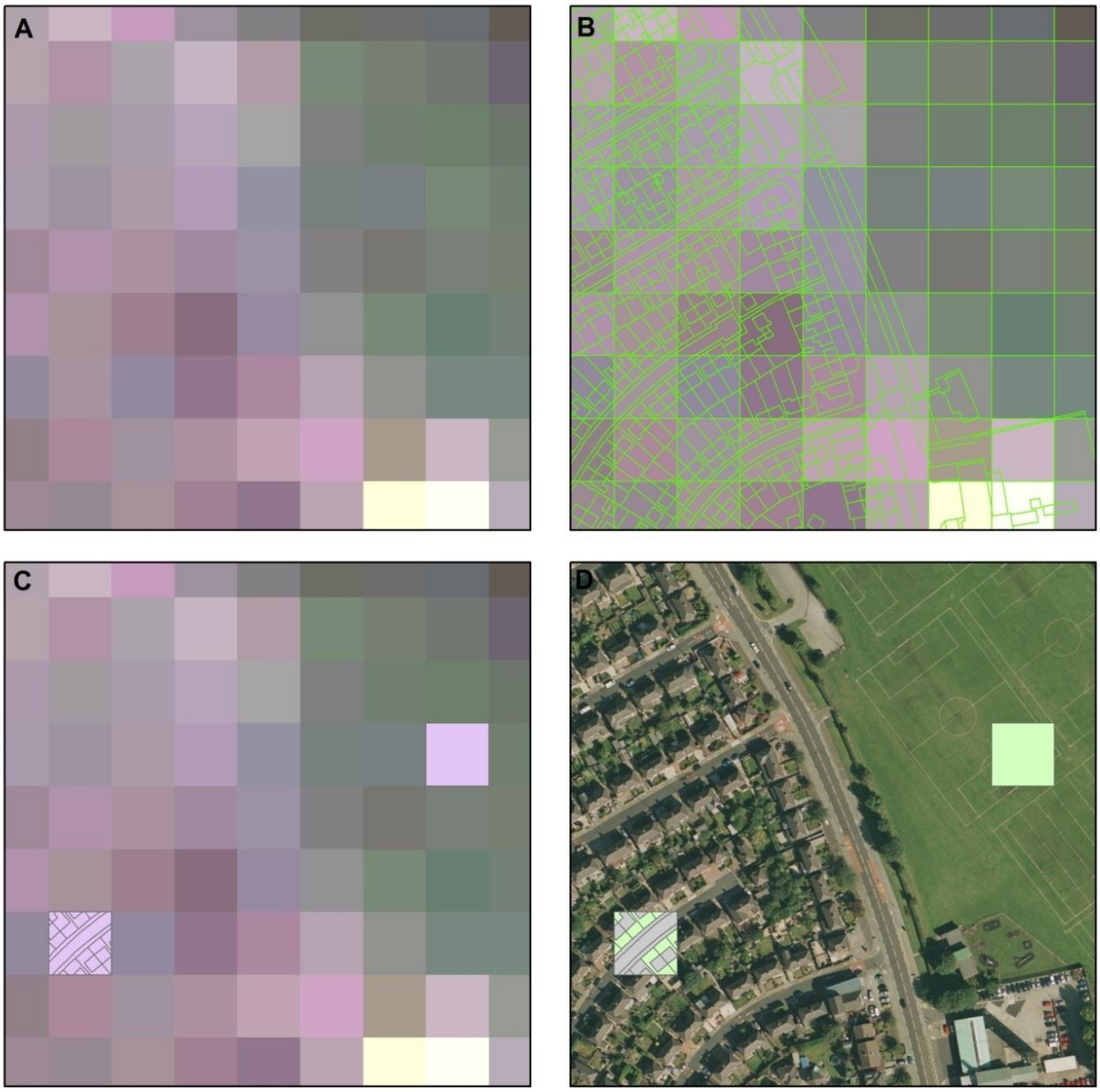

Figure 4.2. Comparison of sample pixels and aerial photography (A) Landsat imagery, (B) Overlaid, gridded OSMM data, (C) Selection of sample pixels, (D) Overlaid aerial photography (Landmap; The GeoInformation Group 2007).

4.2.3. Digital Surface Model (DSM)

Although the topography of Salford is relatively flat, there is a requirement in research objectives 1 and 2 (Sections 2.6.1 and 2.6.2) to determine surface heights across the case study site. The information in Figure 4.1 and Table 4.1 demonstrate that a Digital Surface Model (DSM) feeds into Chapters 5, 6 and 8 and assists in providing unique insights into how some ecosystem services are generated, distributed and experienced across a 3D urban landscape (Nedkov and Burkhard, 2012, Gret-Regamey *et al.* 2013). In addition to the importance of integrating a DSM into water flow modelling, the importance of height variations as outlined in the previous chapter means that a continuous surface of heights is required to develop wider spatial statistics such as mean and standard deviation of heights, which can then provide information on landscape character (Guan *et al.,* 2013). Due to the importance of detailed features such as trees and buildings, a high resolution DSM is required to derive building footprints and heights to provide a richer picture of the urban environment.

Produced by the GeoInformation Group and acquired from Landmap, based at the University of Manchester (Landmap, 2013), the Cities Revealed dataset is a Light Detection And Ranging (LiDAR) DSM with a horizontal resolution of 2 m and a vertical error of ± 0.15 m (The GeoInformation Group, 2010). This airborne mapping technique enables very fine spatial resolution, perfect for mapping and modelling the urban environment.

The DSM needs to be hydrologically accurate to model water flow (Jackson *et al.,* 2013). Sinks are areas in the DSM where one pixel of a small height is surrounded by pixels of larger height values. When hydrological modelling is conducted, water pools in these sinks rather than flowing through the DSM. Therefore sinks in the model need to be removed to allow modelled water to flow more accurately through the rest of the surface. The sink holes in the DSM were filled using ArcGIS hydrology tools in Spatial Analyst. This tool fills the sinks in by increasing the height value of the lowest pixel. To produce a hydrologically consistent DSM, present river networks were taken from OSMM and ‘burned’ into the DSM by replacing the DSM height values of rivers with ‘0’. This ensured that rivers were the lowest features in the DSM, acting as final destination areas for water. The DSM was resampled to 5 m to capture features as small as buildings and tree canopies.

4.2.4. Building heights

Building heights were used as ancillary dataset in the land cover classification (Chapter 5), the land use characterisation (Chapter 5) and the viewshed analysis of accessibility (Chapter 8) (as shown in Figure 4.1 and Table 4.1). A building heights dataset was acquired from Landmap (Landmap, 2013). The data is derived from the DSM described above and demonstrated in Figure 4.3. The data was created by identifying building footprints, extracting DSM heights and producing an average for each building (Figure 4.3, B). The dataset is a vector layer of polygons representing building footprints, each with its own height taken from an average of LiDAR recordings taken within the polygon boundary.

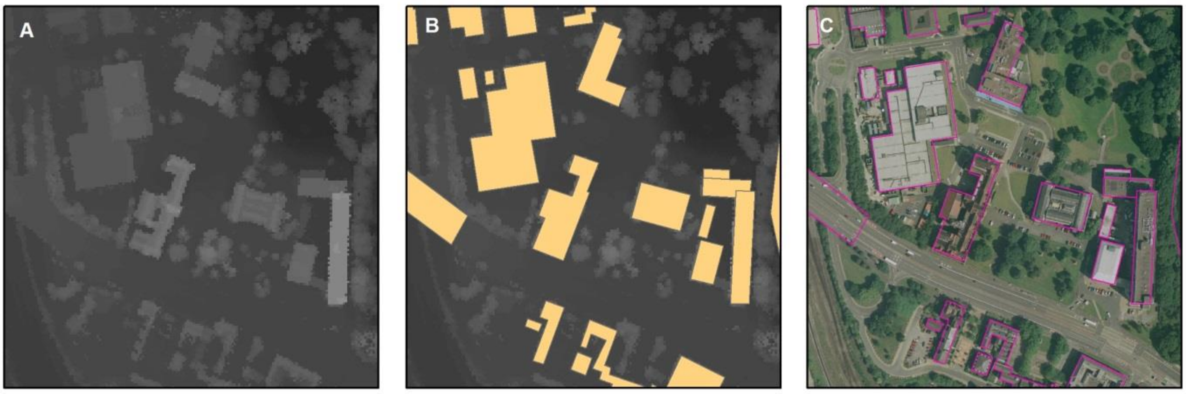

Figure 4.3. Example of building height data extracted from LiDAR (A), LiDAR height information (light pixels indicate higher features), (B) LiDAR data with derived building footprints, (C) footprints overlaid onto aerial photography. (Landmap; The GeoInformation Group (2014), Landmap; The GeoInformation Group, 2007)

4.2.5. Tree heights

When using Landsat data alone, the presence of buildings and trees as separate features in urban areas is lost and distinguishing between impervious surfaces such as car parks and buildings is difficult (Gao *et al.,* 2012). Consequently, ancillary datasets are used in this research to introduce additional information to the land cover classification and land use characterisation (Chapter 5), as an input to the carbon storage generation layer (Chapter 6) and the viewshed analysis (Chapter 8). The 3D spatial arrangement of trees and buildings in urban environments is important for characterising the urban environment (Cionco and Ellefsen, 1998; Herold *et al*, 2002), which provides information on differing land use as well as relating different urban morphologies to different social and economic groups. This is important in residential areas, where estates with larger houses are likely to include a higher proportion of trees (Wolfe and Mennis, 2012).

A digitised tree survey provided by Red Rose Forest and produced by Bluesky International Ltd (2015). displays the heights and position of each tree in Greater Manchester in 2009. The digital boundary dataset contains polygons representing tree crowns and attributes within polygons describing the base height of the tree above sea level and the height of the tree itself. The data was created through expert interpretation of aerial photography and application of a Digital Terrain Model (DTM). Where individual trees could not be identified (e.g. dense forest), treelines were created as single polygons covering the whole area, including height data as a point data set covering the polygons at 20 m intervals. A section of this data is provided in Figure 4.4 alongside comparative aerial photography (Figure 4.4, C).

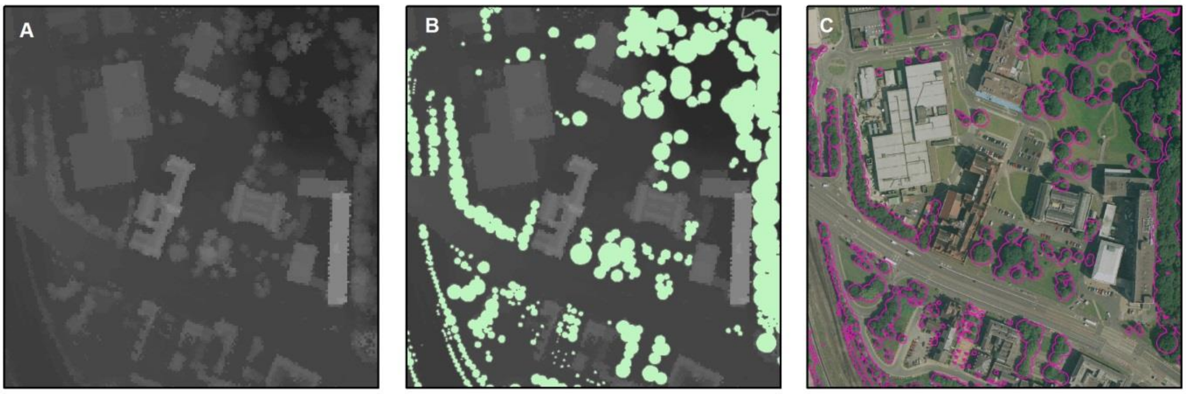

Figure 4.4. Example of tree height data. LiDAR height information (light pixels indicate higher features), (B) LiDAR data with tree canopy footprints, (C) Building footprints overlaid onto aerial photography. (Landmap; The GeoInformation Group 2007)

For integration of building and tree information into the land cover map in Chapter 5, the building heights and tree survey datasets were converted to a 5 m raster to align with the remote sensing imagery discussed in 4.2.1. This was to ensure that individual buildings and tree canopies could be identified. Buildings were assumed to be flat roofed and directly re-sampled. Individual trees were converted to raster grid format using the tree heights in metres as the grid value. The heights of the tree-lines were interpolated from the given heights points, using inverse distance weighting and the tree-line polygons as masks before adding the two tree datasets (rasterised tree points and interpolated tree lines) together. Finally, building heights raster data was merged with tree height data to produce a normalised DSM, where pixel values represent the height of the feature from ground level (i.e. ground level pixels = 0 height) and tree heights and building heights within pixels are stored separately.

4.2.6. Urban greenspace data

Produced by Salford City Council for their 2006 Green Space Audit (SCC, 2011), this vector dataset displays different categories of formal green spaces of Salford including parks, sports pitches public gardens, allotments and cemeteries as well as more strategically designated local and natural green spaces. The strategic Development plan (SCC, 2006) outlines the approach taken to create the audit greenspace boundaries. The audit aimed to map greenspaces, primarily with a formal or informal recreational function. The audit was created in four stages:

1) Collection of previous council audits of sports pitches and youth recreational areas, which mapped greenspaces using Ordnance survey base mapping and GIS digitisation of aerial photography;

2) A playing pitch assessment conducted by KKP Leisure Management, which established the provision and demand for sports pitches and golf courses. Mapping was completed through GIS digitisation of aerial photography as part of a wider assessment including in-depth interviews with local schools and sports teams;

3) A desktop-based study of other types of greenspace (primarily informal greenspaces) using aerial photography and Ordnance Survey Mastermap data;

4) Utilisation of information across SCC for greenspace dual functions. This data is more descriptive rather than spatial.

Descriptive statistics for this dataset have been produced in Section 3.2. Figure 4.1 and Table 4.1 demonstrate that the greenspace audit data will be used as an input into the land use characterisation (Chapter 5), aesthetic and recreation ecosystem service layers (Chapter 6) and accessibility to greenspaces 2 ha or larger (Chapter 8).

For Chapter 5, all green space audit layers were merged to form a single greenspace layer (Figure 4.5). To maintain simplicity and in accordance with Natural England's Accessible Natural Greenspace Standard (ANGST) guidelines, areas above 2 ha were extracted as significantly sized green spaces (Natural England, 2010). Figure 4.5 demonstrates a dasymetric approach to integrate this layer into the Output Areas (OAs) to improve characterisation of residential areas within OAs.

Figure 4.5. Integration of 2 ha green spaces into OA layer. (A), OA layer, (B) overlaid green spaces, (C) union function, (D) final product overlaid onto aerial photography (Landmap; The GeoInformation Group 2007).

Dasymetric mapping is an example of areal interpolation – where geographical information is transferred from one set of boundaries to another (Mennis, 2003). Dasymetric mapping uses finer resolution ancillary data to augment coarser datasets. Attributes can then be redistributed more accurately across the characteristics of added features (Maantay and Maroko, 2009). For example, an area of land may be entirely classified as vegetation, but still contain a residential population. Adding smaller building features into this dataset provides building footprints as locations to concentrate populations rather than spreading them evenly across the whole area.

The Salford City Council Green Space Audit vector data was overlaid with the OAs (Figure 4.5 B – OAs are shaded pink, Greenspaces shaded green), using a Union function to merge the two layers together (Figure 4.5, C). This preserves all the information from both layers and ensures that large green spaces can be separated from smaller residential estates without affecting urban characterisations.

4.2.7 Aesthetics data

To capture a richer picture of the aesthetic value of specific landscape features as described in Section 3.3.2 (for implementation in Chapter 6), landscape photographs were collected from the open-source photo site, Geograph.org (Geograph Project Ltd, 2012). Geograph.org stores photographs uploaded by volunteers by 100 m grid squares, or centisquares, according to the OSGB co-ordinate system. For each centisquare, the location of each photo is collected along with the direction and time of capture, the identity of the photographer and descriptive tags. A screen grab of the programme showing the number of photos captured in each centisquare is presented in Figure 4.6. Geograph.org data was manually collected from the site and stored in a spreadsheet for further analysis in Chapter 6. The OS GB co-ordinates for centisquare centroids over Salford were collected into a spreadsheet. For each centisquare, tallies were collected for the number of photos taken, the number of individual photographers recorded and the number of times each descriptive tag appeared. Tags relating to aesthetic quality were then used to tally photos that could potentially indicate aesthetic value (This is described in more detail in Section 6.2.2.5).

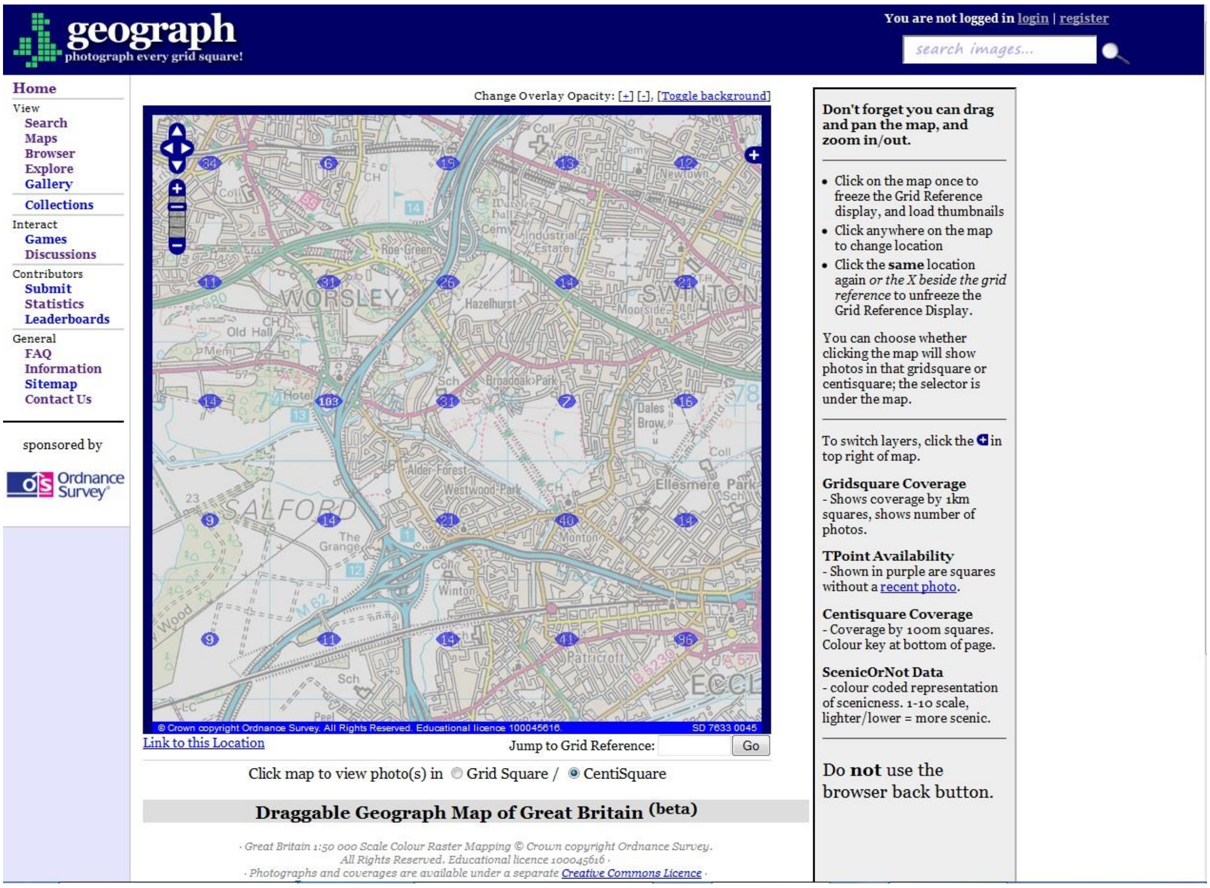

Figure 4.6. Screen grab from geograph.org showing the number of photos captures in 100 m grid centisquares across a section of Salford (Geograph Project Ltd, 2012).

4.2.8 Transport network data

The review in Section 3.6.1 demonstrated a requirement to measure travel times from residential homes to urban greenspaces as sources of ecosystem services. To model the physical transport network that people travel along, Ordnance Survey Integrated Transport Network (ITN) data has been chosen. ITN uses edges and nodes to depict the road structure of Great Britain from busy motorways down to small local roads. (Ordnance Survey, 2015b). It has been selected for use in this analysis as it has local detail suitable for city-scale research. National coverage of data also provides the potential to easily transfer the research methods to other sites. Additional attribute information is provided on the road category, although paths are not included. This data was downloaded from Digimap and used as the network model for chapter 8 (Edina, 2013).

To model travelling time, each vertex was given an impedance value based on walking speed. ANGSt guidelines outlined in Chapter 3 suggest that residents should be 300m or a 5 minute walk from their nearest greenspace, which equates to a walking speed of 1 m/s (Natural England, 2010). This is slower than the cited average walking speed of 1.42 m/s (3 mph) (Browning *et al.,* 2006), but may be more relevant to less mobile members of society. Equation 4.2 was used to convert distance (m) into time (minutes) for 1 m/s, where t = time taken to traverse a vertex and d = length of the vertex.

Equation 4.2.
$$t = \frac{d}{60}$$

The resulting travel times were stored in the attribute table for the road layer and used as the impedance values for the network dataset in ArcGIS 9.3 (described in more detail in Section 8.2.1).

4.2.9 Population data

To determine origin points for local populations for use in research objective 3 (described in Section 2.6.3 and implemented in Chapter 8), a dataset is required that holds information on the location of households. This thesis uses Ordnance Survey AddressBase Data for this purpose. AddressBase identifies the location of current addresses where post is delivered and whether the address is residential or commercial (Ordnance Survey, 2015c). The data was provided by OS as a spreadsheet with OSGB co-ordinates for each address point and additional attribute information. Multiple addresses in the same building (e.g. apartment blocks) have the same geographical co-ordinates.

For the physical accessibility analysis, address co-ordinates were converted into a point shapefile in ArcGIS 9.3. To preserve temporal concurrence, address points were intersected with building footprints outlined in Section 4.3.4 to remove addresses with no associated building. Overlapping addresses were retained to reflect population density (n = 100305).

The observer visibility analysis is concerned with the coverage of visible space over a 3D surface from different observation points. Consequently, duplicate records are not required. Therefore, building centroids were derived from the building heights data and used as observation points. To tackle the issue of observation points being within buildings and thus internally obstructed, the points were offset to the OS ITN network. This effectively models views from the front door of a property.

4.2.10 Socio-economic data

To relate measures of social and economic inequalities against access to ecosystem services and urban greenspaces, the Index of Multiple Deprivations (IMD) 2010 was collected for the Lower Super Output Areas (LSOA) in Salford. The IMD measures relative levels of deprivation over England. The index incorporates seven themes of deprivation: Income, Employment, Health, Education, Barriers, Crime and Environment. These themes are derived from census statistics (DCLG, 2011). The research in Chapter 8 used the index as a whole and also assessed relationships with the individual streams. One issue with the IMD is that it is only collected in LSOAs, which are larger than OAs. This preserves disclosive details, but obscures variation that may otherwise be present.

4.3. Validation

This section outlines the methodology for validating the ecosystem service layers created in Chapter 6. Validation plays a critical role in research and the importance has been outlined in Section 2.3, particularly with respect to the neglect of this area in ecosystem service research. In this thesis, validation was completed using desktop and field surveys. The results of these validations are presented in Chapter 6.

4.3.1. Desktop validation

Desktop validation was used to validate the water flow mitigation and climate stress mitigation layers. The validation used STAR tools (The Mersey Forest and The University of Manchester, 2011), which were developed from scientifically established and commonly used methods for measuring surface runoff (Whitford *et al.,* 2001) and surface temperature (Tso *et al.,* 1991) by Lower Super Output Area (LSOA). Although the outputs of these tools are presented using larger spatial units than the research produced in Chapter 6, STAR is deemed suitable for validation against the ecosystem service layers because it has been designed specifically for use in the North West of England and as such has detailed land cover information integrated. The STAR model values were used to correlate against the derived ecosystem service layers. To better understand the patterns within the validation, the dominant land character type was calculated, based on percentage of LSOA covered.

For water flow mitigation, the model was used. By selecting sites of interest, the model collects pre-calculated information on the composition of land cover derived from OS MasterMap, related land cover-based run-off rates, and hydraulic soil properties derived from the British Geological Survey. The model also provides a series of rainfall scenarios. The scenario chosen for use in Chapter 6 was the rainfall depth for the 99th percentile daily winter precipitation from the baseline 1961-1990 period. This provides a realistic worst-case scenario for surface runoff. This is suitable for measuring trends against the ecosystem service water mitigation model, which does not use specific volumes of water. The output of the STAR tool is the percentage and volume of surface runoff for each LSOA.

For climate stress mitigation, the surface temperature model of STAR was used. The Landsat image used was captured in Mid June (Section 4.2.1). The temperature in Manchester at 11am (Time of Landsat data capture) was recorded as 24 °C (WeatherOnline, 2015), which is higher than the average June temperature of 18.4 °C (averages taken from 1981 – 2010, Met Office, 2015). Consequently, the scenario representing the 98th percentile daily summer mean temperature between 1961 and 1990 was used in the model to describe a hot summers day. The output was the mean surface temperature for each LSOA.

4.3.2. Field surveys

Two field surveys were conducted to validate the creation of carbon storage, recreation and aesthetics layers. The first field survey was conducted to validate aesthetic and recreational services. Stratified sampling selected 10% of OAs by landscape character type (derived in Chapter 5) and highlighted in light grey in Figure 4.7. The field survey was then conducted to determine values for aesthetic and recreation services using Tables 4.3 and 4.4, which were adapted from a method developed by Radford and James (2013). Descriptors for deriving aesthetic scores are found in Appendix A.

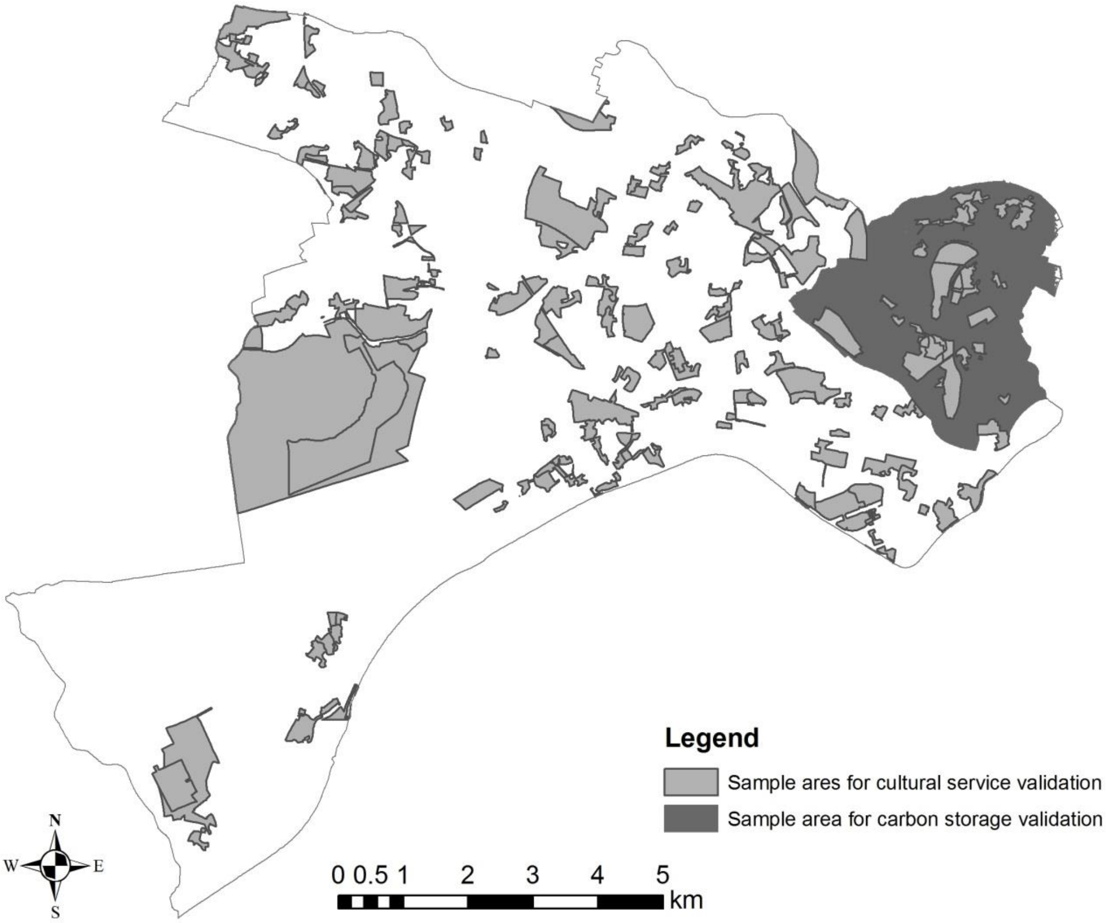

Figure 4.7. Field survey sample sites for cultural and carbon storage service validation (Author's own)

Where access was restricted, interpretation of aerial photography was used. The final output of the survey was normalised by dividing each score by the maximum achievable (Aesthetics: 54, Recreation: 82). Limitations with the survey have arisen due to the sample sites representing a single land character type. Specifically, the landscape character types defined as 'woodland' and 'green and blue' areas do not have private properties on them rendering some of the categories in Tables 4.3 and 4.4 obsolete. In these instances, a maximum value was attributed to reflect the importance of greenspaces for ecosystem service generation as highlighted throughout Chapter 2. Further, the survey appears to consider managed greenspaces to be of more value than wilder, more natural spaces. This is largely related to potential use, with managed spaces having a larger capacity for more activities and multi-functional greenspaces having the largest value.

Table 4.3. Field Survey for aesthetics services

Private - Maximum score 3	
1.1.1 There are no broken/boarded up windows.	
1.1.2 There is no vandalism to private properties.	
1.1.3 There are no burnt out properties present.	
1.1.4 Property maintenance is of a high level.	
1.1.5 There are trees in front gardens.	
1.1.6 The site is not built up.	
1.1.7 Defensible territorial spaces are large.	
Public - Maximum score 3	
1.2.1 There are no stray dogs roaming.	
1.2.2 There is no dog fouling.	
1.2.3 The space is free of litter and vandalism.	
1.2.4 Furniture is present, well designed and located.	
1.2.5 Water features are present are in good condition.	
1.2.6 There is green space present (excludes private gardens).	
1.2.7 Trees are present.	
1.2.8 Vegetation (excluding street trees) is present and well maintained.	
1.3.1 There are no abandoned cars.	
1.3.2 Cars are all legally parked.	
1.3.3 The outlook is not industrial or commercial.	
1.3.4 The predominant outlook is green.	

Table 4.4. Field Survey for recreation services

Communal Active and Passive Recreational Facilities (No = 0; Yes, but in a poor state or very limited = 1, Yes = 2)					
Walking/strolling (off road)		Cricket pitch		Athletics track	
Nature trail		Football pitch		Designated car park	
Bowling		Grass “kickaround” area		Ornamental garden	
Seating areas		Dog walking		Sensory garden	
Picnic facilities		Basketball/netball court		Toilets	
Teen shelter/“hang out” area		Tennis court		Fountains	
Skateboard ramps		Pond/ornamental water		Petting zoo	
Children’s play area		Toddlers play area		Model boats	
Golf		Multi-use games area		Flower beds	
Signed footpath/cycle route		Bandstand		Fishing	
Fitness trail		Heritage building/features		Art features/monuments	
3.2 Private active and passive recreational facilities (No = 0, Yes, but only in ≤5% of properties = 1, Yes, >5% of properties = 2)					
Trampoline		Swing set/slide		Football nets	
Swimming pool (not paddling pools)		School playing field/sports ground		Basketball net	
Pond		School play area			

The second field survey was used to collect validation data for the carbon storage layer. Empirical tree measurements were collected from a sample area of Salford, shaded dark grey in Figure 4.7. This area represents approximately 10 % of Salford and includes representative land uses characterised in Chapter 5. Using the tree survey (Section 4.2.5) as a template, a field survey was undertaken to confirm the presence of each tree, the genus, canopy area (m^2) and the height (m). Application of Equation 4.3 converted the horizontal distance to the tree and angle from the ground to the top of the tree into vertical height, where h = vertical tree height, d = horizontal distance to tree, $tan\theta$ = the angle from point of observation to the highest point of the tree canopy and h_{obs} = the height of the clinometer.

Equation 4.3. $$h = (d \times tan\theta) + h_{obs}$$

When taking measurements on slopes, Pythagoras was used to amend height discrepancies. Validation was completed in two steps. Firstly, the tree heights in the Bluesky tree survey were correlated against the field-collected tree heights. Secondly, the modelled carbon stored in the surveyed trees was compared against an estimate made by iTree (Mason *et al.,* 2014). iTree derives carbon storage information based on detailed field data. Inputs for iTree included the DBH, tree height, genus and canopy radius.

4.4. Conclusions

Datasets chosen for use have been described and justified in this chapter. This includes pre-processing required to convert data into the correct format, or to produce secondary datasets for further use. Appropriate validation methods have been described and two experiments have produced appropriate moving windows to reflect the landscape properties of Salford as well as the spectral index thresholds for the decision tree classification. The results of these experiments will be implemented in the next chapter, which is the first of four research chapters. The first research chapter considers physical classification and characterisation of the urban landscape to satisfy objective 1 (Section 2.6.1).

5. Characterising the physical urban landscape

5.1. General Introduction

Analysis of ecosystems and the services they provide requires detailed knowledge of the surrounding landscape to provide context for measurement and evaluation (Haines-Young and Potschin, 2008). Remote sensing techniques are well matched to meet the landscape-scale requirements of this research and there is a rich history of its use within urban land cover classification (Guindon *et al.,* 2004; Lu *et al.,* 2011; Gao *et al.,* 2013).

The research in this chapter addresses research objective 1: *Characterising the physical 3D urban environment* (Section 2.6.1). An innovative methodology is presented, which produces a land cover classification and subsequent land use characterisation of the urban environment using detailed three dimensional feature data (as detailed in Sections 4.2.3, 4.2.4 and 4.2.5). The requirement for more improved and more appropriate representations of the physical landscape for ecosystem service research as highlighted in Section 2.6.1 is addressed in this chapter. This is completed by developing a method to create a land cover map suitable for ecosystem service mapping and a land use map more appropriate for considering the distribution and flows of related ecosystem services and their links to existing social systems. The latter map characterises patterns of land cover to infer broad land uses (Section 2.5.3). Aggregating land cover data into wider neighbourhood-scale landscape features aligns the landscape information more appropriately with ecosystem service patterns (Section 3.4.5). The output maps provide landscape information required for Chapters 6, 7 and 8. The structure of this chapter reflects the fact that the initial creation of a detailed land cover map is required to create a more sophisticated land use characterisation. Consequently, the land cover classification is addressed in Sections 5.2 – 5.7. This is followed by creation and analysis of the land use characterisation in sections 5.8 – 5.11. Final conclusions for the chapter are considered in Section 5.12 to summarise the research.

5.2. Land cover introduction

The methodology applied to create the land cover classification is described in this section. Due to the diversity of land cover types in the urban landscape mosaic, compromises must be made between pixel size, image coverage and selection of land cover types (Lo and Faber, 1997). Landscape fragmentation in urban areas means that image pixels are likely to include a mixture of spectral signatures representing the presence of multiple land cover types. Epstein *et al.,* (2002) found that this led to high levels of misclassification, especially in suburban areas that are characterised by a mixture of large gardens, buildings and transport infrastructure. The discussion in section 4.2.1 highlights the selection of Landsat imagery, which trades spatial quality through larger pixel sizes than other remotely sensed imagery, but enhances radiometric quality through the provision of a larger number of spectral bands, which allow the identification of a wider range of land cover types. In particular, the lack of a thermal infra-red band means that it would not be possible to calculate the NDBaI (Used for Bare Earth and Water mapping in this thesis (Sections 5.3.2 and 5.3.5)). Additionally, reducing pixel sizes reveals smaller features with their own spectral signatures. In urban areas, this includes different building materials, chimneys on roofs, and automobiles on roads (Wentz *et al.,* 2014).

Misclassification is also present between land cover types, where spectral signatures may become alike (Herold *et al.,* 2004; Alberti, 2005). For example, Stefanov *et al.,* (2001) aggregated the number of land cover classes from 27 to 8 to reduce misclassification of spectrally similar land covers types such as asphalt and river gravels. Similarly, Owen *et al.,* (1998) highlighted the similar signatures of impervious surfaces and wet bare earth and soils. This misclassification is important because the two land cover types have different runoff rates and potential for vegetation growth. In particular, the transience of bare earth is noted by Zhao and Chen (2005), who discuss differences between permanent, primary bare earth and secondary bare earth that is seasonally bare from activities such as agriculture.

A flow diagram of the methodology for land cover classification is presented in Figure 5.1. Experiments to determine suitable spectral indices for classification are described in Sections 5.3. The method for creating the land cover map from remotely sensed imagery is described in Section 5.4. This method uses spectral indices to achieve a higher state of autonomy in the methodology as discussed in Section 3.4.3. Classification of land cover is represented in the top half of Figure 5.1. A decision tree classification based on a method created by Chen *et al.,* (2006) and outlined in Section 3.4.3 is compared against a Maximum Likelihood Classification using raw satellite bands, which is the most commonly used method. The second step of classification integrates feature height data to include building and tree canopy information (Section 5.4.3). The results and accuracy assessments are presented in Section 5.5 (bottom half of Figure 5.1), which is followed by a discussion and interpretation of the results in Section 5.6.

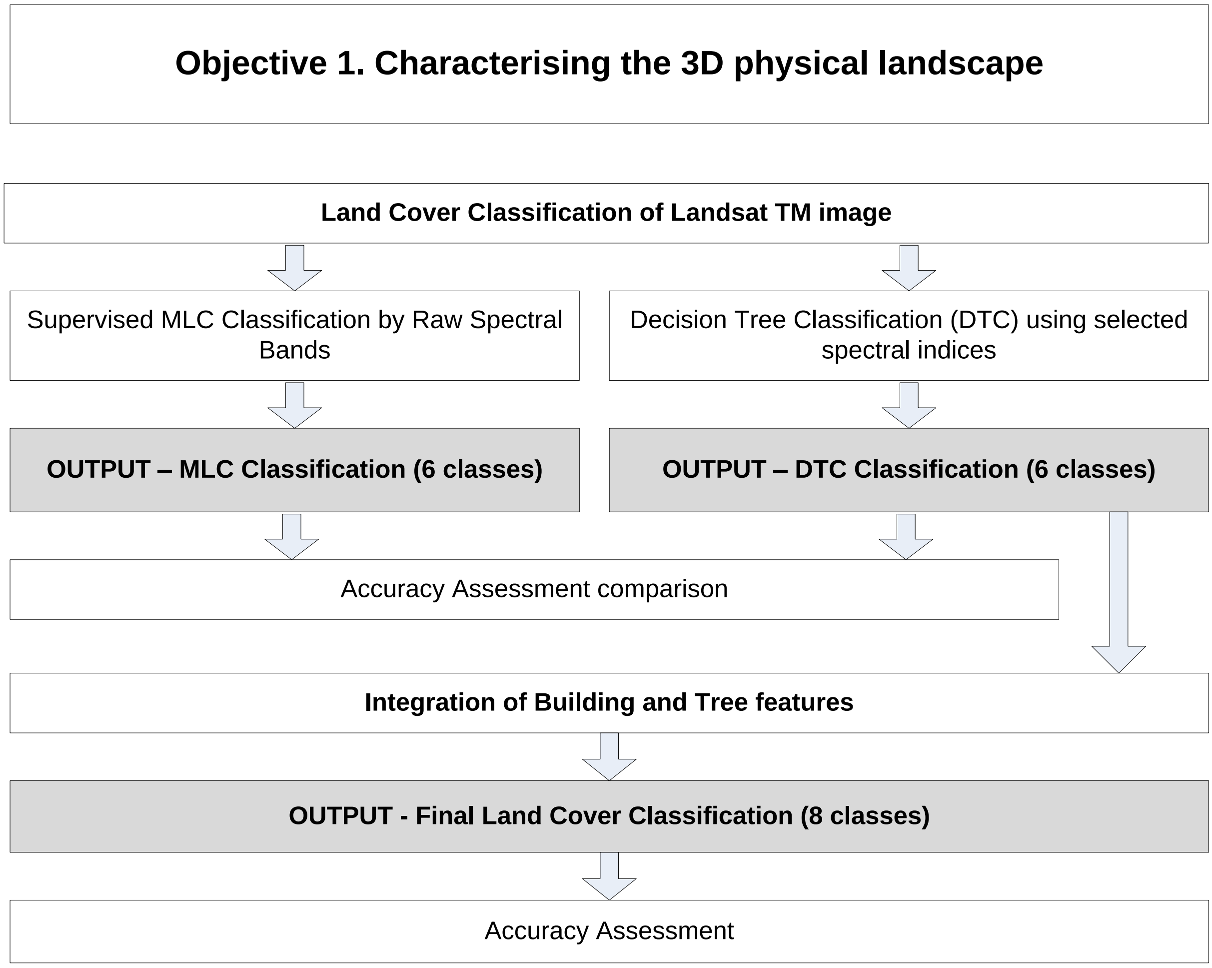

Figure 5.1. Flow diagram of land cover mapping methodology.

5.3. Spectral indices for land cover classification

Spectral indices have been chosen as input classification parameters because they offer a standardised method of interpreting remotely sensed imagery. This means that using indices allows a more autonomous approach because little or no manual calibrating is required to run the classification. This is appropriate for ecosystem service research in urban areas as it allows rapid analysis of multiple areas and ensures that methods can remain the same in studies that consider landscape mosaics that change over time. An investigation to identify the final list of indices for use in this research chapter is discussed in this chapter. The method for identifying the indices is based on extraction of land cover types through index value thresholding as implemented by Chen *et al.,* (2006).

5.3.1. Methodology

Following a methodology implemented by Chen *et al.,* (2006), a random stratified sample of grid squares was selected. Areas composed entirely of a single land cover type were selected as sampling points, covering the six broad land cover types listed in Section 3.8. 100 grid squares were chosen for each land cover type. Due to low representation in the landscape, the sample size for the peat land cover type was reduced (n = 60). Sample pixels were created from the topographical layer of Ordnance Survey (OS) Mastermap, which has been intersected with a 30 m x 30 m grid. This grid corresponds with the spatial resolution of Landsat TM, which is used to create the land cover map (Section 4.2.1).

Index maps were derived from the Landsat image and created in ERDAS Imagine™, applying equations from Table 3.5. Soil adjusted Vegetation Index (SAVI) was not used due to a high correlation against the Modified Soil adjusted Vegetation Index (MSAVI) using a default *L* value of 0.5 ($r = 0.995$, $P < 0.001$) (Baret *et al.,* 1991). The range of index values for each land cover is shown in Figure 5.2. The distribution of the index values is represented in Figure 5.3, where the x-axis measures pixel value and the y-axis measures the frequency of pixel for each value. The information in Figures 5.2 and 5.3 was used to identify candidate indices to be tested for classification of each land cover. This is based on selecting indices that highlight unique peaks in index values. For example, when measuring Normalised Difference Bareness Index (NDBaI) values, pixels with values below 0.516 can only be water although the Modified Normalised Difference Water Index (MNDWI) and the Normalised Difference Water Index (NDWI) also present index values that belong solely to water pixels (Figure 5.2).

The selection of indices used to measure each land cover type is described in Sections 5.3.1 – 5.3.6. The overall methodology was address the most easily classified land cover types first before moving onto more challenging land covers. This was based on patterns presented in Figure 5.2 and Figure 5.3. For example, Peat and Water produce the most distinct distributions as indicated by isolated dark brown / blue peaks in MNDWI (Figure 5.3 D), the Normalised Difference Built-up Index (NDBI) (Figure 5.3 F), the Urban Index (UI) (Figure 5.3 G) and the Index-based Built-up Index (IBI) (Figure 5.3 H). Extraction of pixels belonging to each land cover type was conducted using index value thresholds derived from data presented in

Figure 5.2. The thresholds were defined as the median of the range of index values shared by other land cover types. In this thesis, the results have been called binary classifications as they state only the presence or absence of a single land cover type. Information from Figure 5.3 is used here to prioritise land covers that have a higher frequency of pixels. For example, Peat and Bare Earth occupy similar ranges of index values (Figure 5.2), but the frequencies of index values show that MNDWI has a much higher frequency of Peat pixels between -0.8 and -0.55 than Bare Earth. Binary classifications are made for each of the candidate indices and the accuracy of each is tested against the sample points reserved for this purpose. Unless otherwise stated, accuracies were assessed in a confusion matrix, using reference points taken directly from the aerial photography (Discussed in Section 3.4.3). Once an index and a threshold have been determined, a rule for the decision tree is created. For example, “NDBaI values < -0.516 = Water”. The pixels that conform to this rule are removed from the sample and the next land cover is assessed.

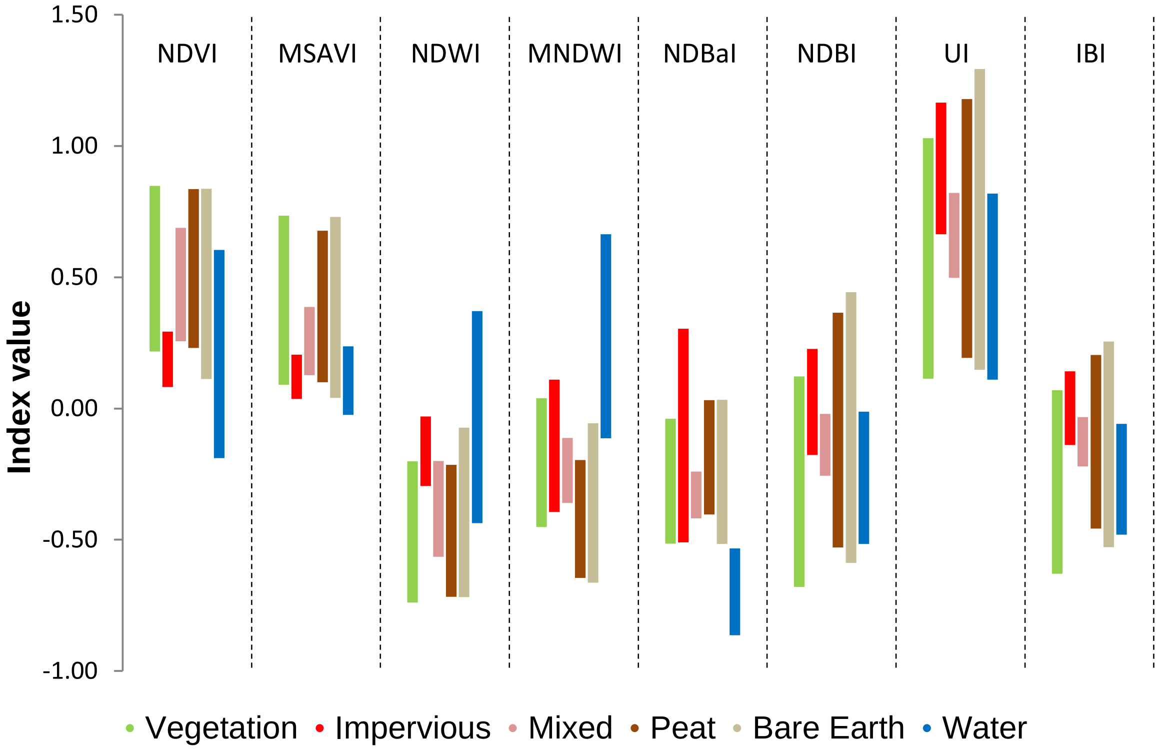

Figure 5.2. Spectral index value ranges by land cover type as identified by sample points taken from OS MasterMap and 2006 aerial photography. Column headings refer to the spectral indices used. These are listed in Table 3.5 (Author’s own).

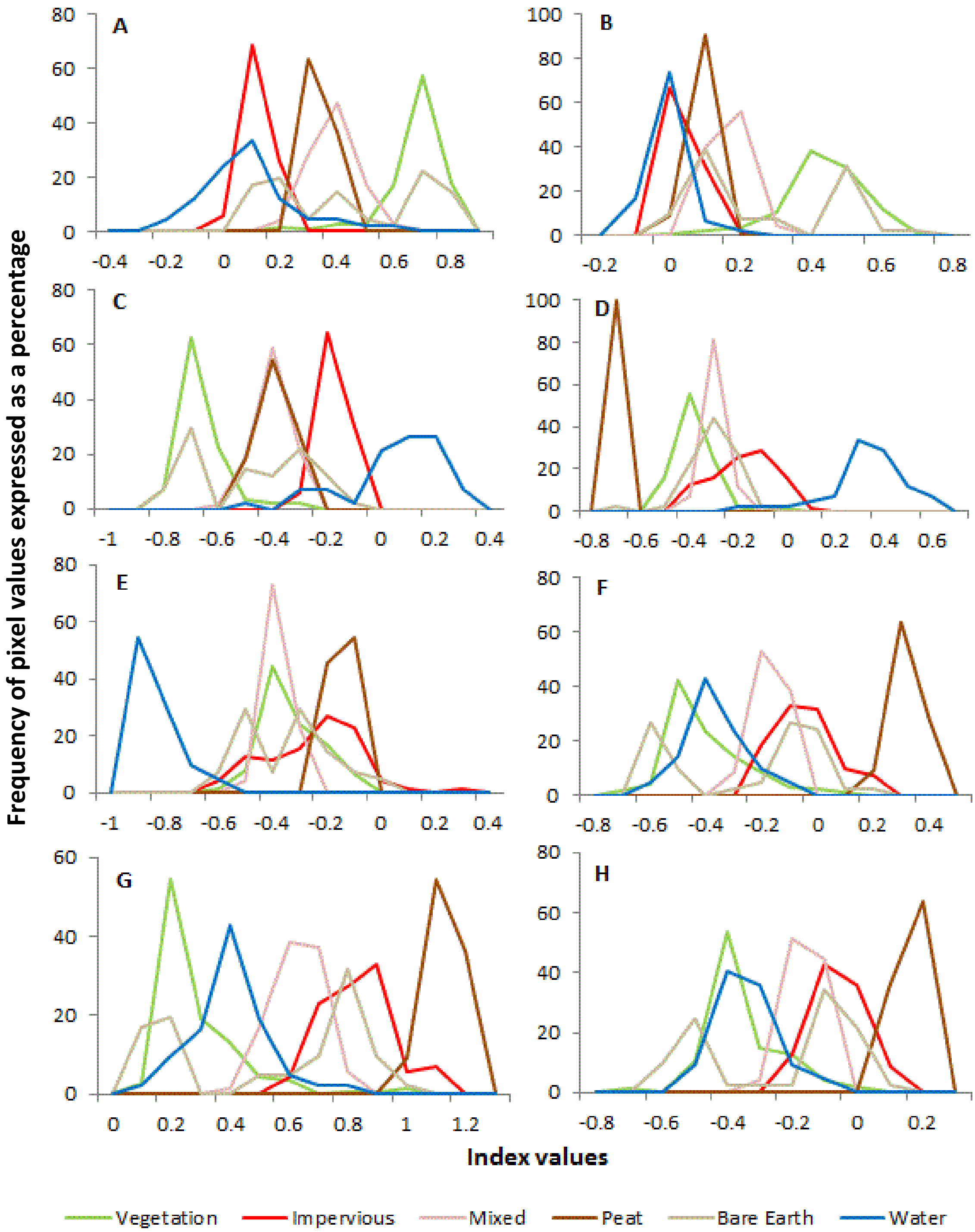

Figure 5.3. Polygons representing the frequencies of pixel values by land cover type. (A) NDVI, (B) MSAVI, (C) NDWI, (D) MNDWI, (E) NDBaI, (F) NDBI, (G) UI, and (H) IBI (Author's own).

5.3.2. Water

Water is the most easily distinguished land cover type (Figures 5.2 and 5.3, water is shaded blue). The value range for water is unshared in three indices (NDWI, MNDWI and NDBaI). Figure 5.4 presents the water classification for NDWI (A), MNDWI (B) and NDBaI (C). Accuracy reference data were taken from OS MasterMap data (Figure 5.4 D), where pixels identified as water in the 'theme' field were classified as such. Table 5.1 contains an accompanying accuracy assessment. Larger water bodies appearing outside the Salford boundary in Figure 5.4 A, B and C are not included in the reference image or in the accuracy assessment. Data in Table 5.1 shows that NDBaI was found to separate water most effectively and consequently will be used in this research. Values below -0.516 are water. Overall accuracies are high, but NDBaI has a higher kappa coefficient compared to the other indices. This is evidenced by Figure 5.4, C, (NDBaI), which presents an improved classification of the river Irwell (to the North East of the image) than Figure 5.4, A or B.

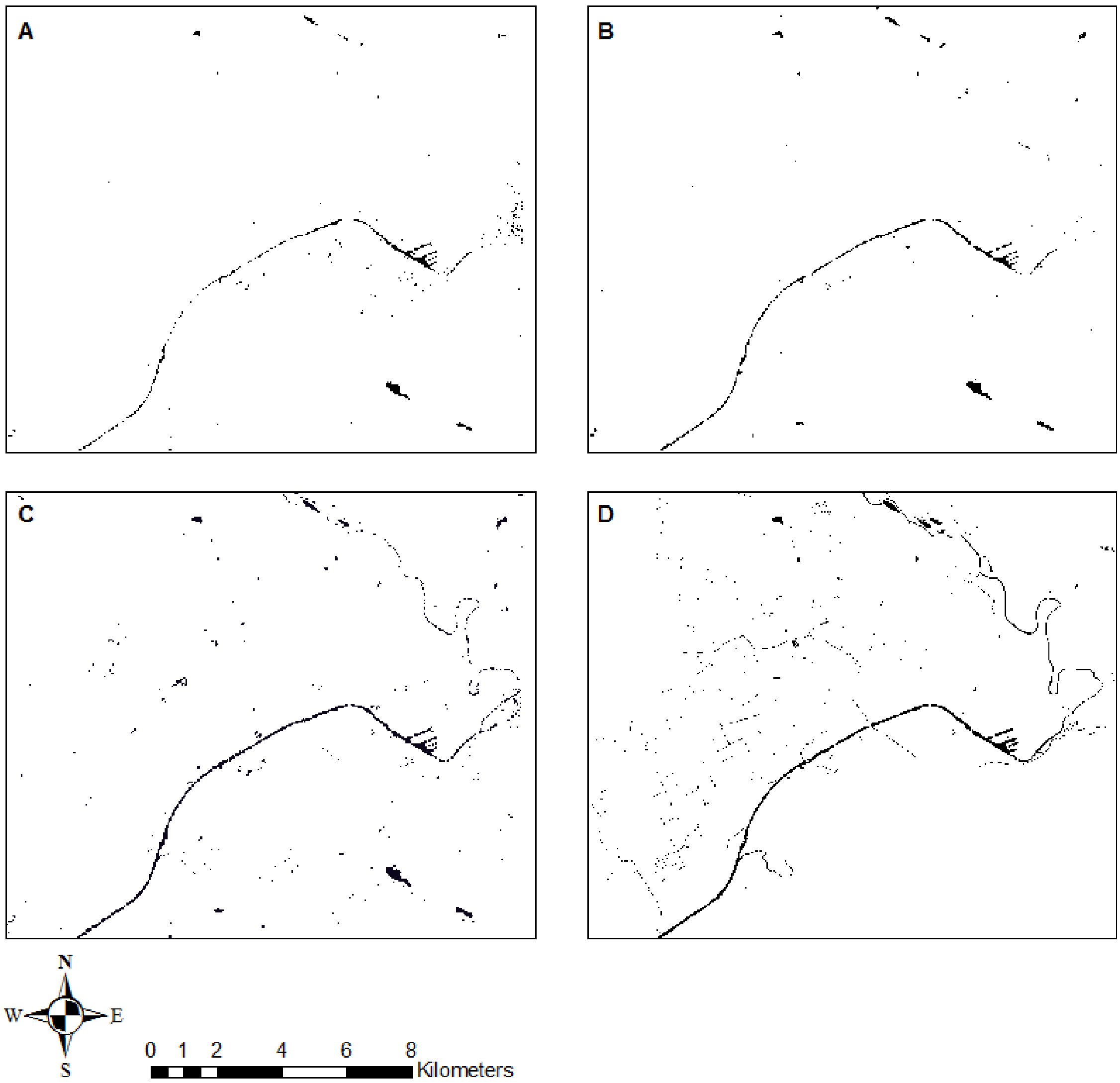

Figure 5.4. Reclassified water images from (A) NDWI, (B) MNDWI, (C) NDBaI and, (D) OS MasterMap reference data (Author's own).

Table 5.1. Accuracy assessment for water classification using NDWI, MNDWI and NDBaI.

		Producer's Accuracy	User's Accuracy	Overall Accuracy	Overall Kappa
NDBaI	**Water**	0.53	1.00	0.99	0.69
	Not Water	1.00	0.99		
MNDWI	**Water**	0.33	1.00	0.99	0.49
	Not Water	1.00	0.99		
NDWI	**Water**	0.26	1.00	0.98	0.40
	Not Water	1.00	0.98		

5.3.3. Peat

The index value ranges of peat lie within those of bare earth (Figure 5.2). However, MNDWI, NDBI and UI show isolated peaks in peat pixel frequencies (Figure 5.3 D, F, G). IBI and NDBaI also have high peat frequencies towards one end of the overall index range, but the similar percentages of bare earth and impervious pixels within this range created a high level of misclassification. The binary classified images for peat are presented in Figure 5.5, with accuracies displayed in Table 5.2. The peat lands of Salford are in clearly defined patches, which are best represented by MNDWI in Figure 5.5 B, which contains the lowest level of noise. MNDWI will be used in the following chapter using MNDWI values below -0.5 to classify peat.

5.3.4. Vegetation

For identification of vegetation, NDVI was compared against MSAVI as the most prominent vegetation indices indicated in Table 3.5. Accuracies in Table 5.3 indicate that MSAVI performs better with an overall accuracy of 0.96 compared to NDVI (0.91). The research will use MSAVI, where values above 0.35 represent vegetation.

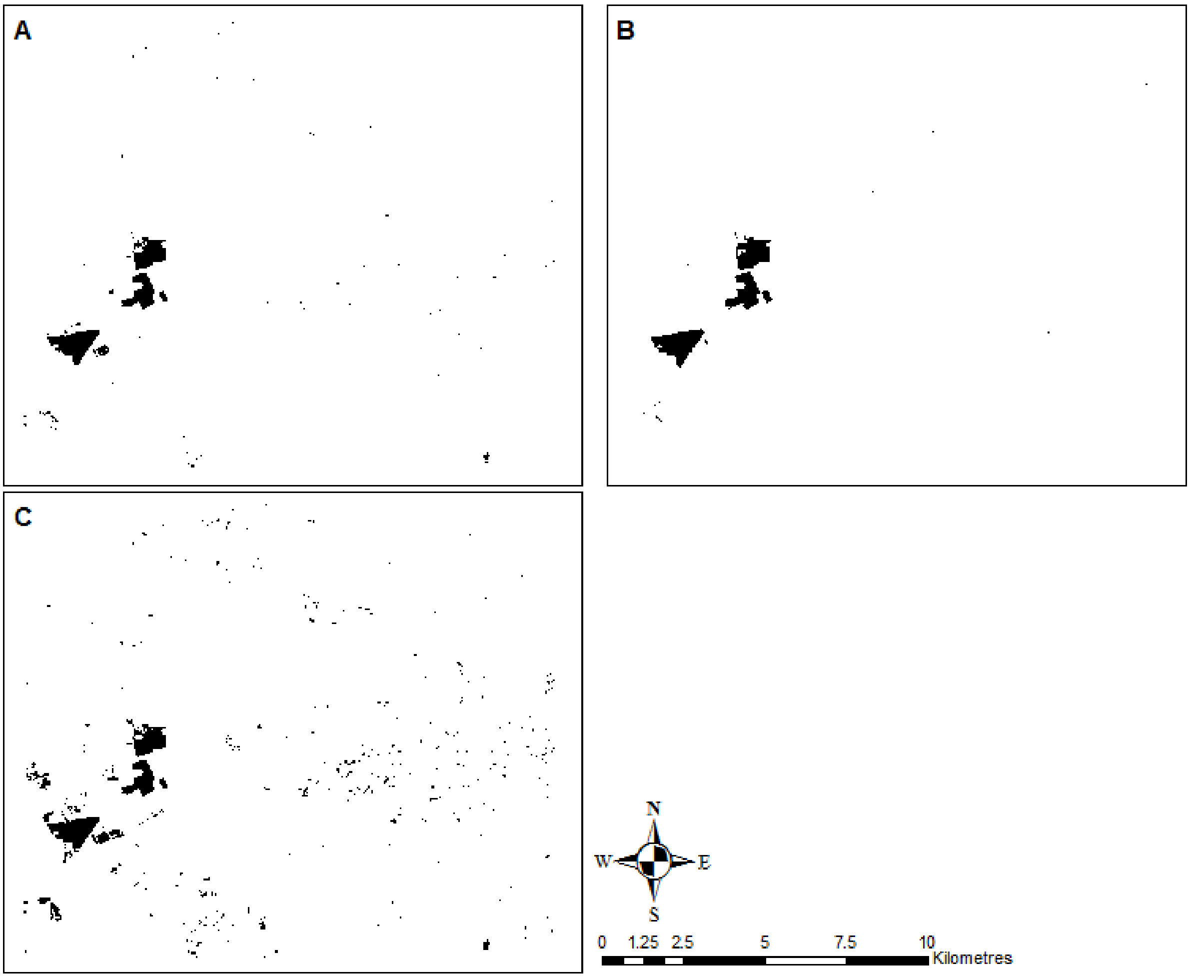

Figure 5.5. Reclassified peat images from (A) NDBI, (B) MNDWI, and (C) UI (Author's own).

Table 5.2. Accuracy assessment for peat using NDBI, MNDWI and UI

		Producer's Accuracy	User's Accuracy	Overall Accuracy	Overall kappa
NDBI	Peat	0.37	0.60	0.95	0.44
	Not Peat	0.99	0.97		
MNDWI	Peat	0.24	0.60	0.93	0.31
	Not Peat	0.99	0.94		
UI	Peat	0.60	0.60	0.97	0.59
	Not Peat	0.99	0.99		

Table 5.3. Accuracy assessment for vegetation using NDVI and MSAVI

		Producer's Accuracy	User's Accuracy	Overall Accuracy	Overall kappa
NDVI	**Vegetation**	0.88	0.95	0.91	0.69
	Not Vegetation	0.95	0.86		
MSAVI	**Vegetation**	0.99	0.95	0.96	0.84
	Not Vegetation	0.93	0.99		

5.3.5. Bare Earth

Bare earth is challenging to classify through interpretation of frequency polygons (Figures 5.2 and 5.3). Visual analysis of the Peat classification using MNDWI showed that bare earth surfaces could be distinguished by implementing a lower threshold (below -0.35). However, this does not provide a complete classification so the unique band combination used in NDBaI (see Table 3.5) was employed to classify additional areas of Bare Earth that were missing using NDBaI values below -0.45.

5.3.6. Impervious and Mixed

IBI, UI and NDBI were compared for performance of impervious surface identification as indices specifically designed for impervious surfaces. UI produced the highest accuracy results for impervious surface identification (Table 5.4), and also had the highest overall accuracy results. Although ranges of impervious and mixed land cover overlap for UI, there is a dip at 0.75 between Impervious and Mixed peaks (Figure 5.3). This value will be used as a threshold to classify remaining pixels into impervious (≥ 0.75) and mixed pixels (< 0.75).

Table 5.4. Accuracy assessment for impervious surfaces using NDBI, UI and IBI

		Producer's Accuracy	User's Accuracy	Overall Accuracy	Overall kappa
NDBI	**Impervious**	0.84	0.96	0.89	0.64
	Not Impervious	0.96	0.81		
UI	**Impervious**	0.93	0.95	0.95	0.81
	Not Impervious	0.96	0.93		
IBI	**Impervious**	0.83	0.66	0.89	0.63
	Not Impervious	0.96	0.80		

The most appropriate index/indices have been selected to map each of the land cover types listed in Table 3.8. Suitable index values have been determined through analysis of accuracy assessment information in Sections 5.3.1 – 5.3.6. These index values will be used to create rules for the decision tree classification described in the following section.

5.4. Implementation of the classification

The implementation of the decision tree classification and the maximum likelihood classification are discussed in this section. This is followed in Section 5.4.3 by the approach used to integrate ancillary tree and building information into the classification. The classification used in this research includes the land covers justified in Section 3.4.1: Vegetation, Impervious, Bare Earth, Water, Peat and Mixed (Table 3.8). A shadow classification is often used with high resolution sensors (Xu, 2013), but by using an image from summer, captured close to midday, shadows are minimised and do not need to be considered.

5.4.1. Maximum likelihood classification

As the most commonly applied supervised classification method (Section 3.4.3), maximum likelihood classification (MLC) was used as a comparison method to the decision tree approach and was implemented using Erdas Imagine^{TM}. The sample pixels described in Section 4.3.2 were used as training areas to highlight 'spectrally pure' pixels representing single land cover type. For each land cover type in turn, the reflectance levels of each band of the Landsat image were saved as a unique spectral signature to assist in the final classification. MLC classifies a pixel based on calculating the probability that it belongs to each land cover class. This is calculated through comparative analysis of its spectral signature against the land cover signatures. The pixel is then assigned to the most likely class (Lillesand *et al* 2008).

5.4.2. Decision tree classification

Four indices were selected in Section 5.3 to identify the six land cover types represented in the case study (selected in Section 3.4.1): MSAVI, NDBaI, UI and MNDWI. Figure 5.6 presents the hierarchical decision tree classification, based on a series of subsequent steps classifying individual land cover types in turn, created using knowledge engineer in Erdas Imagine^{TM}. Values in the white boxes represent the rules for classifying a pixel as belonging to a particular land cover type. Values in grey boxes represent final land cover types. For example, pixels with an NDBaI value less than 0.52 are classified as water. Of the remaining pixels, those that have an MNDWI value less than -0.5 are classified as water etc. The hierarchical model classified each land cover in turn before using Boolean logic to remove previously classified pixels from the remainder of the procedure. This ensures that each pixel is member to only one land cover type. The decision tree method is described in more detail in Section 3.4.3.

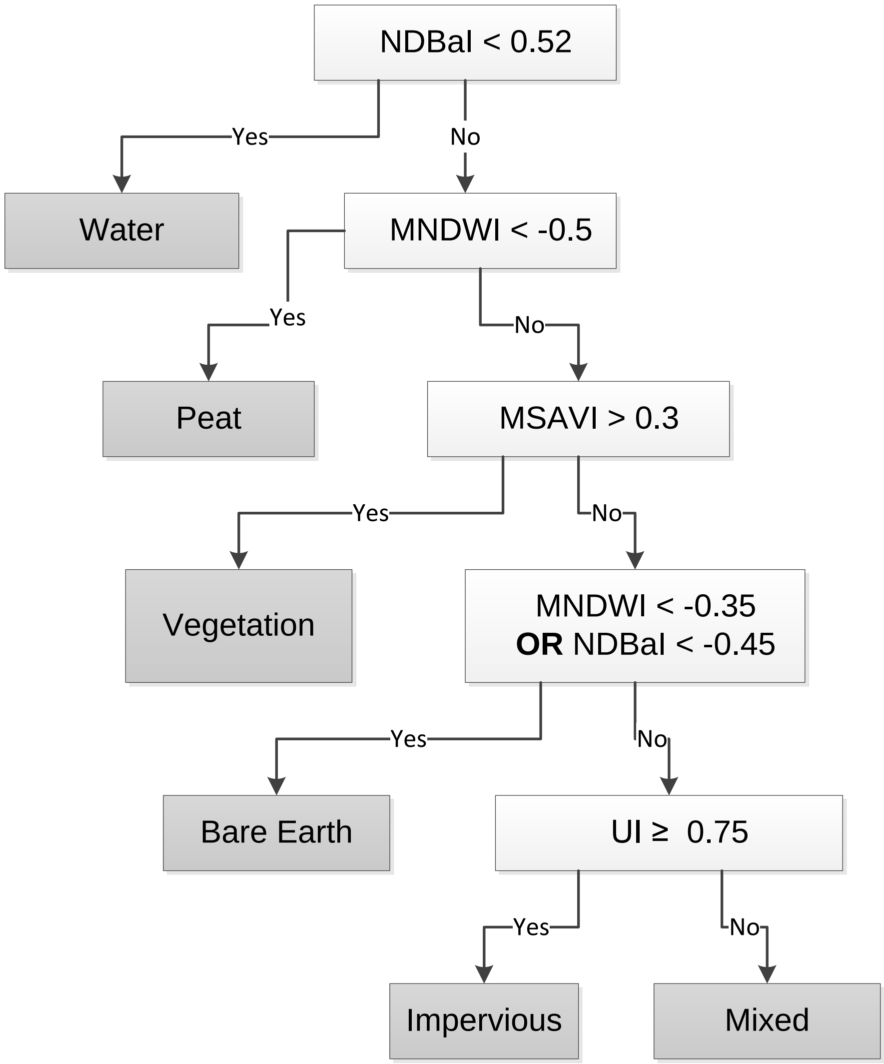

Figure 5.6. Decision tree classification rules for broad land cover classification. White boxes contain the rules applied at each stage of the decision tree classification. Grey boxes contain the name of the final land cover classes.

5.4.3. Buildings and trees

The use of medium resolution imagery necessitates the addition of mixed pixels as a class, particularly in urban areas. However, to improve the information in these pixels and throughout the rest of the classification, the broad land cover classification was augmented with the inclusion of finer resolution feature data for building boundaries and tree canopies. This does not reduce the number of mixed pixels, but it does provide a method to add important features that would not be otherwise represented. This provides a richer picture of the city and allows a better informed interpretation of urban functions within the city through analysis of feature configuration and distribution. This approach is adopted by Lu and Weng (2006) who integrate population data and an impervious surface layer into a land cover decision tree classification, and Rozenstein and Karnieli (2011) who found that integration of GIS land use data into a classified land cover map improved the producer's accuracy by up to 10%.

Trees and building land cover classes were incorporated into the decision tree model before all other land cover types using the normalised tree and building Digital Surface Model (DSM) described in the final paragraph of Section 4.2.5. The following logic based on feature heights was employed to classify the features where T = the normalised tree heights in a pixel and B = normalised building height in a pixel. Equation 5.1 states that a pixel is classified as Tree land cover if the Tree height for the pixel is above 0 and if the tree height value is larger than the building height for that pixel. Equation 5.2 reverses the logic of Equation 5.1 to identify Building pixels.

Equation 5.1: IF T > 0 AND $T > B$, THEN $T=1$

Equation 5.2: IF $B > 0$ AND $B > T$, THEN $B=1$

This method does not consider features obscured by overhanging land cover types, but at the meso-scale of research adopted here, this is acceptable (Sung *et al.,* 2012). The flowchart in Figure 5.7 presents the rules for the final decision tree classification, created using knowledge engineer in Erdas Imagine™.

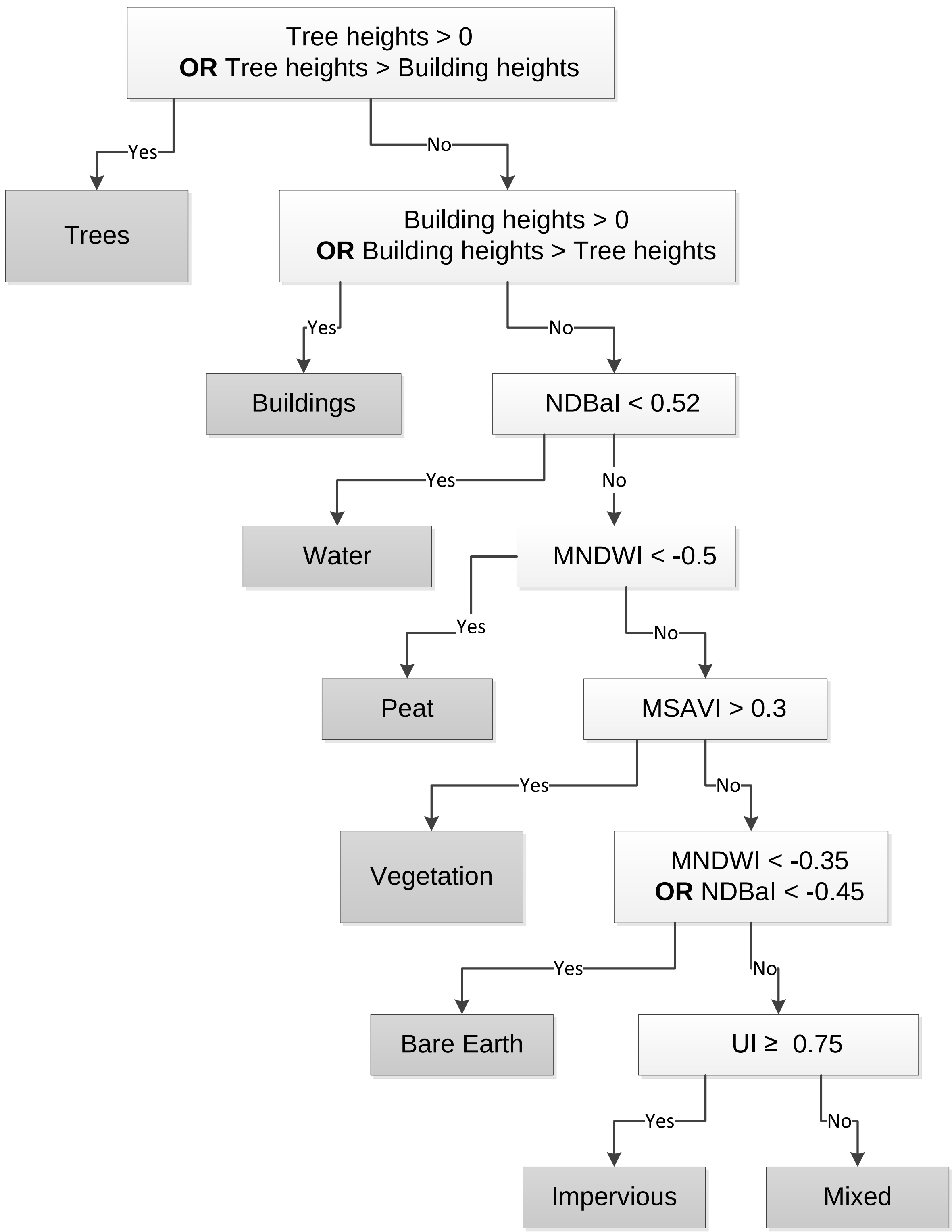

Figure 5.7: The final decision tree classification. White boxes contain the rules applied at each stage of the decision tree classification. Grey boxes contain the name of the final land cover classes.

The land cover of sample pixels was manually verified by referencing aerial photography from 2006, which coincides with the Landsat image date (Section 4.2.1).

Half of the sample pixels were used as training areas to build the classification. The other half of the sample pixels were reserved for accuracy assessment purposes. Accuracy assessments in the form of confusion matrices were completed for the two six-class broad land cover maps (index-based decision tree and maximum likelihood classification) and for the final eight class land cover map.

5.5. Classification results

The decision tree classification and maximum likelihood classification are shown in Figures 5.8 and 5.9 respectively. Visual analysis of the maps suggests that apart from a higher percentage of impervious land cover in the decision tree classification (Figure 5.8) and a higher percentage of bare earth in the maximum likelihood classification (Figure 5.9), the two classifications are very similar. This is reflected by very close accuracy scores shown in Tables 5.5 and 5.6. The producer's accuracy is created by dividing the total number of correctly classified pixels for each class by the number of sampling points taken for that class (column total). This measures how good the classification has been. The user's accuracy is the total number of correctly classified pixels in each class divided by the total number of sampling points classified as that class (row total). This indicates the probability that a pixel with this class will actually be the correct land cover (Lillesand *et al.,* 2008). The index-based classification producing a higher accuracy (85.36% compared to 78.11%) and kappa score (Table 5.7) (0.8234 compared to 0.7443). However, a key difference in accuracies is that of the bare earth, which is higher for the decision tree where it is highlighted as an increase in kappa value from 0.37 to 0.79, an increase in producer's accuracy of over 30% and an increase in user's accuracy of almost 20%. As discussed in Section 3.4.3, any kappa value above 0.6 is deemed acceptable (Landis and Koch, 1977).

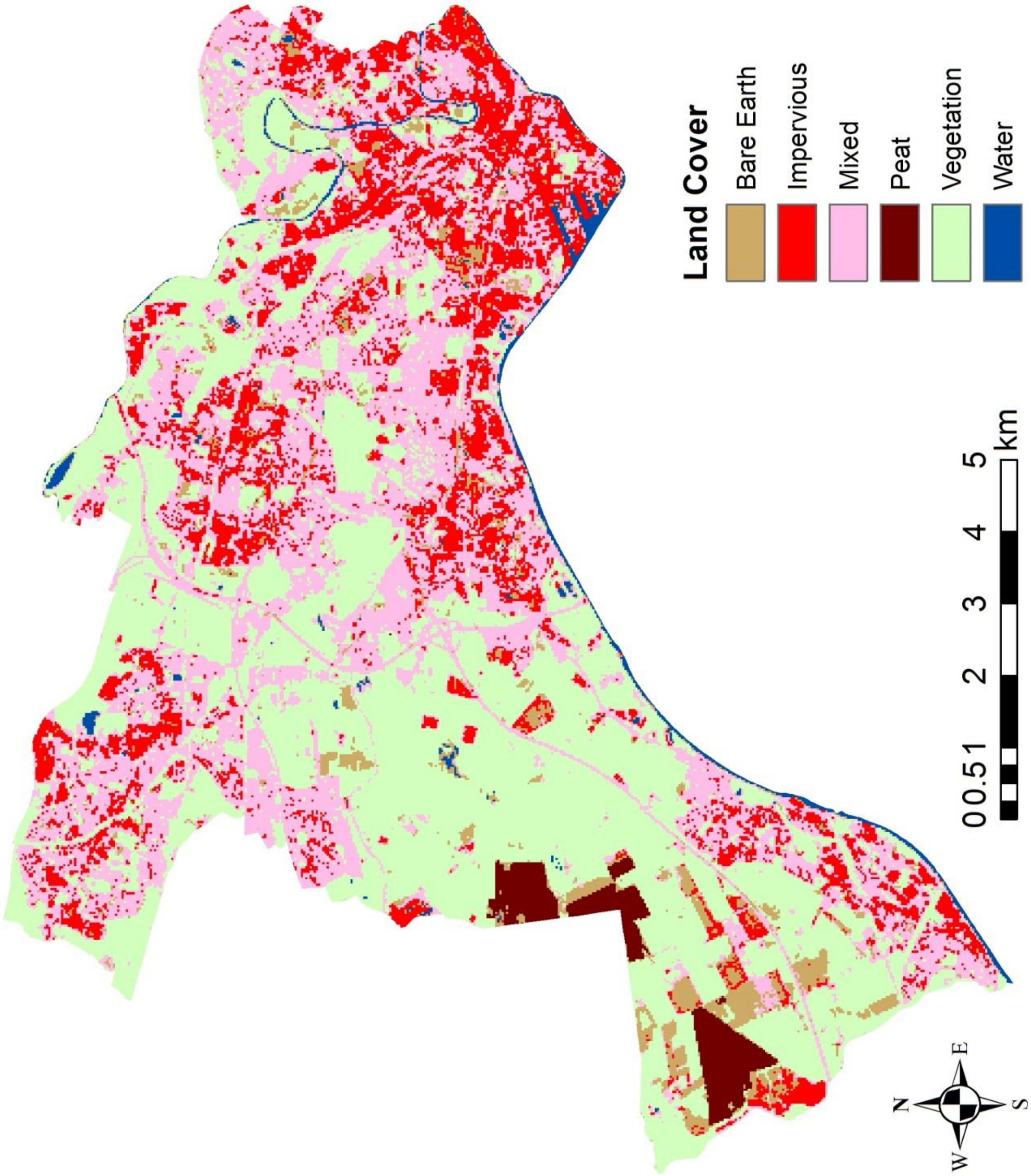

Figure 5.8. Decision tree classified map using index-based bands (Author’s own).

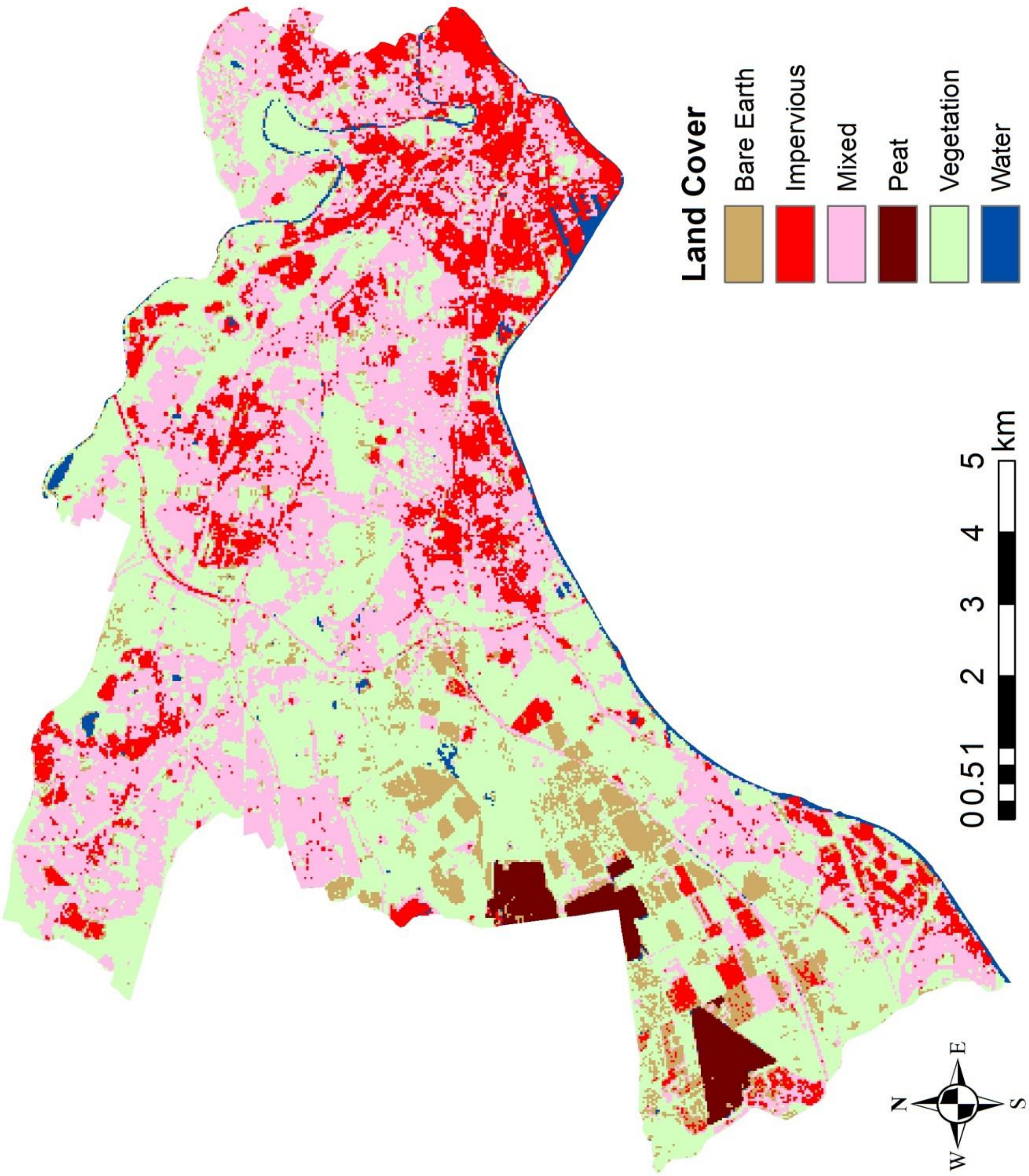

Figure 5.9. Maximum likelihood classified map using raw Landsat bands (Author's own).

Table 5.5. Decision tree Index-based accuracy matrix

Classified Data	Reference Data						Producers Accuracy (%)	Users Accuracy (%)
	Veg.	Imp.	Bare Earth	Peat	Water	Mixed		
Vegetation	**47**	0	0	6	0	0	**94.0**	**88.7**
Impervious	0	**43**	0	7	0	8	**86.0**	**74.1**
Bare Earth	0	0	**30**	0	0	0	**56.0**	**82.4**
Peat	3	3	0	**28**	0	0	**100.0**	**100.0**
Water	0	0	0	0	**49**	0	**98.0**	**100.0**
Mixed	0	4	0	9	1	**42**	**84.0**	**75.0**

Table 5.6. Maximum likelihood Landsat band accuracy matrix

Classified Data	Reference Data						Producers Accuracy (%)	Users Accuracy (%)
	Veg.	Imp.	Bare Earth	Peat	Water	Mixed		
Vegetation	**44**	1	10	0	3	0	**88.0**	**75.9**
Impervious	1	**47**	21	1	0	0	**94.0**	**67.1**
Bare Earth	3	0	**7**	1	0	0	**14.0**	**63.6**
Peat	0	0	0	**13**	0	0	**86.7**	**100.0**
Water	1	0	1	0	**46**	0	**92.0**	**95.8**
Mixed	1	2	11	0	1	**50**	**100.0**	**76.9**

Table 5.7. Kappa scores for the maximum likelihood and decision tree classification

Class Name	MLC	Decision Tree
Vegetation	0.80	0.86
Urban	0.60	0.69
Bare Earth	0.37	0.79
Peat	1.00	1.00
Water	0.95	1.00
Mixed	0.71	0.70

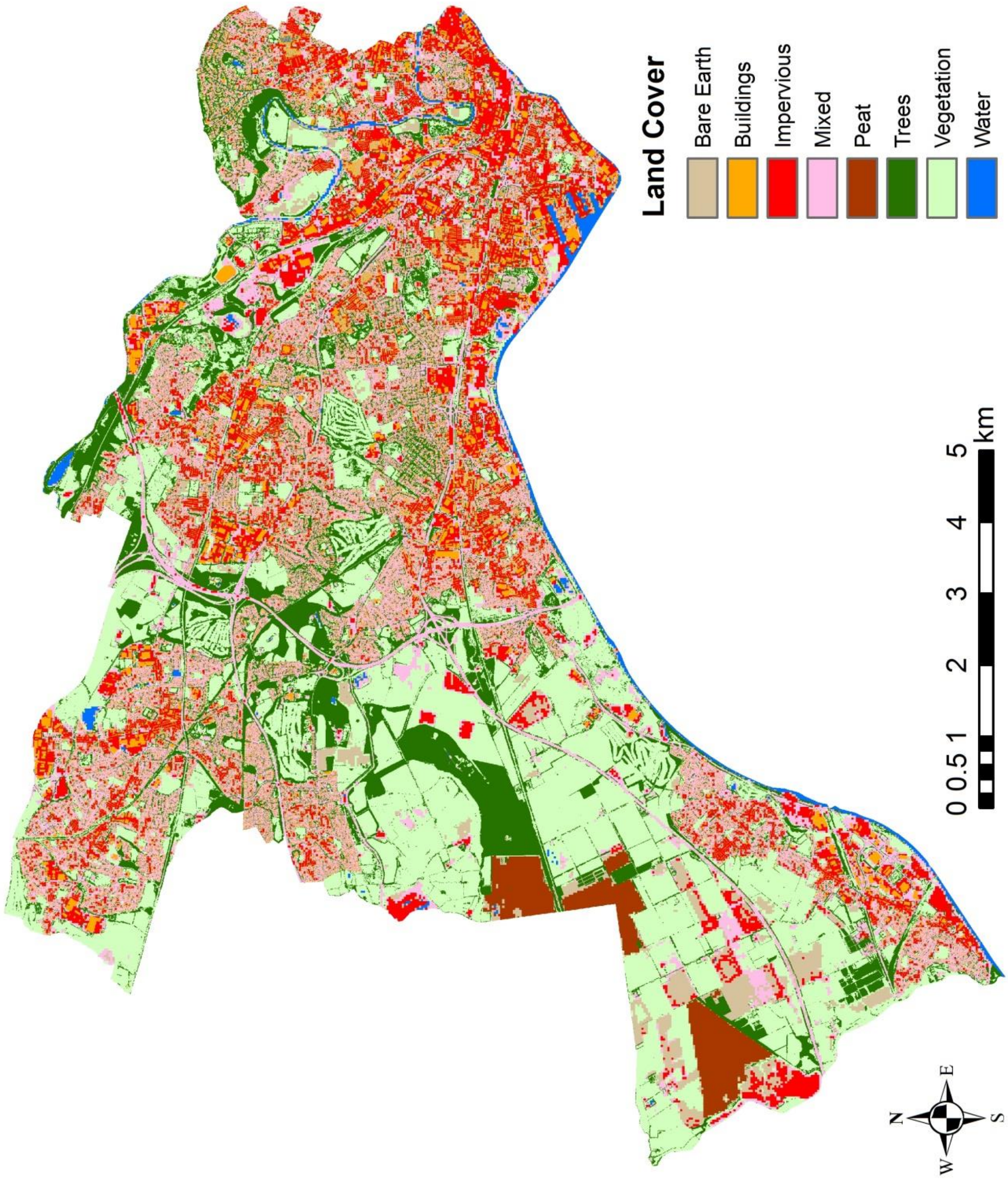

Figure 5.10. Final classified image (Author's own).

Figure 5.10 shows the final classification using eight classes via incorporation of buildings and tree data. The overall accuracy of the final classification is 83.16% (Kappa = 0.81), which is slightly lower than the six band decision tree, but higher than the maximum likelihood classification. The lowest user's accuracies are Impervious and Bare Earth land covers, while Peat and Water have the highest, followed by very high Tree and Building accuracies. The accuracies presented in Tables 5.8 and 5.9 are similar to Table 5.5, but the Mixed, Impervious and Bare Earth display lower accuracies in the 8 class map (Table 5.8).

Table 5.8. Final land cover map accuracy assessment

Classified Data	Reference Data								**Producers Accuracy (%)**	**Users Accuracy (%)**
	Trees	Buildings	Grass	Imp.	Bare Earth	Peat	Water	Mixed		
Trees	**41**	0	0	0	1	0	0	0	**82.0**	97.6
Buildings	0	**46**	0	0	1	0	0	0	**92.0**	**97.9**
Grass	9	0	**47**	0	3	0	0	0	**94.0**	**79.7**
Impervious	0	1	0	**40**	5	1	0	0	**81.6**	**63.5**
Bare Earth	0	1	3	5	**28**	0	0	0	**56.0**	**75.7**
Peat	0	0	0	0	0	**30**	0	0	**96.8**	**100.0**
Water	0	0	0	0	0	0	**50**	0	**100.0**	**100.0**
Mixed	0	2	0	4	12	0	0	**16**	**68.0**	**65.4**

Table 5.9. Kappa values for 8 class land cover map

Class Name	**Kappa**
Trees	0.97
Buildings	0.98
Vegetation	0.77
Urban	0.58
Bare Earth	0.72
Peat	1.00
Water	1.00
Mixed	0.60

5.6. Classification discussion

This chapter has presented a decision tree method to create a land cover map suitable for urban studies in general and specifically for ecosystem service assessment. The classification is based on spectral indices instead of raw band information. The use of spectral indices is more efficient as they have reduced the original number of Landsat TM bands from seven down to four thematic indices (MNDWI, NDBaI, MSAVI and UI). Data redundancy has been reduced and the extraction of selected land cover types has been optimised (Section 5.3). These conclusions reinforce those found by Xu (2007) who used the Soil Adjusted

Vegetation Index (SAVI), MNDWI and NDBI to extract urban/impervious surfaces. Further, Xu (2007) found that a logic-based approach similar to the decision tree approach adopted here yielded the highest accuracies.

The data in Tables 5.6 and 5.7 show that the indices perform better than raw bands, particularly with the fusion of digital boundary feature data. The differences in accuracies are small, but the data in Tables 5.6 and 5.7 suggest that the index-based classification performs better through identification of bare earth pixels, which (Zhao and Chen, 2005) highlight as a key feature of urban areas as they identify land available for development, areas of recent development or demolition and patterns of agriculture in urban areas. Further analysis of bare earth change through time could provide useful information into flows of urban regeneration as is made possible through the use in this research of Landsat imagery (Bannari *et al.,* 2006). The methodology has emphasised the importance of using spatial datasets in concert with spectral data through the development of the classification and creation of more meaningful patterns from physical landscape patterns (Weng, 2012). It is anticipated that hyperspectral or higher resolution imagery would yield greater accuracy (Thenkabail *et al.,* 2004; Hermosilla *et al.,* 2012). However, these data can be challenging to collect, are problematic when dealing with large areas and lack temporal archives.

Determination of suitable indices in Section 5.3 has shown that NDVI is not necessarily the most useful index and can in fact obscure vegetation data (Xu, 2007). Other options are available and should be seriously considered in future studies. Taking a decision tree approach means that following a cross-calibration of satellite imagery, similar land cover classifications should be feasible using the decision tree rules in Figure 5.7. Interpretation of the mathematical ratios means that different indices may be required to maximize accuracies in different sites. This may depend on representative land cover types and climate. However, the transparency of the approach allows amendments where necessary (Pal and Mathers, 2003).

Barbosa *et al.,* (2007) suggest that identification of peripheral and private green spaces in urban areas is a commonly ignored key issue. Figure 5.11 displays the difference between estimations of green space coverage (vegetation and trees) using land cover data and the green space audit. The map demonstrates an increase in green space identification using the land cover map (Figure 5.11). This is expected as the green space audit only includes areas bigger than 2 ha. Even considering this, differences are large, with most differing by at least 25%. In a few OAs (shaded red), the green space audit estimate a higher percentage of green space.

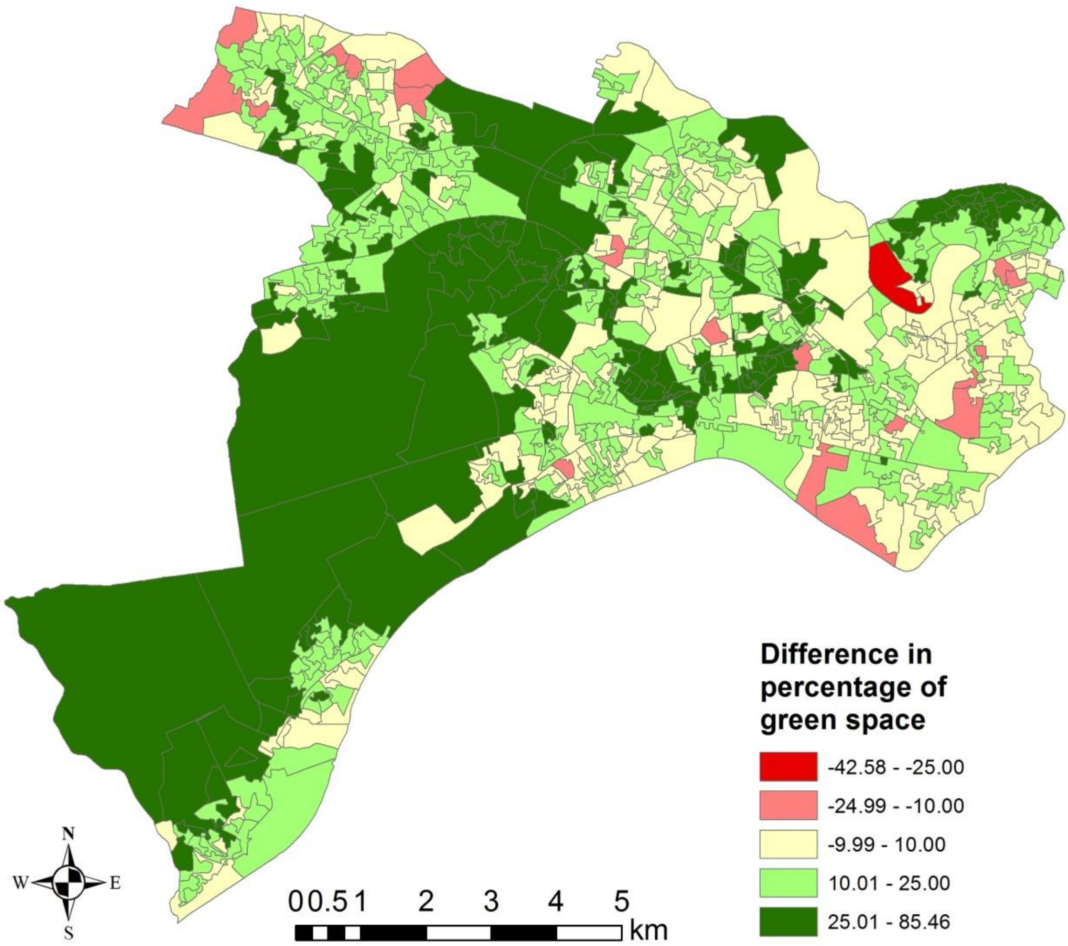

Figure 5.11. Comparison of differing green space estimates. Positive percentage change shows that remote sensing classification identified more green space than that presented by the audit (Author's own).

Referring back to Figure 5.10, these areas are represented by large, un-fragmented coverage of vegetation or water. Elsewhere, discrepancies may be related to the presence of green spaces such as tow paths along the water bodies. These results suggest that integration of remote sensing should be a key input for a more comprehensive audit of urban greenspaces to capture the full picture. When used in conjunction with additional datasets such as land cover maps from ordnance survey, or property boundaries from the Land Registry, further greenspace land uses such as private gardens could be inferred and integrated more confidently into ecological management. Consideration of these spaces is developed in Chapter 8 in terms of the potential contributions they make in increasing the accessibility of local populations to urban ecosystem services.

The high level of automation in the decision tree framework allows easy repetition over different urban areas. As the system is based on Landsat imagery, this opens potential for temporal studies over more than three decades of remote sensing information. The only requirement is for the image to be spectrally calibrated to the image used in this research. Image calibration involves ensuring that pixel values across different images are the same (or in similar ranges) for land covers of interest (Teillet *et al.,* 2001). Potential applications for this include spatial analysis of Salford's place within Greater Manchester, or temporal analysis that focus on how ecosystem service flows have changed due to the development of Salford Quays, or the M60 motorway. Additionally, a focus could be placed on landscape change. By amending the composition of the base land cover map to reflect changes in land use, ecosystem service generation and accessibilities could be recalculated to derive estimates of resource budget changes and related sustainability of scenarios that could include greening of bare earth land cover, or the development of urban greenspaces into residential estates or industrial parks.

5.7. Land use characterisation introduction

The remainder of this chapter considers the land use characterisation based on the land cover map produced in the first half of the Chapter. The purpose of characterising land uses is to create homogenous landscape patches that represent a broad land use, similar to approaches adopted by Herold *et al.,* (2002) and Gill *et al.,* (2008). This is based on patterns of landscape features (measured using landscape metrics) that can be matched to reference areas selected in Section 4.3.2 using aerial photography. As boundaries between land uses can be blurred, there is a requirement to incorporate neighbourhood impacts. These are included using focal statistics in Section 5.8 as suggested by Reginster and Goffette-Nagot (2005). Implementation, results and discussion for the landscape characterisation are discussed in Sections 5.9 to 5.11. The characterisation method applies landscape metrics and building and tree height information to derive a physical characterisation of land use. The method applies k-means clustering approach (Vickers *et al.,* 2007) using character types discussed in Section 3.3.1 (Table 3.8). The training sample of OAs selected in Section 4.3.2 was used to determine influential metrics, based on zonal averages. K-means clustering was performed using the landscape metrics selected in section 3.4.5. The methodology for this section is presented in Figure 5.12.

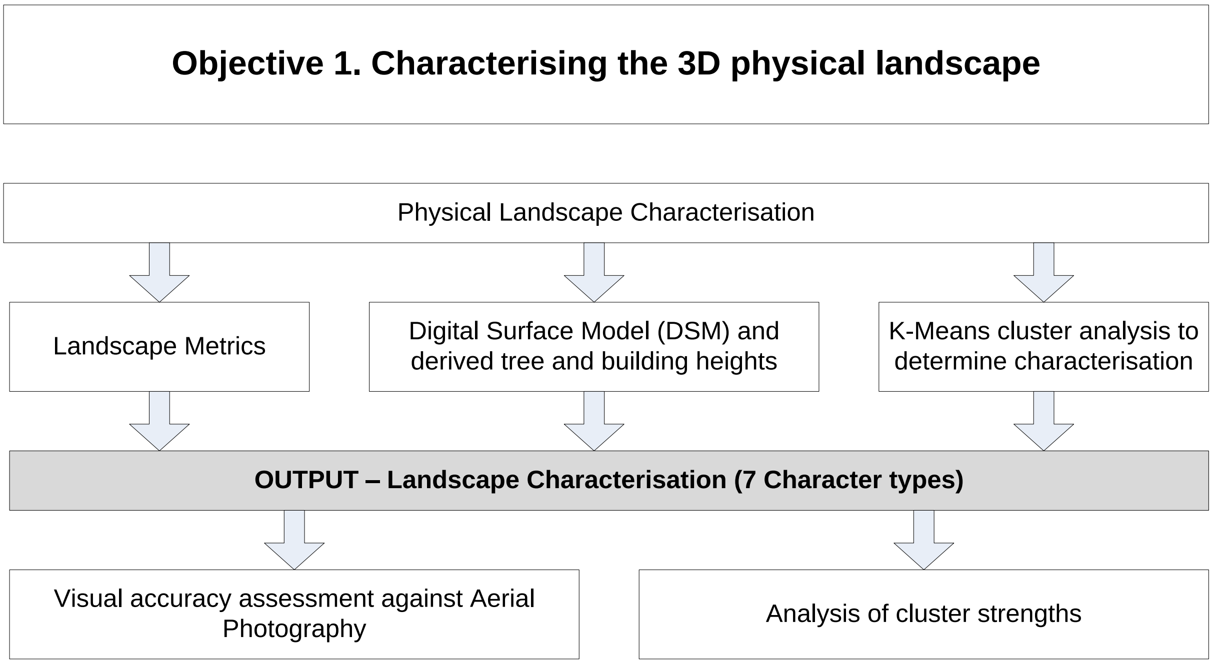

Figure 5.12. Flow diagram of land use characterisation methodology

5.8. Determining a moving window size for land use characterisation

Direct relationships between ecosystem service and land cover have been shown to produce relatively poor indicators for ecosystem services (Eigenbrod *et al.,* 2011). Consequently, this research uses focal statistics to include landscape neighbourhood influences as suggested by Reginster and Goffette-Nagot (2005) and Zhang *et al.,* (2013) (Section 2.3.1 and Section 2.5.3). Focal statistics use statistical or arithmetic operations to derive new values for the central pixel surrounded by a neighbourhood of pixels, commonly using a moving window across an image (Stuckens *et al.,* 2000). Focal statistics can be used to derive additional information on surrounding neighbourhoods. For example, Acharya and Bennett (2001) determined the proportion of open space using a majority operation, while Hale *et al.,* (2013) identified street light positions by determining the brightness of pixels from digital camera imagery.

The purpose of using focal statistics in this thesis is to emphasis the differences in the physical pattern of the landscape mosaic. Many studies have used moving window analysis to measure levels of urbanisation (Luck and Wu, 2002; Wu *et al.,* 2006; Kong and Nakagoshi, 2006). However, there are few established methods to determine appropriate window size. This can alter analysis by reducing land cover variability if the window is too small, or by over-smoothing variability if the window is too large (Kong and Nakagoshi, 2006). Zhang *et al.,* (2013) found that different urban areas produced different optimum window sizes when measuring landscape fragmentation. They used the Simpsons Diversity Index (SIDI) at different window sizes. The SIDI essentially measures the probability that two pixels from a dataset will belong to different categories. The value of SIDI increases as landscapes get more diverse. Zhang *et al.,* (2013) assume that the window size with the largest SIDI value represents potential for the highest level of landscape fragmentation.

Based on the method by Zhang *et al.,* (2013), the optimum moving window size for this research is derived through analysis of maximum landscape metric values in different sized windows. Zhang used four measures relevant to patch composition and building configuration: Simpson's Diversity Index (SIDI), mean patch size of buildings, patch size standard deviation of buildings and the Euclidean nearest neighbour (ENN) between building patches. Circular focal windows are used in this research, which are more appropriate for ensuring that ENN measurements have an equal potential maximum regardless of the bearing from the centre pixel. The maximum value of each metric was recorded for a range of window sizes to determine a peak in maximum scores. The maximum values of the four metrics at different window diameters are represented in Figure 5.13. Peaks are identified in each graph on application of a window with a diameter of 150 m. This suggests that for the site of the current study, Salford, a window radius of 75 m is optimal for maximising the differences in metrics. This information can be used for enhanced clustering of data to build the land use characters.

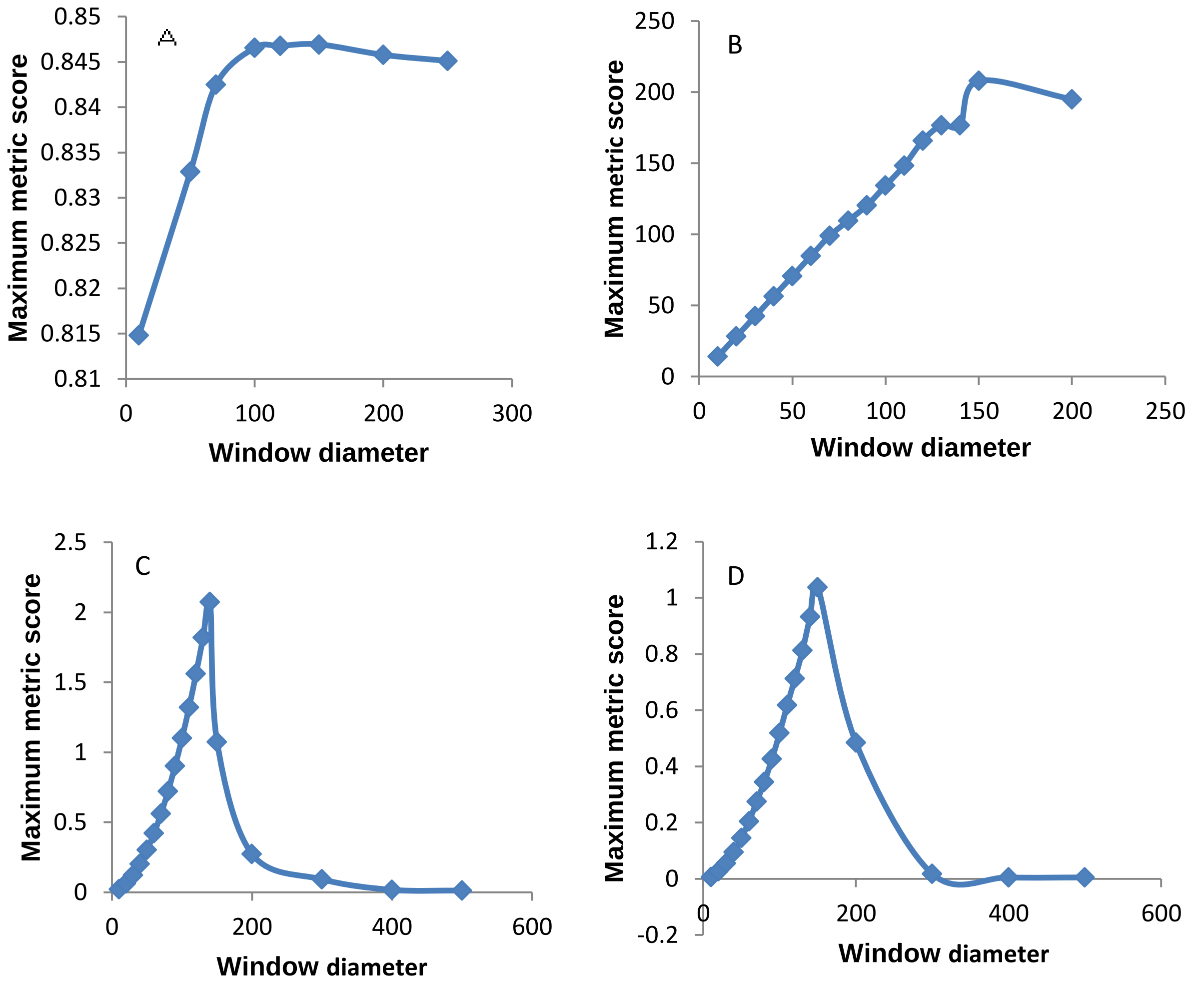

Figure 5.13. Moving window diameter against maximum landscape metric scores (A) SIDI, (B) Mean Euclidean nearest neighbour, (C) Mean patch size of buildings and, (D) Patch size standard deviation of buildings.

5.9. Implementation of the characterisation

The land use characterisation applies landscape metrics selected in Section 3.4.5 to identify patterns in the spatial configuration of features in the landscape mosaic of land covers. These patterns are aggregated to Output Area (OA) level. OAs that share similar patterns are aggregated into land use character types using cluster analysis (Section 5.9.2). This process develops interpretation of the pixel-based land cover map produced in Section 5.5. Attention is paid to broad land cover composition and specific spatial form of buildings in urban areas as well as the heights of buildings and trees to provide information on urban functions as these features represent physical and visible barriers (van Herzele and Wiedemann, 2003).

5.9.1. Landscape metric parameters

The classified land cover map from Section 5.5 was extended to 100 m outside the boundary of Salford before the landscape metrics were calculated. This was done to avoid external pixels that contain a value of NoData. For the purposes of calculating landscape metrics, the land cover map is expressed as a pixel-based series of land cover patches. Pixels that share the same land cover and that also share an edge are grouped into larger, homogeneous ‘patches’. Patches that share a land cover type, but are not joined by a cell edge are identified as different patches of the same land cover class. This arrangement of data allows calculation of patch shape, size and quantity across a landscape. This can be calculated per patch, per class or over the whole landscape (Herold *et al.,* 2006). As an alternative, patches of the same class that only share a corner may be grouped into a single patch, but this was deemed inappropriate for this research as there is a focus on optimising the characteristics of individual buildings and trees, which requires a high level of detail and fragmentation.

The top five landscape metrics identified in Table 3.6 were calculated for each OA in Salford using Fragstats 4.1 (McGarigal *et al.,* 2012). To capture a broad description of land cover patterns, the landscape-level Simpson’s Diversity Index (SIDI) was calculated, as well as the percentage of land covered by Vegetation. SIDI provides a statistical measure which represents the number of different land cover types present in an OA. Percentage vegetated land cover was chosen due to the importance of greenspace in terms of ecosystem service generation highlighted throughout the study so far. To differentiate urban land uses across Salford, a number of metrics were calculated for the building land cover class. These included the Percentage covered by buildings, the mean patch size (footprint) and the standard deviation of building patch per OA. Collectively, these provide information on the size and variability of the built environment in an OA. To complement these measures, the percentage of land, edge density and standard deviation of tree patch sizes was also measured. This provides additional information on how wooded an OA is and whether tree cover in an OA is clumped into large urban forests, or scattered as separate urban street trees. Finally, the three dimensional characteristics of each OA were explored to provide more information on characterising land use. To this end, the mean and standard deviation of building and tree heights was captured based on information used to create the land cover map. A moving window option was selected for class and landscape metrics with a circular local kernel changed to a radius of 75 m, justified in Section 5.8. This includes the values of surrounding pixels, which serves to smooth the data. This means that individual features that may skew characterisations can be more easily included into characterisation. This better reflects the variability within the broad land use descriptions used in this research and listed in Table 3.8.

5.9.2. Normalisation and characterisation

Each landscape metric calculation produced a single value per area. The overall mean and standard deviation of these values were calculated and used to convert the landscape metric values into normalised z-scores using the equation below. Where z = the normalised z-score, x = the raw metric score, μ = the mean metric score and σ = the metric standard deviation.

Equation 5.1: $$z = \frac{x-\mu}{\sigma}$$

The characterisation of land use is aggregated into OAs, but OAs are not of a standard size and have been designed to contain residents. Population density is one of the variables considered in OA creation. Each OA contains approximately 100 households. This means that there are size differences. For example, sparsely populated, rural areas have larger OAs. This is particularly true of the agricultural areas to the South West of Salford. To correct this, dasymetric mapping was used as demonstrated in Figure 4.5 and described in Section 4.2.6.

Following a methodology applied by Vickers *et al.,* (2007), k-means cluster analysis was used to aggregate the landscape metric z-scores into land use character types that displayed similar landscape metric patterns. Decision trees were not used as the land use characters are less distinct, making a rules-based classification awkward. K-means clustering analysis was conducted in SPSS. Five clusters were calculated to align with five urban land use types listed in Table 3.4. The default value of ten iterations was used to determine the cluster means, although clusters had stabilised before this point. Two additional land use characters were added to the green spaces integrated into the OA layer. This better represents large unpopulated greenspaces. Analysis of PLAND trees and PLAND vegetation was used to distinguish between vegetation and woodland character types according to dominant percentage.

5.10. Characterisation Results

Seven character types have been derived comprising three residential categories, three rural/green categories and one non-domestic urban category as described in Table 3.4. The information in Table 5.10 shows that semi-detached housing is the cluster with most cases, followed by Detached and Terraced. Agriculture was least represented in terms of OA numbers. By percentage of Salford, the three residential character types together represent 39.4%, while Agriculture comprises almost a third (29.28%). The remaining 30% is composed of Non-domestic (10.05%) and Green spaces. Agricultural OAs have the largest mean area, while the semi-detached have the smallest, followed by terraced and detached housing.

Table 5.10. Cluster area information. From left to right, the columns present the land use type, the number of OAs, the average OA Area, and the total area expressed in square metres and as a percentage of Salford.

Cluster	Number of cases	Average OA area (m^2)	Sum Area (m^2)	Percentage of Salford covered (%)
Semi-detached	369	47411.11	17494700.97	17.99
Detached	163	73618.69	11999846.51	12.34
Terraced	151	59498.45	8984265.81	9.24
Agriculture	28	1017008.48	28476237.40	29.28
Non-domestic	45	217300.35	9778515.79	10.05
Woodland	75	123805.82	9285436.51	9.55
Green or blue spaces	139	80886.12	11243170.92	11.56

Figure 5.14 displays the results of the land use characterisation. The purple OAs in Figure 5.14, indicate non-domestic urban land use and are situated in or near urban centres including Manchester, Eccles, Irlam and Swinton. Figure 5.15 and Table 5.11 present information on the strength and distribution of values within each cluster and show that these areas are characterised by a high mean patch size and height of buildings. The non-domestic OAs are also characterised by high variability in tree cover and tree heights. The detached OAs are characterised as having the largest proportion of trees as well as the highest mean tree heights. Conversely, semi-detached OAs have the landscape metric values closest to the average with mean values approaching 0 across the range of variables. Agricultural areas are characterised as having a high percentage of vegetated land as well as very low landscape diversity.

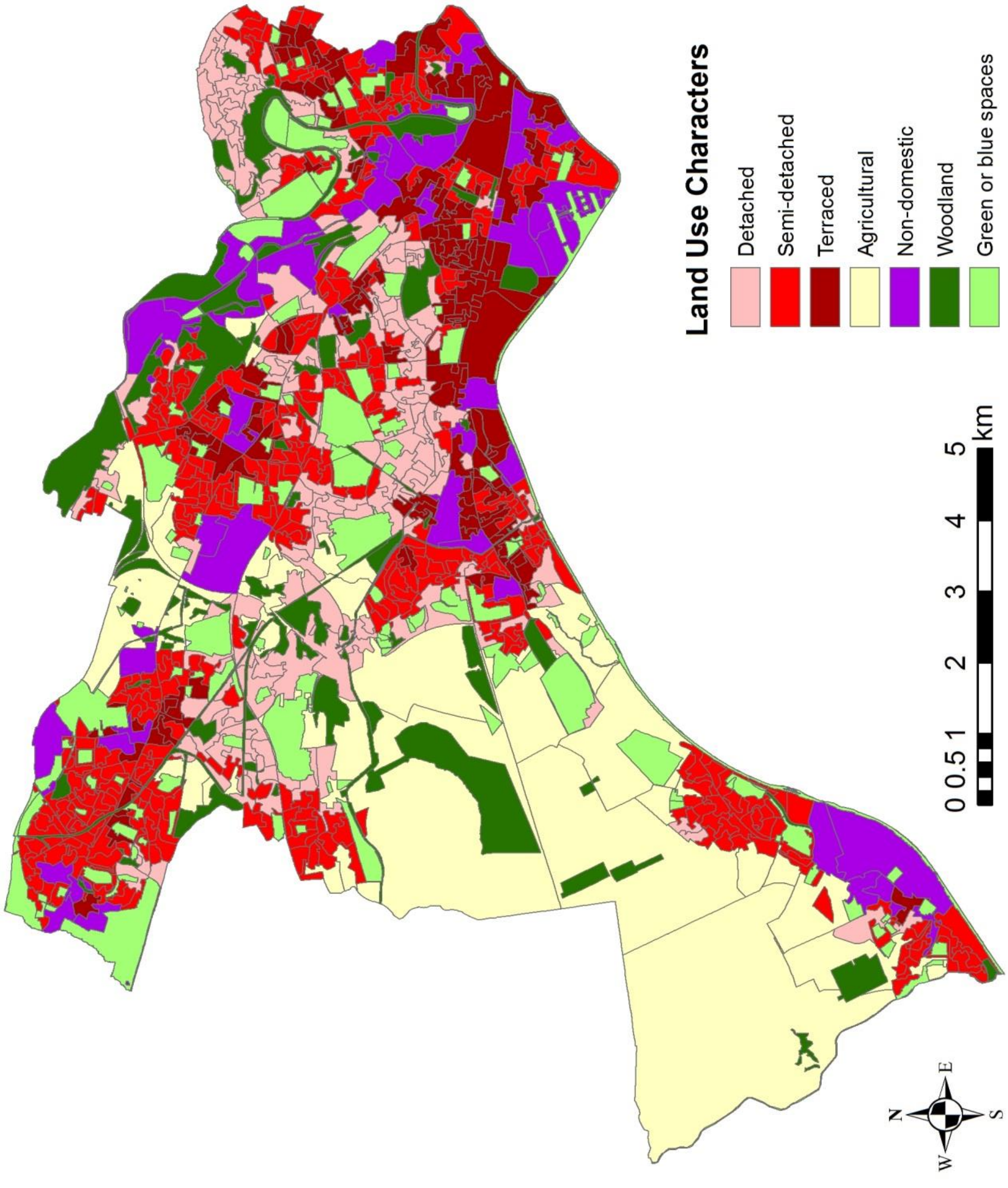

Figure 5.14. Characterisation of urban land use (Author's own).

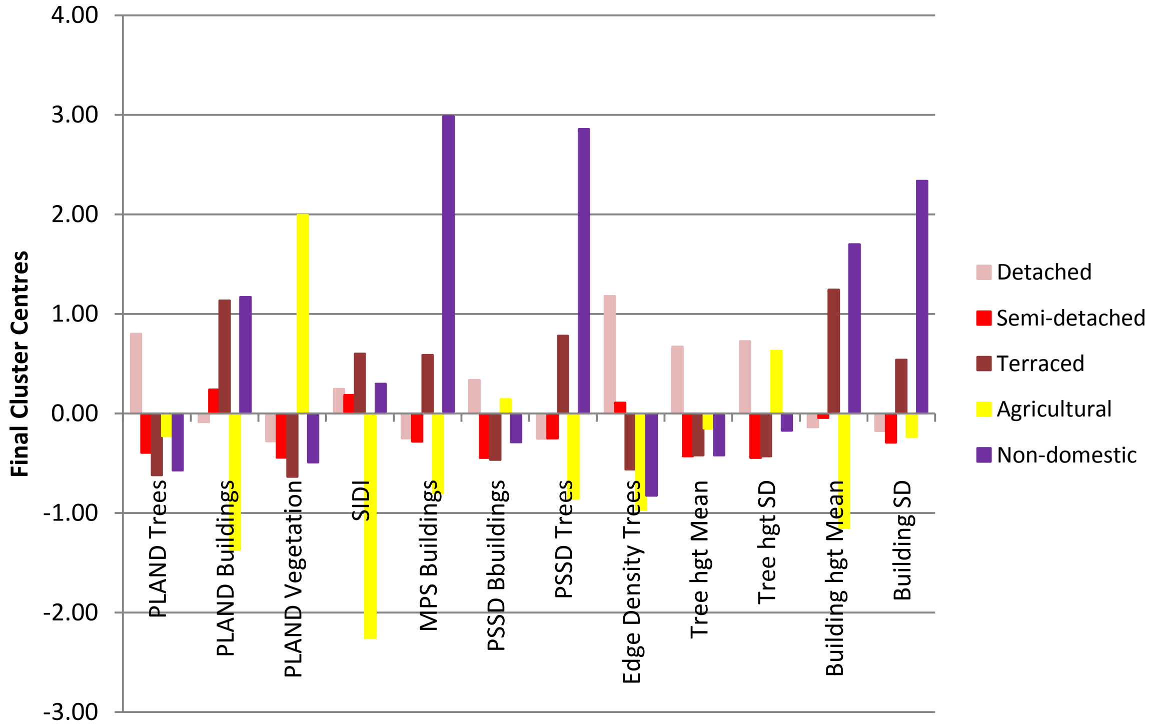

Figure 5.15. Landscape scores for the representative central point of each cluster

Table 5.11. Descriptive statistics for landscape metrics in each cluster. The paired columns for each land use type present information on the mean and standard deviation of landscape metric values.

Landscape Metric	Semi-detached		Detached		Terraced		Agriculture		Non-domestic		Woodland		Green or Blue	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PLAND trees	-0.40	0.32	0.80	0.55	-0.62	0.37	-0.23	0.71	-0.59	0.44	2.11	1.53	-0.15	0.75
PLAND Buildings	0.25	0.45	-0.09	0.47	1.13	0.81	-1.37	0.37	1.16	0.84	-1.17	0.75	-1.23	0.51
PLAND vegetation	-0.45	0.39	-0.28	0.40	-0.64	0.20	1.99	0.70	-0.47	0.35	0.40	0.62	1.72	1.00
SIDI	0.18	0.58	0.25	0.45	0.60	0.52	-2.26	1.14	0.28	0.47	-0.58	1.51	-0.73	1.31
MPS Buildings	-0.25	0.51	-0.25	0.40	0.59	0.48	-0.80	0.23	3.20	1.54	-0.34	0.81	-0.34	0.72
PSSD Trees	-0.45	0.19	0.34	0.60	-0.47	0.20	0.15	0.65	-0.30	0.42	2.29	1.89	0.09	0.71
PSSD Buildings	-0.22	0.57	-0.26	0.43	0.78	0.60	-0.85	0.19	2.82	1.35	-0.42	1.02	-0.47	0.70
Edge Density Trees	0.10	0.67	1.18	0.83	-0.56	0.77	-0.97	0.75	-0.85	0.53	0.02	1.06	-0.58	0.90
Tree height mean	-0.43	0.23	0.67	0.69	-0.42	0.27	-0.15	0.55	-0.44	0.32	1.97	2.02	-0.12	0.60
Tree height SD	-0.45	0.39	0.73	0.76	-0.43	0.37	0.63	1.00	-0.20	0.80	1.47	1.92	-0.07	0.81
Building height mean	-0.01	0.56	-0.14	0.50	1.24	0.75	-1.15	0.21	1.79	1.02	-0.92	0.63	-0.99	0.47
Building height SD	-0.22	0.82	-0.18	0.35	0.54	0.63	-0.24	0.35	2.65	1.82	-0.38	0.56	-0.37	0.64

Figures 5.16 – 5.20 show the spread of values for locations for each landscape character type. Small values represent locations that share similar landscape metric pattern characteristics to the mean values for the overall character (shown in Table 5.10). The residential clusters (Figures 5.16 – 5.18) are strong clusters, indicated by the peaks of the histograms being relatively close to the cluster mean. The histograms for these characters are very similar in size and shape. Conversely, the non-domestic histogram is spread over larger distances, indicating more cases further from the centre and suggesting that the cluster is less easy to characterise. The agricultural cluster is also relatively spread out considering the low number of cases.

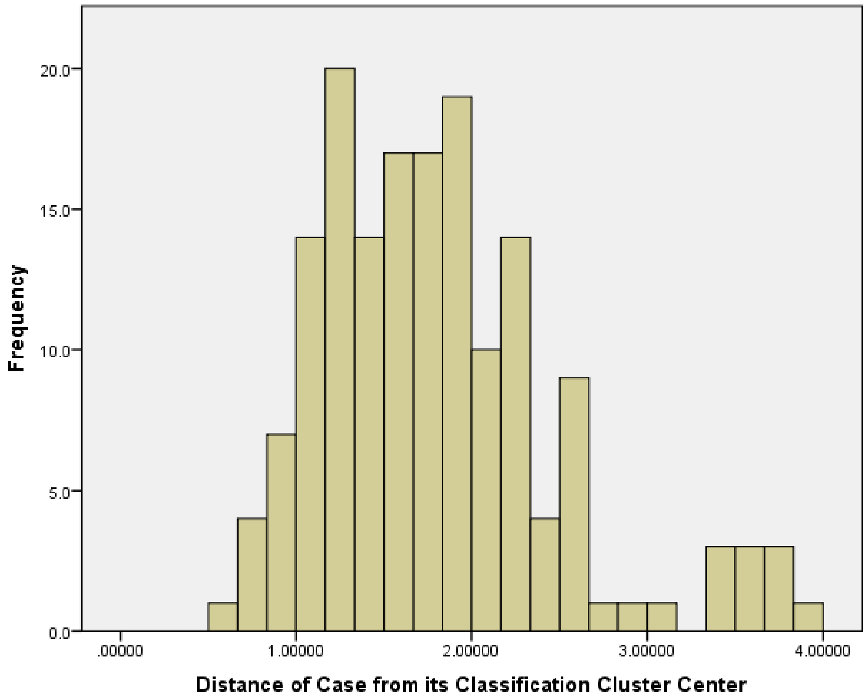

Figure 5.16. Histogram of 'detached' cluster distances from the central point of the cluster

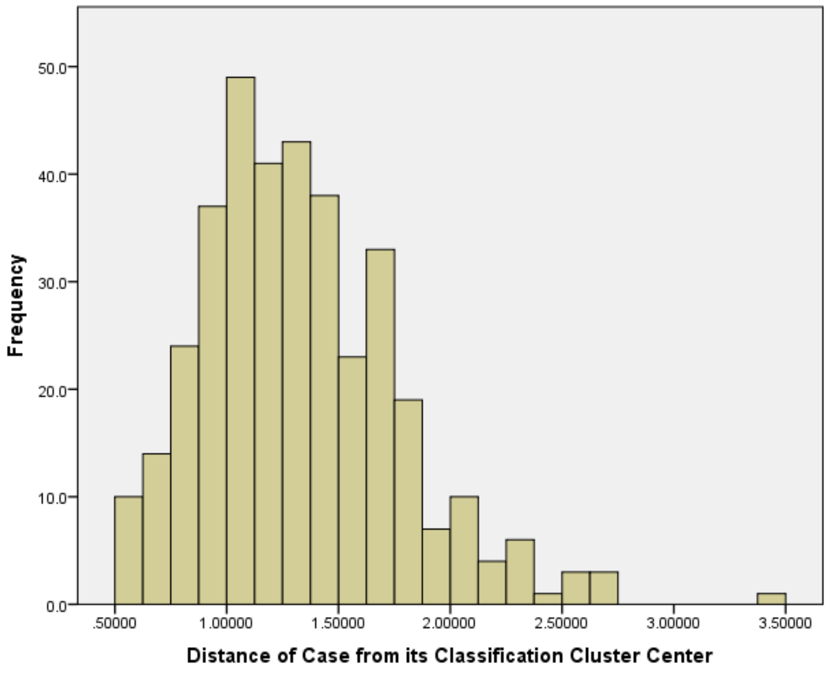

Figure 5.17. Histogram of 'semi-detached' cluster distances from the central point of the cluster

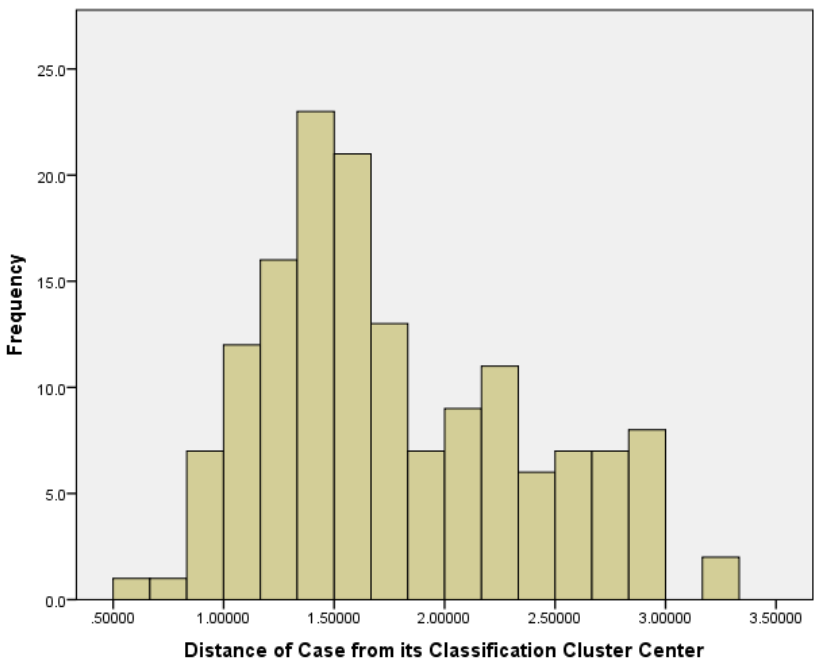

Figure 5.18. Histogram of 'terraced' cluster distances from the central point of the cluster

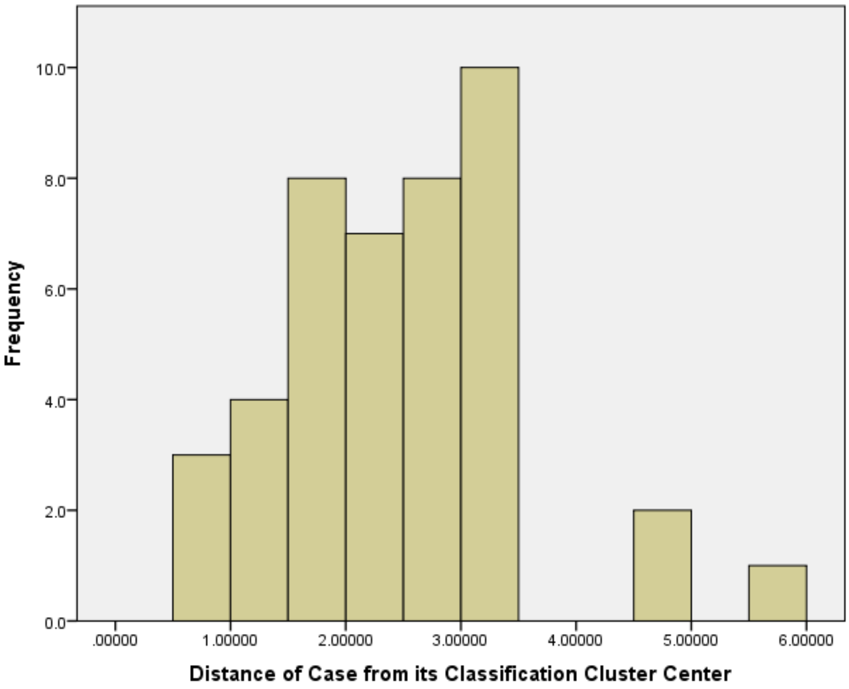

Figure 5.19 Histogram of ‘non-domestic’ cluster distances from the central point of the cluster

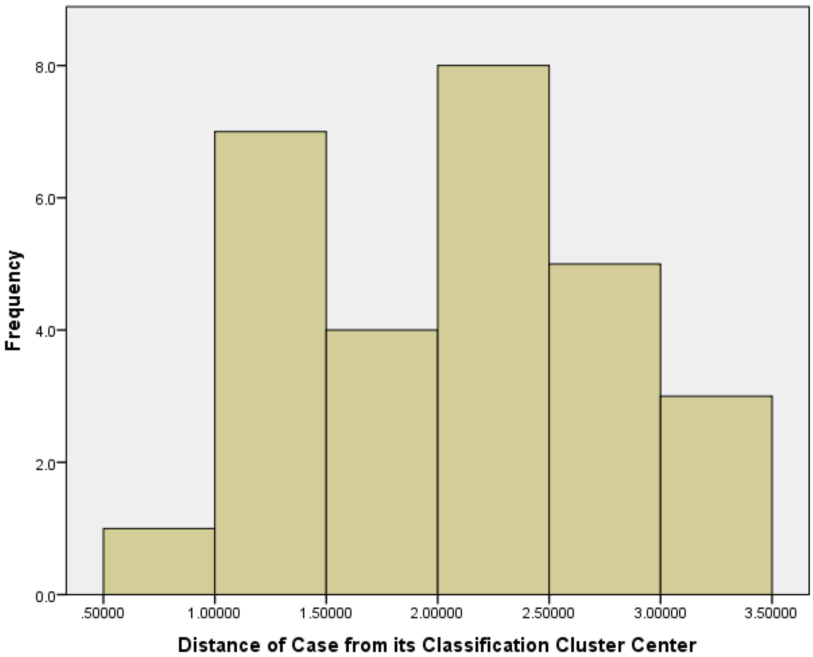

Figure 5.20. Histogram of ‘agricultural’ cluster distances from the central point of the cluster

5.11. Characterisation Discussion

This study represents one of the first to characterise land uses from patterns in the physical landscape using census boundaries. Land use characterisation of the land cover map transforms objective land cover categories into more meaningful landscapes (Brabyn, 2009). However, challenges have been revealed that relate to the size of spatial units used. In particular, the divergent characterisation of non-domestic buildings (evidenced by large values for locations in Figure 5.19), means that industrial and commercial buildings are grouped in together, but may be very different in terms of the composition of the landscape. This replicates the characterisation of Manchester by Hussain *et al.,* (2007), who despite operating at the individual building level, choose just one non-domestic land use category.

Disaggregating non-domestic land use further in this research has proved problematic when focussing only on physical patterns in the landscape. Further disaggregation would be useful for exploring ecosystem services in relation to the flows of people throughout a typical day. This could include measurement of migration between residential areas, where the majority of the population are found during the night, and places of work where the population are most likely to be found during the day. Currently, temporal analysis has only focussed on modelling ecosystem services through larger expanses of time (Pauleit *et al,* 2005; Dallimer *et al.,* 2011). Mapping patterns of ecosystem services against dynamic populations throughout a day would provide new information on whether the ecological importance of different areas changes and if so, how much. Further data would be required to make progress. This could be achieved using AddressBase information. However, an element of method automation would be sacrificed.

The strength in character of the residential character types is highlighted by the low values in Figures 5.16 – 5.18. This highlights the uniformity of physical patterns across these landscape character types. However, without the building and tree footprint and height information, these character types would have been challenging to separate. The integration of tree canopy footprints and heights has also allowed potential differentiation of more wealthy areas (Wolfe and Mennis, 2009). This may be further verified using data collected at administrative area level such as the Output Area Classification (OAC), Experian's MOSAIC data or the index of multiple deprivations, none of which currently acknowledge environmental influences. The use of height information alongside landscape metrics has assisted in characterising physical patterns through incorporation of 3D data. In particular, the differences in building volumes has been invaluable in differentiating between domestic and industrial/commercial and adoption of block geography (Hussain *et al.,* 2007) or individual building characterisation (Hermosilla *et al.,* 2012) may help distinguish between industrial and commercial. Using OAs as spatial units has provided a challenge to validate as the units themselves are based on populations (ONS, 2013). This means that characterisation of spaces dominated by land uses not related to residential estates is compromised to an extent. This has in turn blurred the boundaries between land use character types. This is also noted by Vickers *et al.,* (2005) in their socio-economic classification and reinforced by an invitation on the OAC website for suggestions for OAC cluster titles. The methodology applied here follows results from previous studies and marks an alternative approach to the rising popularity of object-based image analysis (Miliaresis and Kokkas, 2007; Guan *et al.,* 2012). However, complex and similar urban spectral signatures (Herold *et al.,* 2004) using medium resolution imagery challenge this approach. Further, the subjective interpretation within the segmentation stage of object based analysis points to the use of higher resolution imagery (Jellema *et al.,* 2009). The approach adopted here, provides benefits of being fast to implement and easier to update temporally.

The characterisation of landscape features transforms the land cover map into a more meaningful human landscape. This in turn translates usefully into ecosystems service research which is centred on human impacts and benefits provided from the physical landscape. The added value of creating a characterisation is in the deeper analysis of how people use different spaces and from that, the kinds of services that may be more useful or relevant. For example, industrial and commercial areas tend to be workplaces, where the urban heat island may be a particularly important factor, but recreation opportunities may not be as important as aesthetic or air quality. Alternatively, residential neighbourhoods may be more prized for recreational, aesthetic and air quality.

The land cover map and land use characterisation have been designed specifically for ecosystem service assessment, but both can easily be related to other disciplines. Together with the ecosystem layers derived in Chapter 6 along with the underlying DSM could be integrated into a database similar to other GIS projects for integrated analysis into ecosystem service research (Villa *et al.,* 2002; Kareiva *et al.,* 2007; Nelson *et al.,* 2009; Jackson *et al.,* 2013).

5.12. Conclusions

Urban classification has always proven difficult due to dense, fragmented land cover types. With this in mind, a certain amount of error is to be expected. The use of a decision tree approach in this thesis enables extraction of individual land covers at an accuracy that is favourable compared to more commonly used statistical classification methods. The benefits of decision trees as already highlighted by Hu (2009) are in the simplicity and autonomy of the approach. For this to be workable, all that is required is an image radiometrically calibrated to the original used in this research, or amends to index thresholding based on collected training areas. The approach outlined here could be transferred directly to temporal UK urban areas. The introduction of peat into the classification highlights the importance of local knowledge of an area and that further land covers may be required for different sites. For example, wetlands, floodplains, or beaches may need to be included for coastal areas. However, this approach could be amended for different climates where more arid climates may produce drier land cover types, or colder frozen land covers.

The next chapter explores how the physical landscape can be used to measure provision of ecosystem services and how OAs as landscape units can be applied to further analysis and assessment of ecosystem service provision. Ecosystem services operate at different spatial scales, which require more than a pixel-based approach. Analysis of the wider landscape differentiates land cover types in specific locations based on the properties of neighbouring land cover types. Consequently, the maps produced in Sections 5.5 and 5.8 provide appropriate models for ecosystem service research and further analysis and evaluation. The next chapter evaluates how this physical basis can be used as a platform for service accessibility.

6. Characterising Ecosystem Service Generation

6.1. Introduction

This chapter contributes to research objective 2: *Characterising ecosystem service generation,* by tackling the neglected spatial analysis of potential ecosystem service generation to provide insights into how it is distributed across the city and how this may impact on the production of the ecosystem services themselves. The literature review in Section 2.3.1 has revealed that a key step to understanding the distribution and provision of ecosystem services is first to understand how the resources for generating these services are distributed on the landscape. There is a growing base of research conducted at wider scales in rural areas and in regions that contain urban centres (Egoh *et al.,* 2009; Raudsepp-Hearne *et al.,* 2010; Kroll *et al.,* 2012), but there has been very little done at neighbourhood level in urban areas. The importance of urban areas is due to the intensity of human interventions made on the urban landscape. This results in a greater and broader demand for ecological services and goods and has already been emphasised in Sections 2.3.1 and 2.5.1.

The literature review in Section 2.5.1 argues that a current neglect of spatial analysis in ecosystem service research can be addressed by considering methods used more widely in other geographic disciplines. This provides new insights into more meaningful spatial patterns. To address this shortfall, an explicitly spatial approach to determine ecological hotspots will be compared against aspatial methods as applied in current ecosystem service literature to determine provision of a range of important ecosystem services in urban areas. Ecosystem service hotspots are “areas which provide large components of a particular service”. (Egoh *et al.,* 2009, p554). In acknowledgement of criticisms of previous ecosystem service research, the provenance of individual ecosystem service indicator layers will be validated against field surveys and established secondary datasets.

6.2. Methodology

6.2.1. Introduction

The methodology for this Chapter is described in Figure 6.1 and is further discussed in Sections 6.2.2 – 6.2.5. Indicators for individual ecosystem services selected in Section 3.3 were created as described in Sections 6.2.2.1 – 6.2.2.5. This is represented by the five grey boxes in the top half of Figure 6.1 where each box briefly describes the process used to create each layer. Results are presented in Section 6.3.1. The bottom half of Figure 6.1 maps the validation and analysis process. Validation of each layer was completed against secondary datasets and field work in Section 6.3.2 before patterns of individual ecosystem service generation were analysed using hotspot analysis in Section 6.3.3. A spatial approach to hotspot analysis was compared against a traditional threshold-based approach to incorporate a spatial dimension into the identification of ecosystem service hotspots. This has been previously neglected in previous research, but could provide new insights into how spatial distributions can affect the definition of hotspots. These techniques have been discussed in Section 3.5.3.

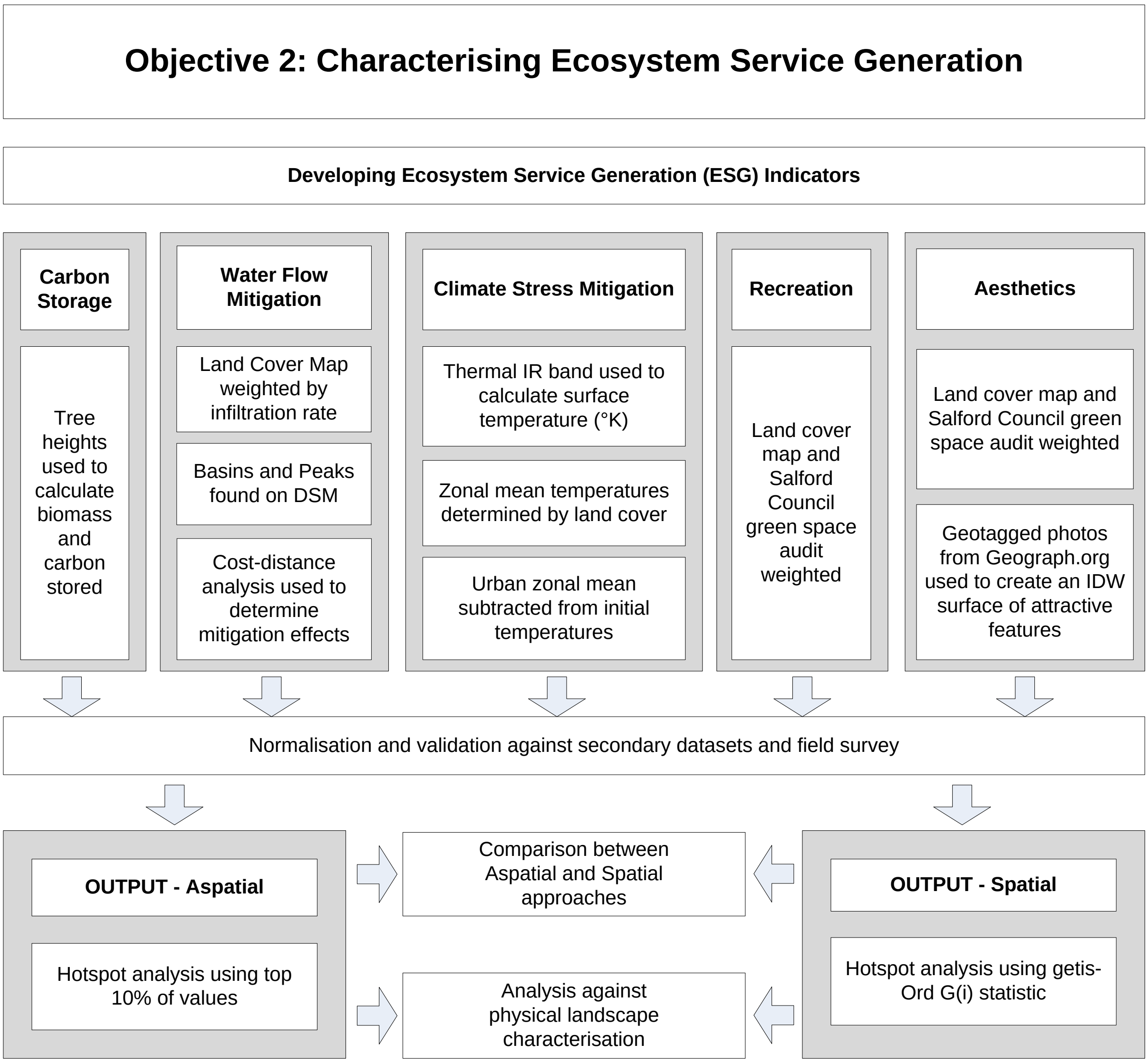

Figure 6.1. Methodology for Chapter 6.

6.2.2. Creating ecosystem service generation layers

6.2.2.1. Carbon storage

The carbon storage map was created using the tree survey data described in section 4.2.5 and an allometric equation developed by Davies *et al.,* (2011), justified in Chapter 3. This research only considered carbon stored in trees because Chisholm (2010) found that carbon stored by soils and grasses to be negligible in comparison with tree storage, although peat storage may be significant (Holden and Connolly, 2011; Grand-Clement *et al.,* 2013; Fyfe *et al., 2014*).

The tree survey represented individual tree canopies using circular polygons to describe canopy area. Heights (m) for each tree were stored in the attribute table. Where trees were too close to isolate, a single encompassing treeline polygon was created. In addition, the tree survey collected heights across treeline, which are represented as separate points as described in Section 4.2.5. These treeline points were interpolated into a surface using inverse distance weighting as discussed in Section 4.3.3. Both the individual trees and treeline vector datasets were rasterised to 5 m raster cells to match up with other datasets (as discussed in Chapter 4). The following equations derived by Davies *et al.,* (2011) were used to convert of tree heights, into biomass and consequently carbon stored in kg C m^{-2} per cell. The generic broadleaf tree equation was chosen as collection of tree species for individual trees across all of Salford was not feasible due to time constraints and access issues.

Equation 6.1 $$b = 0.975(0.566h^{2.315})$$

Equation 6.2 $$C_s = 0.48b$$

Where b = biomass, h = height and C_s = Carbon stored. Equation 6.1 calculates biomass from tree heights and includes consideration of dead trees. Equation 6.2 converts biomass to stored carbon. Finally, a large number of zeroes were produced in areas where there are no trees. This resulted in high skew in the data, the dataset was transformed using a natural log transform (Kanevski and Maignan, 2004).

6.2.2.2. Water flow mitigation

The water flow mitigation map was created using the land cover map created in Chapter 5, and a detailed digital surface model described in Section 4.2.3. The purpose here was not to map surface runoff, but model the mitigating effects of vegetation on potential levels of surface runoff within a catchment. The method presented here is derived from two studies that have modelled water flow and flood risk in a catchment within a GIS using path-distance analysis (Nedkov and Burkhard, 2012; Jackson *et al.,* 2013). To model the mitigating effects of vegetation on water flow, this research follows an approach adopted by Nedkov and Burkhard (2012), which considered mitigation in terms of the capacity for different features of the Earth’s surface and in particular vegetation to absorb or reduce surface runoff. This does not provide information on levels of surface water run-off, but instead provides information on levels of water flow mitigation as an ecosystem service, based on the landscape features present.

The land cover categories in the land cover map were recoded to reflect water flow mitigation, using a scale from 0.1 – 1.0, with 0.1 being the highest mitigating land cover and 1.0 having effectively no effect on reducing water flow. The value represents the proportion of water that successfully travels across the pixel without being absorbed into the earth. These values are based on infiltration and interception rates from different land covers (Pauleit and Duhme, 2000; Xiao *et al.,* 2002; Hirabayashi, 2005; Nedkov and Burkhard, 2012). Armson (2012) found that although grass reduced runoff levels to a greater degree than forested areas, tree canopies intercept more rainfall, increasing lag times for water to infiltrate the ground and tree pits in urban areas also increase infiltration levels. Trees were therefore given the maximum score of 0.1, lower level vegetation, 0.4 and mixed land cover, 0.8. All other land covers were given a score of 1.0 as they were either impermeable, or soils. According to Landis (2013), the major soil types present in Salford are 'slowly permeable, seasonally wet acid loamy and clayey soils with impeded drainage' and 'naturally wet, raised bog peat soils'. The land cover-based water mitigation surface is presented in Figure 6.2.

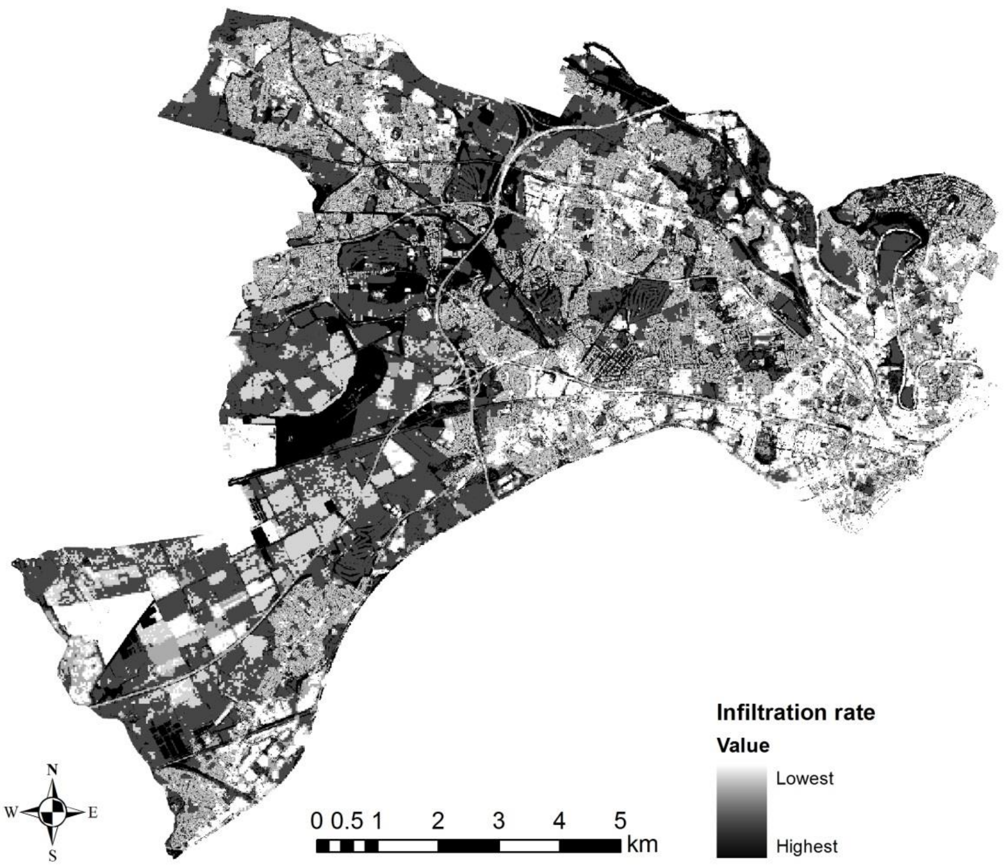

Figure 6.2. Water mitigation surface based on Chapter 5 land cover map (Author's own).

To account for flow accumulation across Salford, path-distance analysis was applied rather than ArcGIS hydrology tools. This is because hydrology tools create flow accumulation channels, where the required output is a mitigating value per pixel. In path-distance analysis the value in each pixel is the 'cost' it takes to get from a particular source pixel. Source points are the locations where water is added into the digital surface model (DSM). These were identified as peaks in the DSM. Peaks were selected by identifying drainage basins in the DSM using slope information. The maximum height value in each basin was calculated. This value was subtracted from the original DSM. Cells that have a value of 0 in the calculation are peaks (the highest points in each drainage basin). Path-distance analysis was calculated in ArcGIS 9.3 running two versions. The first applied no impedance values, effectively giving all cells a value of 1 as shown in figure 6.3. The second version applied the mitigation surface (figure 6.2) to reflect the impact of land cover as shown in figure 6.4. However, to use the mitigating impact surface (Figure 6.4) as it is, overemphasises the impact of mitigation, especially if there is a long distance from the source. To better model the position of a pixel within the overall catchment, the mitigated path-distance analysis was divided by the non-mitigating surface (Figure 6.3) to normalise the mitigating influence of the land cover (Jackson *et al.,* 2013). The output of this operation is a surface where a pixel value relates to the difference in values between the mitigated and non-mitigated surfaces. Very low values represent pixels where the difference in water absorbed is relatively small (i.e. mitigation is having little effect). High values represent the largest difference in water absorbed (mitigation is having the highest effect at these points in the catchment. Resulting values were inverted to produce a final raster surface with values between 0.1 – 1.0, where higher values indicate a higher level of water flow mitigation. However, this method does not take into account the volume of water flowing into a catchment and only models single units of water per pixel.

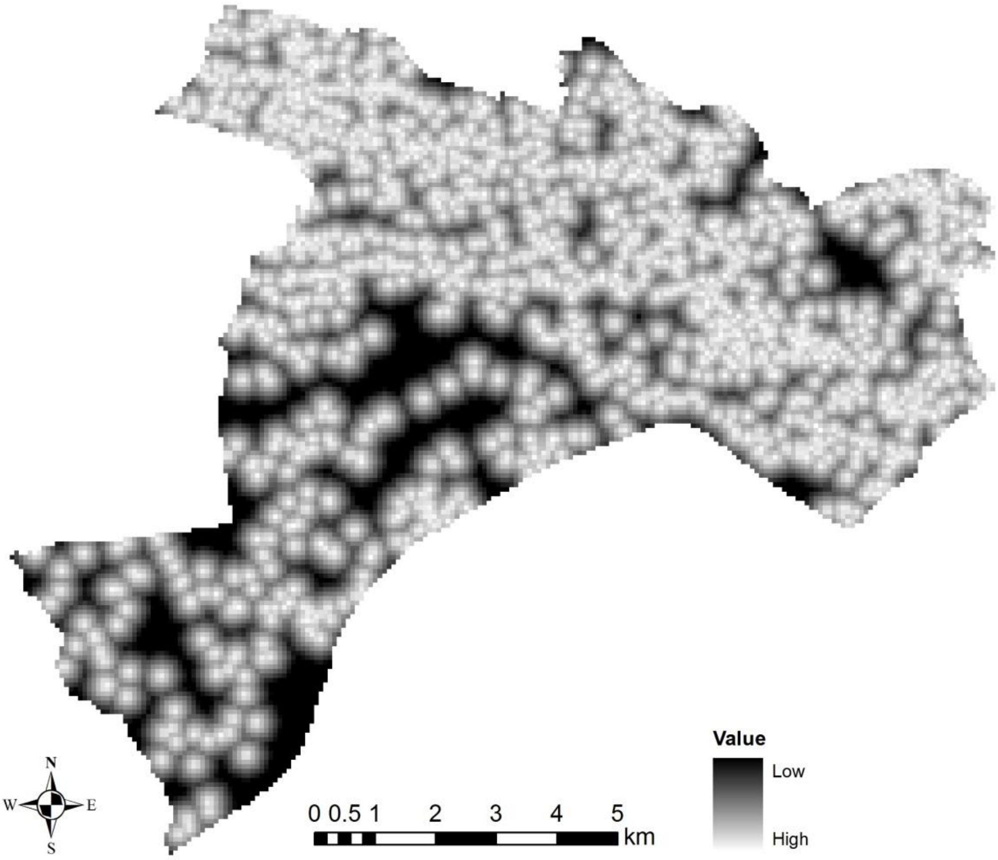

Figure 6.3. Path-distance analysis ignoring potential mitigating properties of Chapter 5 land cover map (Author's own).

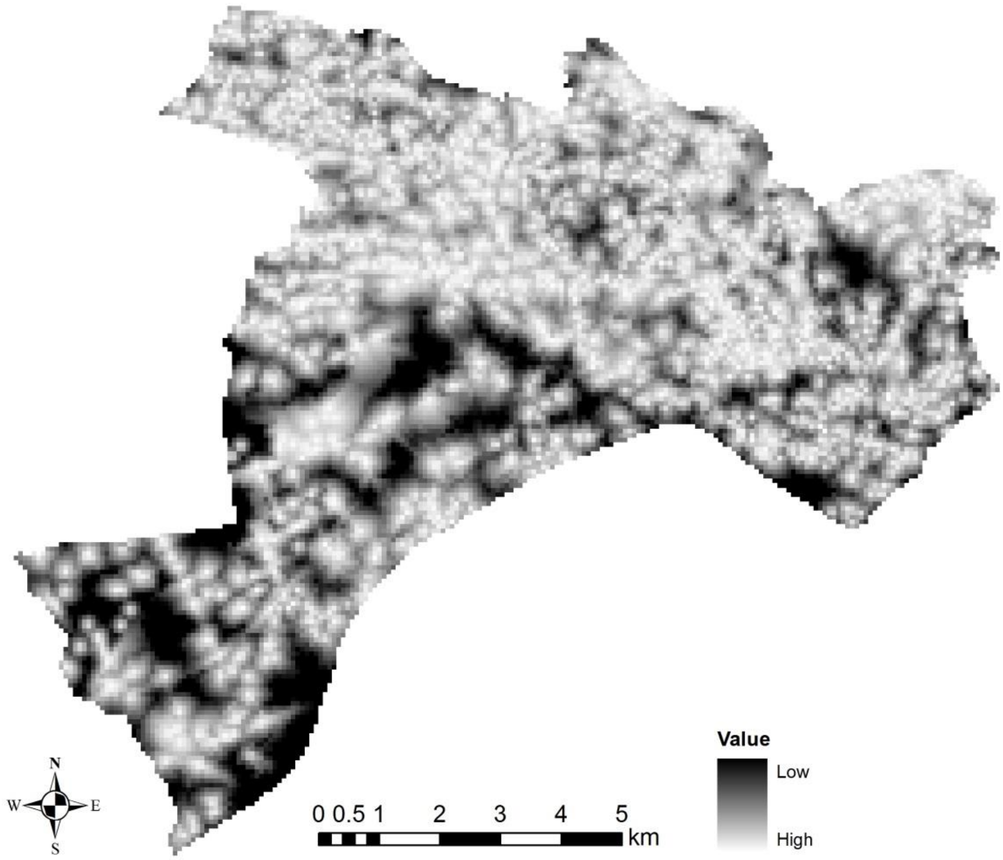

Figure 6.4. Path-distance analysis including land cover-based water flow mitigation properties (Author's own).

6.2.2.3. Climate stress mitigation

The climate stress mitigation layer was produced using the land cover map created in Section 5.5, and the thermal infra-red band of the Landsat TM image (Section 4.2.1). The aim was to produce a layer that reflects the mitigating influence of vegetation on land surface temperatures.

The land cover map was used to derive mean temperatures across land cover types as described in section 4.2.1. The results are shown in Table 6.1, which shows that the highest mean temperatures belong to exposed peat, urban and buildings. Furthermore, buildings, urban and the mixed land covers had the smallest standard deviation, indicating a smaller variation in temperature values for these classes. The lowest temperatures belonged to water, grass, bare earth and trees. Bare earth displayed the highest variation in temperature, further indicative of the difficulty in classification discussed in section 5.6.

Table 6.1. Average temperatures (K) across land cover types in Salford

Land Cover	Area	Mean	Std Dev
Water	999900.00	297.74	2.62
Grass	26190900.00	299.11	2.02
Bare Earth	6791400.00	299.33	3.63
Trees	18824400.00	300.13	2.60
Mixed	23670000.00	302.71	1.60
Buildings	8857800.00	303.30	1.60
Urban	9707400.00	303.76	1.98
Peat	2138400.00	306.14	2.09

The approach used to determine the mitigating effect of vegetation on land surface temperatures is the same as the method used by Voelker *et al.,* (2012) to study the mitigating effects of urban water bodies. The mean temperature for urban (303.76 K) was subtracted from the temperature map of Salford to produce an image of the temperature differences across Salford compared to the urban mean. This was reclassified so that negative values i.e. temperatures higher than the urban mean were reclassified to 0. The final outcome is a raster surface where higher values indicate higher mitigating factors of surface temperatures.

6.2.2.4. Recreation

The recreation layer was produced using the Salford City Council's (SCC) greenspace audit and the land cover map produced in Chapter 5. The audited greenspaces were given a recreational value from 0 – 5 as demonstrated in Table 6.2. The values were determined through assessment of Salford Council's 'Greenspaces user' needs survey, conducted in 2005 (SCC, 2005). The survey suggested that the most popular recreational activities in Salford are playing with friends and family outings, walking, and cycling, with over 70% of recipients walking from their homes to their respective recreational activities (n = 403). Based on this information, it is clear that different landscape features are important for different activities. It also suggests that some landscape features provide a wider range of opportunities. Consequently, the highest recreation values were attributed to the SCC Greenspace Audit neighbourhood parks and sports pitches across Salford. These spaces have been designed and formally recognised to be open and accessible to multiple use. Activities related to sport such as playing, walking and cycling are all important for social and physical fitness and are classed as recreational activities. Apart from these priority spaces, open space is generally desirable for a range of physical activities, but so too are well-maintained paths and tracks through forests and more enclosed natural spaces. A lower value was given to mixed land cover to recognise that it may contain green space, but it is likely to be smaller and therefore potentially less available for recreational activity.

Table 6.2. Weighting table for Aesthetic and Recreation Ecosystem Service Generation (scale of 1-5)

Land Cover	Recreation	Aesthetics
Greenspace Audit	5 (Neighbourhood parks and sports pitches)	5 (Local greenspaces, informal greenspaces, nature reserves, strategic natural greenspaces, woodland)
Trees	3	5
Vegetation	3	3 (Water 3)
Mixed	2	2
Other	1	1

6.2.2.5. Aesthetics

The aesthetics layer was produced using the SCC greenspace audit, the land cover map and data from geograph.org (Sections 4.2.6, 5.5 and 4.2.7). The aesthetic qualities of a landscape include an element of naturalness, quiet and tranquillity, and a wide range of biodiversity and habitat potential for a number of different species. For example, experiences of nature and relaxation are important aesthetic services for maintaining spiritual and mental health and reducing stress levels. The dataset was created by combining local, informal and strategic natural greenspaces with nature reserves and woodland categories of greenspace from the SCC audit. It has been assumed that as these spaces are less formally managed, there is less human activity and an increase in the tranquillity aspect of the areas. The aesthetic values from Table 6.2 were then attributed to the land cover map.

To capture a richer picture of the aesthetic value of specific landscape features as described in section 3.3.2, landscape photographs were collected from the open-source volunteer-contributed photo site, Geograph.org (Geograph Project Ltd, 2012). As an indicator of aesthetic quality, photographs tagged with phrases relating to green or blue spaces were selected. The following list of tags reflects the components of the landscape that are capable of producing ecosystem services:

Canals, Docks/Harbours, Heath/Scrub grassland, Golf, Lakes/Wetland/Bogs, Nature reserve, Park and public gardens, Rivers/Streams/Drainage, Woodlands/Forest. A final tag *Other,* was also included. These photos included a large range of landscapes, including man-made and natural, desirable and undesirable. As such, approximately half of these images were included. In total, 2132 photos of aesthetic importance were selected out of 5093, with an average of 11 photographers per centisquare (100 m x 100 m). The total number of photos was divided by the aesthetically positive photos to provide a proportion of 'green photos' per centisquare. These were then multiplied by the number of individuals taking those photos to produce a weighting across centisquares (100 m x 100 m) in Salford. This approach follows that of Jiang *et al.* (2013); Wood *et al.* (2013) and Lee *et al.* (2014) as discussed in Section 3.3.2, but by adding the weighting of volunteer photos to the land-cover aesthetic values from Table 6.2, this research integrates the aesthetic value of the wider landscape as well as specific 'hotspots'.

6.2.3. Validation

The individual ecosystem service layers were all validated against independent data sources. However, only the carbon sequestration and climate maps can be properly quantitatively validated as the other three services produce maps with no units. Details of the methodologies used to validate each of the datasets are discussed in Section 4.4. The water flow mitigation and climate stress mitigation layers were validated at a Lower Super Output Area against the surface runoff and temperature tools of the STAR model (STAR tools, 2011). The carbon storage layer was validated against iTree software available the USDA Forest Service (itreetools, 2013) through comparison of tree heights and diameter at breast height, and the cultural services were validated against a ground survey adapted from Radford and James (2013) discussed in Section 4.4.2.

6.2.4. Analysing patterns in ecosystem service generation

Patterns in individual ecosystem service generation were analysed using hotspot analysis to measure the level of local clustering. The hotspot analysis applied regular 75 m square cells, in line with the radius of the optimum moving windows derived in section 5.8. This distance of influence reflects the maximum potential change in composition of an area (Hein *et al.,* 2008). The alternative hotspot analysis was based on the method proposed by Wu *et al.* (2013) described in Section 3.5.3. The top ten percent of cell values were reclassified as hotspots. Each ecosystem service layer was reclassified to present hotspot and non-hotspot cells. Although the output results for the alternative approach are still mapped, they are based on non-spatial, spreadsheet values and do not consider spatial references in any way. For this reason, this approach is described using the term ‘aspatial’ throughout the study. This follows the terminology and approaches applied by Wong (2004) who considered spatial and aspatial approaches for deriving segregation indices for demographic data.

The spatial methodology for hot spot generation employs the Getis-Ord Gi* statistic, described in Section 3.5.3, which can be implemented in the Spatial statistics toolkit in ESRI’s ArcGIS 9.3. The final Gi* statistic is a z-score, based on spatially weighted distance from all other squares. High z-scores indicate that high value points are clustered and low scores indicate low value points are clustered. The process in ArcGIS 9.3 requires defined regions. Due to the environmental nature of ecosystem service generation, a grid of uniform square cells was created. A cell size of 75 m x 75 m was chosen to match the moving window radius selected in Section 5.8. 75 m squares are also an appropriate size to capture smaller urban parks. The 75 m grids calculated the mean scores for each ecosystem service layer. Zonal statistics were then used to input the mean score within each of the polygons. Following an approach adopted by Bai *et al.,* (2011), a measure of significance was measured by mapping hotspots at $z \geq 1.65$ ($p < 0.1$). This research also maps hotspots at $z \geq 1.96$ ($p < 0.05$), and $z \geq 2.58$ ($p < 0.01$) to provide information on patterns of significance in different hotspot clusters. This definition follows the traditional hotspot definition more closely as it identifies areas that are unusual in their values. In this research, hotspots were saved at 1, 2 and 3 standard deviations: $z \geq 1.65$ ($P < 0.1$), $z \geq 1.96$ ($P < 0.05$), and $z \geq 2.58$ ($P < 0.01$). This reflects hotspots produced at different confidence intervals. The spatial patterns were analysed between each confidence interval and finally between spatial and aspatial methods.

6.3. Results

Table 6.3 displays a Kolmogorov-Smirnov test for normality for each of the individual ecosystem service layers. The p value is less than 0.05 for each layer, so it can be assumed that the data are not normally distributed. As a result, the service layers were all normalised using the range method (equation 6.3).

Equation 6.3. $$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Table 6.3. Kolmogorov-Smirnov test for normality

Ecosystem Service	Kolmogorov-Smirnov		
	Statistic	Df	Sig.
Aesthetics	0.06	17823	0.00
Climate	0.13	17823	0.00
Carbon	0.31	17823	0.00
Water flow	0.06	17823	0.00
Recreation	0.14	17823	0.00

6.3.1. Ecosystem service layers

Figures 6.5 to 6.8 present the normalised results for the ecosystem services. The carbon storage map is shown in Figure 6.5. The white shaded cells represent the highest values, approaching 1 and highlight wooded areas, giving little weight to any other land cover types. The largest areas of service generation appear in the large woodlands to the central West of Salford and the North East, near Kelsal Moor and the border of Prestwich. Water regulation generation is spread widely across Salford, although there is a trend towards higher generation of service in the South near Irlam and Botany Bay Woods (Figure 6.6). Climate regulation is generated most highly in the West of Salford (Figure 6.7). Forested areas are ranked highly, although influences are more gradual than either carbon storage or water regulation due to the consideration of distance from urban thermal heat sources. The highest values of recreation are located in urban municipal parks including Buile Hill Park, Lightoaks Park and Oakwood Park in the East, Princes Park in the South and Blackleach country park in the North of Salford (Figure 6.8). The highest valued cells in the Aesthetics layer (Figure 6.9) highlight wooded areas such as Botany Bay in the West and Blackleach Country Park and Kersal Moor in the North of Salford. Conversely, the lowest values in Figures 6.8 and 6.9 are represented by built up areas in the East and peat land covers such as Chat Moss in the South. The aesthetic and recreational service layers show higher generation in specific areas of Salford due to the nature of the service composition. The carbon storage layer is weighted towards the woodland, giving little value to areas not covered by trees. The climate stress mitigation and water flow mitigation layer shows patterns of high value to the west of Salford, where large areas of agricultural land lie. High values are also found along river banks. Additionally, the water flow mitigation layer allows for more mitigation amongst the denser urban centres.

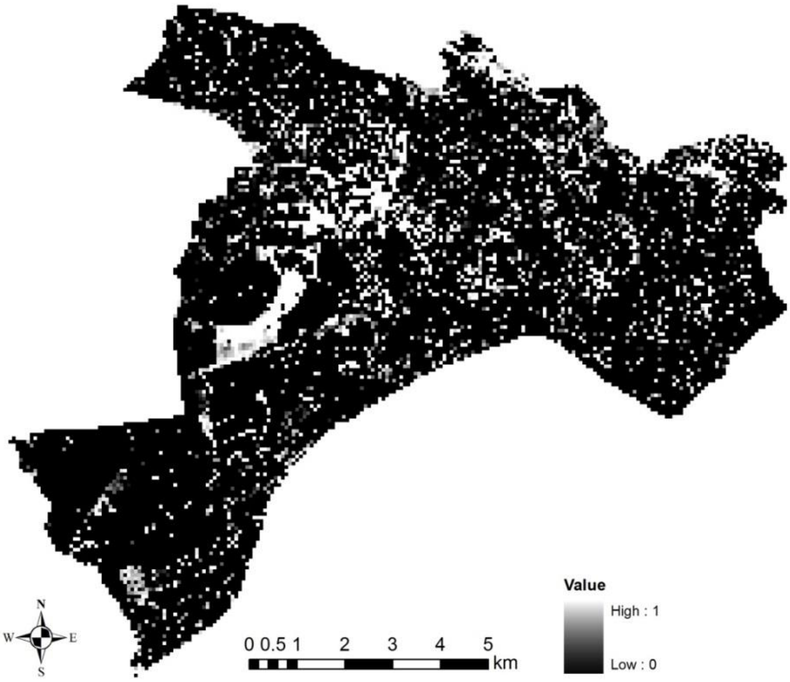

Figure 6.5. Carbon storage ecosystem service generation layer (Author's own).

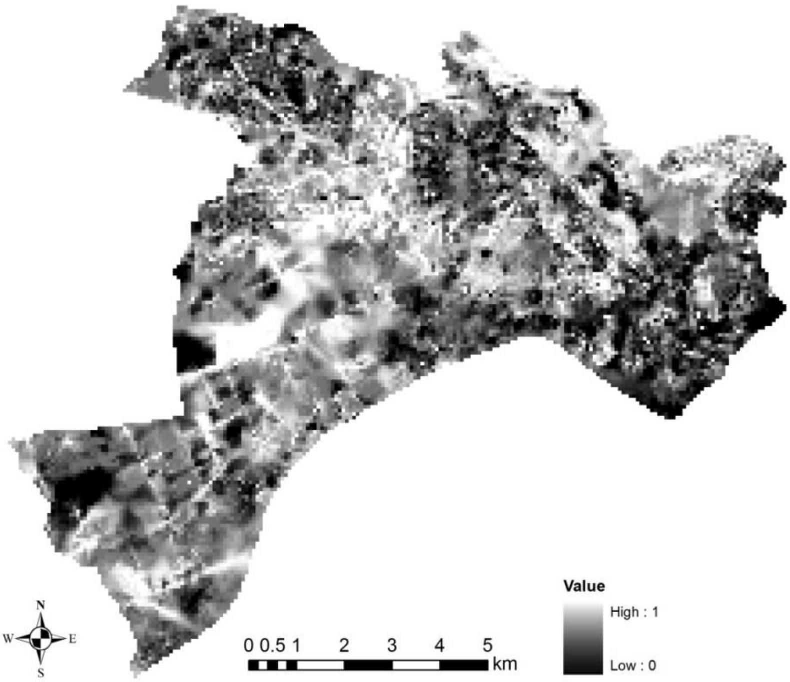

Figure 6.6. Water flow mitigation ecosystem service generation layer (Author's own).

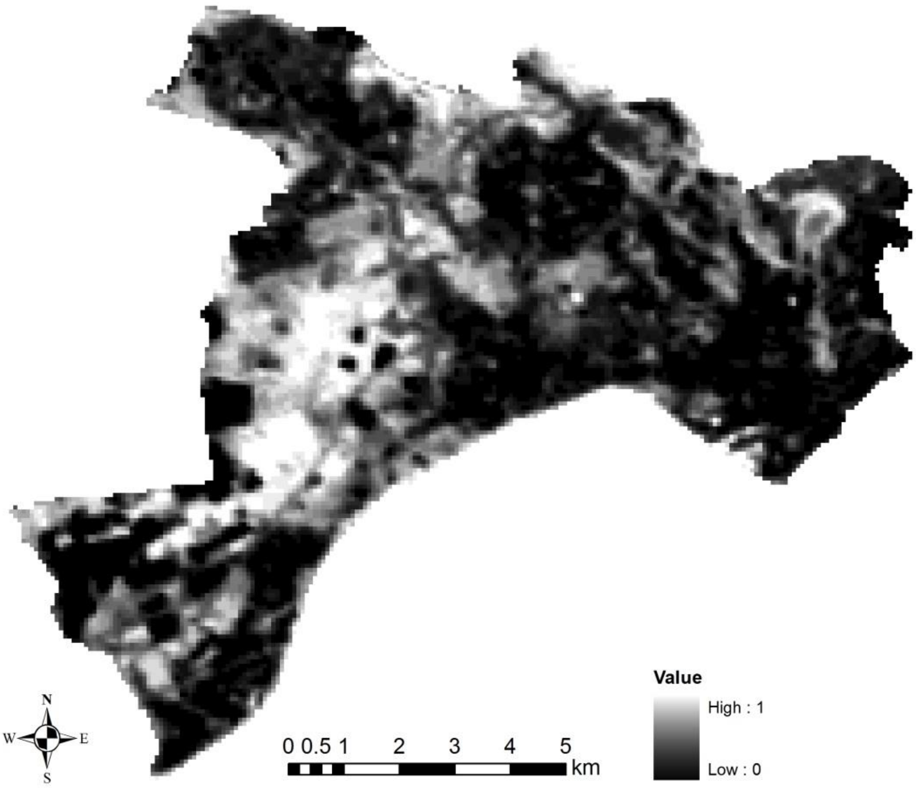

Figure 6.7. Climate stress mitigation ecosystem service generation layer (Author's own).

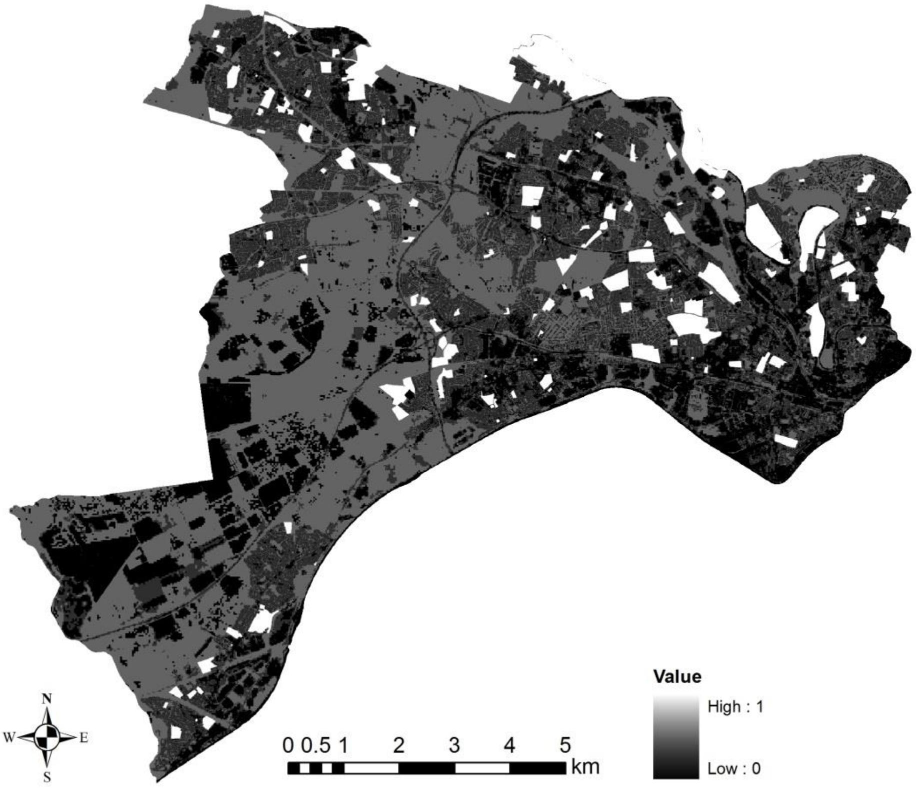

Figure 6.8. Recreation ecosystem service generation layer (Author's own).

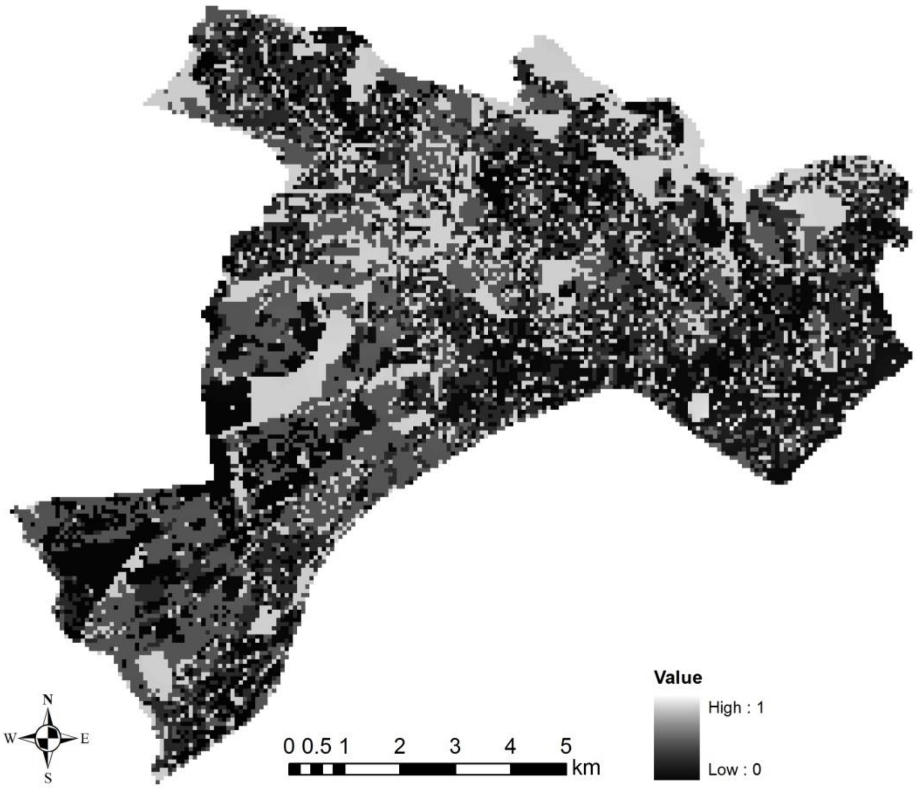

Figure 6.9. Aesthetics ecosystem service generation layer (Author's own).

Calculation of Moran's I statistic for spatial autocorrelation on each of the individual services shows that all ecosystem service layers are significantly spatially clustered ($p < 0.01$). The climate mitigation has the highest Moran's I statistic (0.93), while the lowest is carbon storage (Moran's I = 0.67), although this is still significantly clustered as presented in table 6.4.

Table 6.4. Moran's I statistic for spatial autocorrelation applied to each of the ecosystem service generation layers

Statistic	Aesthetics	Climate	Carbon	Water Flow	Recreation
Moran's I	0.76	0.93	0.67	0.81	0.77
expected	0.00	0.00	0.00	0.00	0.00
variance	0.00	0.00	0.00	0.00	0.00
z score	141.94	174.05	125.58	151.96	143.75
P value	0	0	0	0	0

6.3.2. Validation of ecosystem service layers

6.3.2.1. Carbon storage

There is a strong correlation between the 2009 LiDAR heights and the 2013 tree survey heights ($r = 0.90$, $p < 0.01$) (Figure 6.10). This suggests that tree heights across Salford are consistent over time and that the structure of urban trees has changed little. The correlation between Carbon storage derived from the Bluesky data and with that from the corresponding field data as calculated in iTree suggests that the relationship is relatively strong ($r = 0.77$, $p < 0.01$, Figure 6.10). The correlation is weaker than individual tree height data (Figure 6.11) because the ecosystem service tree height data takes the single value at the centre of each tree height polygon (Section 4.2.5), while the stored carbon data is captured from the mean value within the tree height polygons.

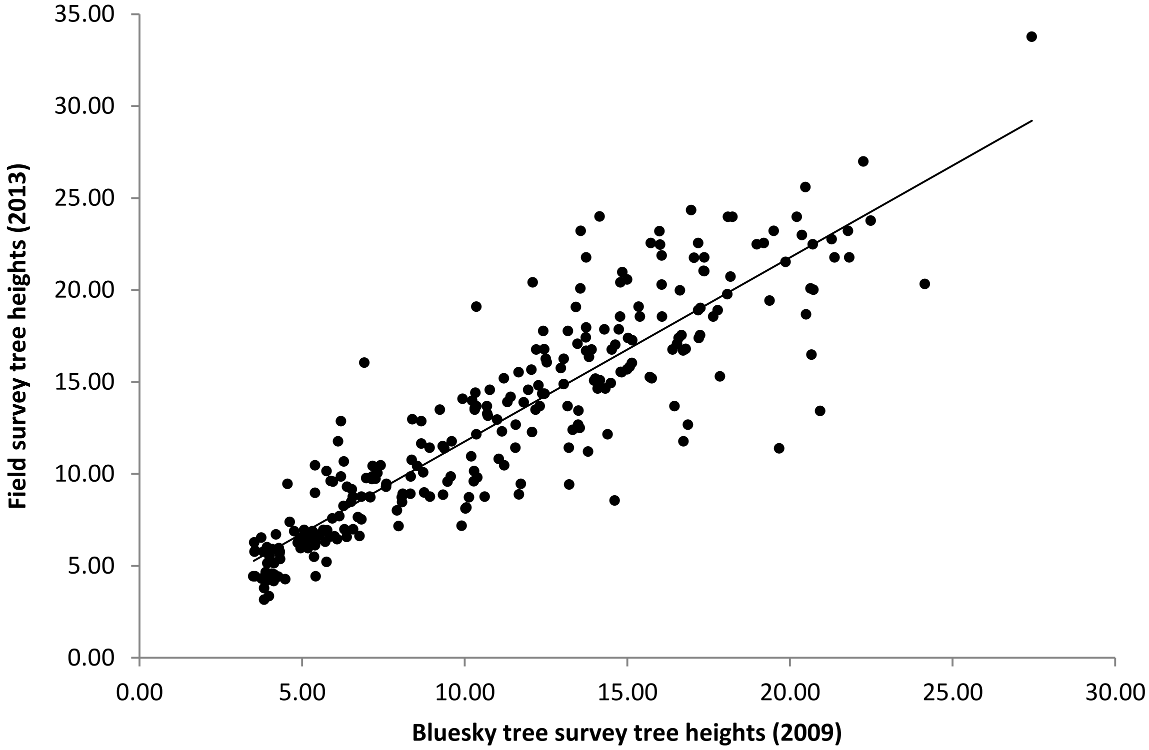

Figure 6.10. Correlation between tree heights from ecosystem service layer and field survey.

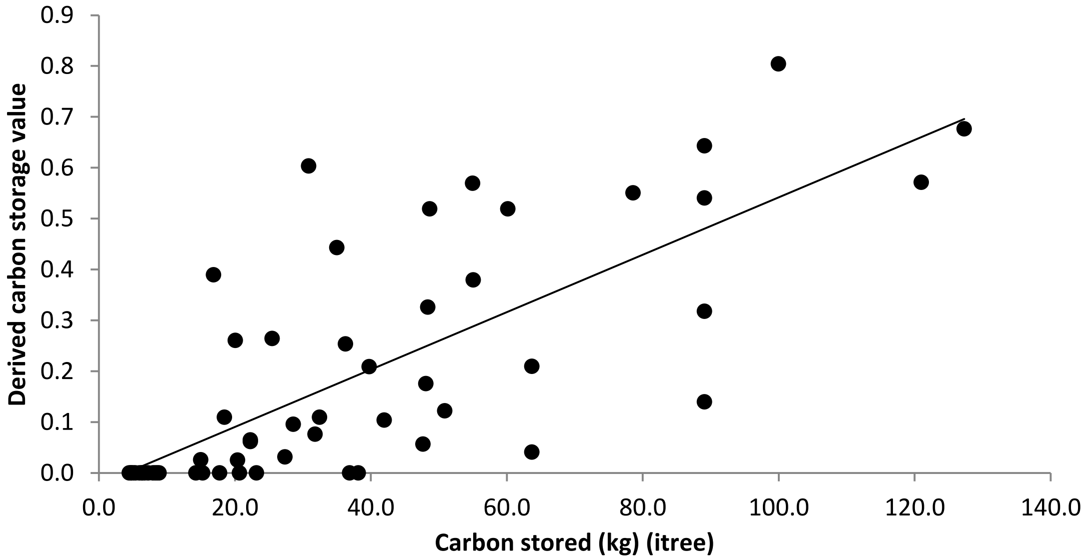

Figure 6.11. Correlation between derived carbon stored from ecosystem service layer and estimates from iTree.

6.3.2.2. Water flow mitigation

Figure 6.12 displays a scatter plot correlating the derived ecosystem service values from the STAR tools, using the runoff percentage values. Different coloured points represent the dominant land use character type for each sample Lower Super Output Area (LSOA). The colours match those in the original characterisation map (Figure 5.14). The overall point cloud shows a weak positive correlation (r = 0.40). The weak correlation can be explained at least in part by the fact that the STAR tool does not consider slope as a variable. Further, the STAR tool measures runoff percentage, which is related to but not the same as the amount of water that infiltrates into the ground. Analysis of dominant land use characters present weak correlations. This information is outlined in Table 6.5 which shows that only semi-detached LSOAs produced a significant relationship compared to STAR (shaded red in Figure 6.12).

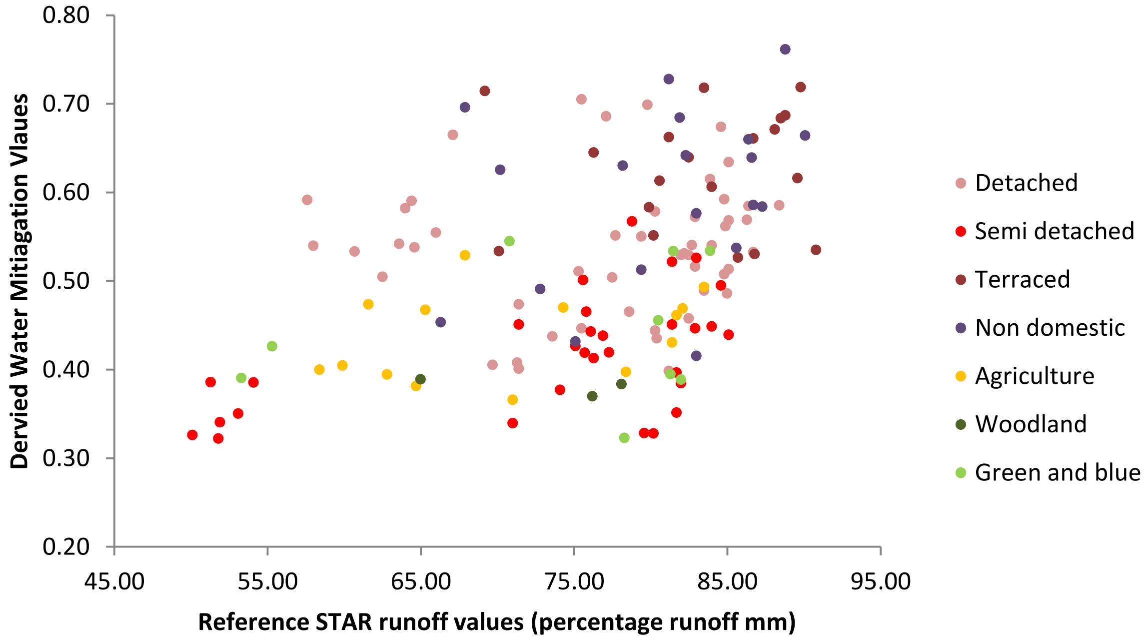

Figure 6.12. Correlation between water flow mitigation derived through the ecosystem service layer and STAR tools.

Table 6.5. Correlations for percentage water flow by land use type. Rows in bold are significant at p < 0.01.

Land Use	r	p
Detached	0.06	0.68
Semi detached	**0.53**	**0.01**
Terraced	0.06	0.82
Non domestic	0.33	0.17
Agriculture	0.31	0.28
Green and blue	0.19	0.62
Woodland	-0.62	0.57
Overall	**0.42**	**0.00**

A high correlation is shown for the volume of water per LSOA against summed water flow regulation service values ($r = 0.98$, $p < 0.01$). Although LSOA size has a large influence on these values. This relationship is presented in Figure 6.13 and Table 6.6. All land use relationships are significant at $p < 0.01$ apart from agriculture and Woodland, although this is due to particularly large agricultural LSOAs, encouraging heterogeneity and small Woodland sample sizes.

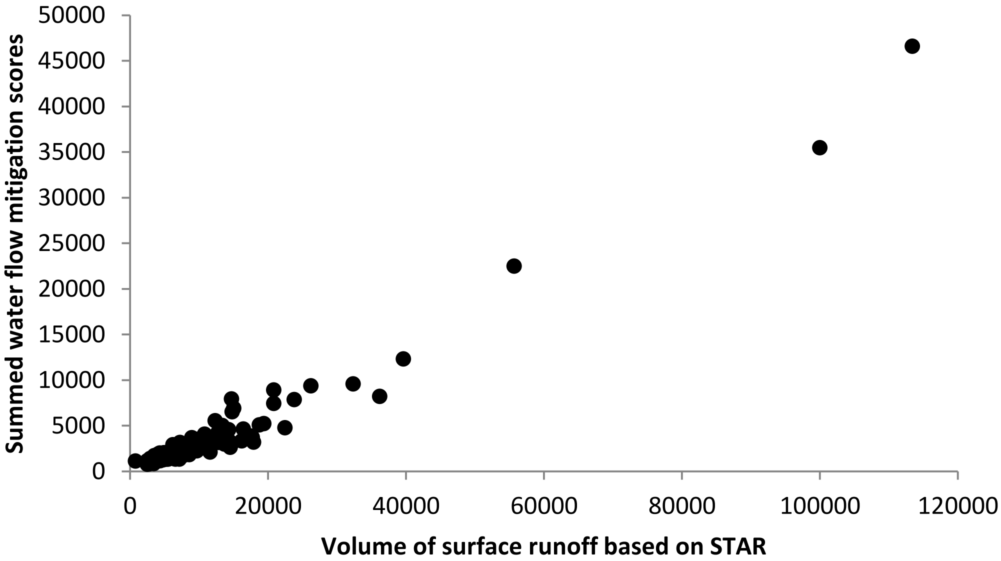

Figure 6.13. Correlation between water flow mitigation derived through the ecosystem service layer and STAR tools, considering total LSOA volumes of surface water runoff.

Table 6.6. Correlations for volume of water flow per LSOA by land use type. Rows in bold are significant at p < 0.01.

Land Use	r	p
Detached	**0.83**	**0.01**
Semi detached	**0.89**	**0.01**
Terraced	**0.98**	**0.01**
Non domestic	**0.90**	**0.01**
Agriculture	0.99	0.28
Green and blue	**0.54**	**0.01**
Woodland	0.99	0.61
Overall	**0.98**	**0.01**

6.3.2.3. Climate stress mitigation

Figure 6.14 displays a scatter plot correlating the derived ecosystem service values against STAR tools data. The overall point cloud shows a negative correlation (r = -0.51, p < 0.01). The distribution of data suggests a non-linear relationship, which means that the r value stated can be taken as a guide only (Table 6.7). However, there is a clear pattern within dominant character types, with agricultural and greener characters types typically having lower surface temperatures that approach 20 C, while denser urban forms typically have higher surface temperatures between 24 C and 30 C.

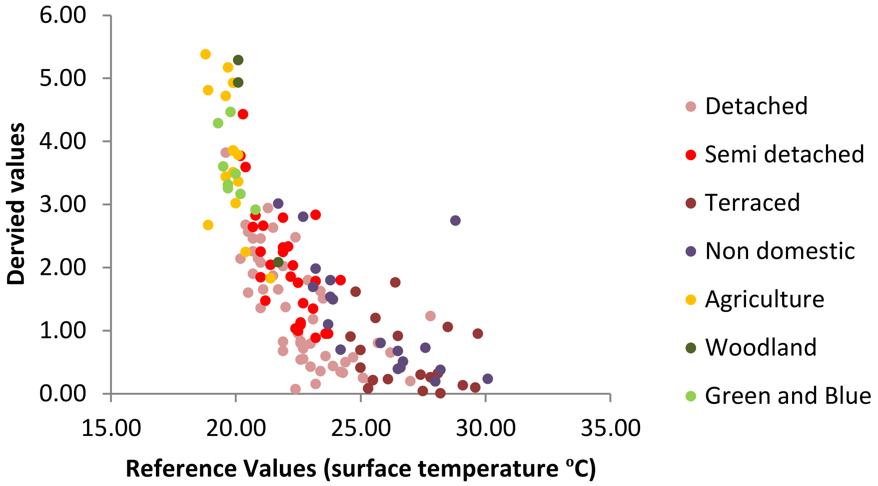

Figure 6.14. Correlation between climate stress mitigation derived through the ecosystem service layer and STAR tools.

Table 6.7. Correlations for average temperature per LSOA by land use type. Rows in bold are significant at p < 0.01.

Land Use	r	p	Number of LSOAs
Detached	**-0.35**	**0.01**	**50**
Semi detached	-0.07	0.73	30
Terraced	-0.31	0.20	19
Non domestic	**-0.61**	**0.01**	**19**
Agriculture	-0.62	0.18	14
Green and blue	-0.30	0.43	9
Woodland	-0.99	0.07	3
Overall	**-0.51**	**0.01**	**144**

6.3.2.4. Recreation

Table 6.8 presents correlations and medians based on the derived recreation and values in the derived service layer and the field survey described in section 4.4.2. In general, the results show that correlations are low for each land cover and for the overall coverage, but the pattern of medians is similar. Table 6.8 shows that non-domestic and semi-detached housing have higher positive correlations with recreational scores. High median values for both methods belong to the woodland and green or blue spaces although the derived values place detached housing and non-domestic characters above those. This is largely due to the fact that industrial estates in Salford commonly lie next to water bodies such as the Manchester ship canal, or in peripheral regions, which are typically greener, in both cases non-domestic areas perform better than residential. The lowest values in both cases belong to Agricultural land and residential areas, with terraced housing performing the worst of those.

Table 6.8. Correlation between recreation measurements derived through the ecosystem service layer and from the field survey by land character type

Land character type	derived median	field median	r	p	Number of records
semi-detached	0.23	0.03	0.48	0.01	29
detached	0.31	0.02	0.02	0.93	30
terraced	0.18	0.00	0.04	0.83	30
non-domestic	0.36	0.09	0.44	0.39	6
agricultural	0.14	0.02	-0.14	0.70	10
woodland	0.26	0.13	2.50	0.48	12
green and blue	0.26	0.13	-0.17	0.41	26
Total	**0.25**	**0.05**	**0.20**	**0.02**	**143**

6.3.2.5. Aesthetics

Analysis of Table 6.9, which shows correlated aesthetic values, displays low correlations apart from non-domestic and woodland character types. Analysis of median values shows that the trends are similar as both methods of data collection agree on the highest values, which belong to the green or blue and woodland land character types. On the other hand, the derived lowest medians belong to more urban land character types, while the lowest field median belongs to agricultural and terraced.

Table 6.9. Correlation between aesthetics measurements derived through the ecosystem service layer and from the field survey by land character type

Land character type	derived median	survey median	r	p	Number of records
non-domestic	0.29	0.79	0.85	0.03	6
agricultural	0.27	0.58	0.29	0.42	10
semi-detached	0.25	0.67	-0.05	0.78	29
green or blue	0.42	0.89	-0.11	0.60	26
detached	0.30	0.77	-0.14	0.45	30
terraced	0.29	0.58	-0.23	0.22	30
woodland	0.41	0.89	-0.40	0.20	12
Total	**0.28**	**0.74**	**-0.03**	**0.59**	**143**

6.3.3. Ecosystem service generation hotspots

Table 6.10 presents the areas of each hotspot. The total area of Salford, calculated from the land cover map in Section 5.5 is 96958130 m^2. The areas of the aspatial hotspots, should equate to 9695813 m^2, which represents 10% of the area of Salford. In fact there are large inconsistencies in areas. These inconsistencies occur because some of the indicator layers contain a large number of cells that have the same value. This means that the threshold cell value that defines the top 10% of Salford may include a larger number of cells than a simple cell count. Aesthetics and water produce the largest hotspots in the aspatial analysis. Carbon storage produces the smallest hotspot area, which corresponds to the tree cover of Salford, which is less than 10% of the whole area. All other values are 0 and not included in the top 10% of values across Salford.

At the $p < 0.1$ confidence level, aesthetics and climate mitigation have the largest hotspots. These also shrink at a faster rate as the confidence levels increase. On the other hand, carbon storage and recreation shrink at a much slower rate, such that at $p < 0.05$, both are larger than climate mitigation. There are no significant hotspots identified for water flow mitigation. The percentage of overlap between the aspatial hotspots and spatial hotspots of different significances is presented in Table 6.11. The values in the table represent the shared hotspot area as a percentage of the total hotspot coverage. High values represent spatial patterns that are very similar. Low values suggest that patterns are different. Figures 6.15 – 6.16 display the hotspot areas defined using aspatial methods, outlined in red, and spatial methods, where lighter shades indicate lower confidence levels.

Table 6.10. Hotspot areas across Salford (m^2)

Ecosystem Service	Aspatial	Spatial		
		P<0.1	P<0.05	P<0.01
Aesthetic	8077500	9911250	7841250	0
Climate	5827500	8004375	3982500	399375
Carbon	2002500	5540625	4612500	3183750
Water flow	9320625	0	0	0
Recreation	6502500	5883750	5332500	4207500

Table 6.11. Overlap of spatial and aspatial hotspots for each ecosystem service. Cell values are the hotspot areas shared expressed as a percentage of the total hotspot area.

Ecosystem Service	P<0.1	P<0.5	P<0.01
Aesthetic	24.50%	21.73%	0.00%
Climate	71.46%	65.77%	6.08%
Carbon	20.00%	27.62%	21.67%
Recreation	87.85%	82.80%	66.32%

Figure 6.15 presents the significant hotspots of carbon storage. The spatial hotspots appear to better reflect the overall patterns presented in Figure 6.5. Major wooded areas including Botany Bay wood, Kersal Moor and densely wooded neighbourhoods of Worsley and Broughton. This is less well reflected by the aspatial hotspots, but they do coincide with the most significant spatial hotspots (p < 0.01, shaded in black). Table 6.11 shows that carbon storage has the lowest overlap percentage at the p < 0.1 level, but that this value remains the most constant of the services suggesting that while there is a relatively low overlap, it is strongly significant.

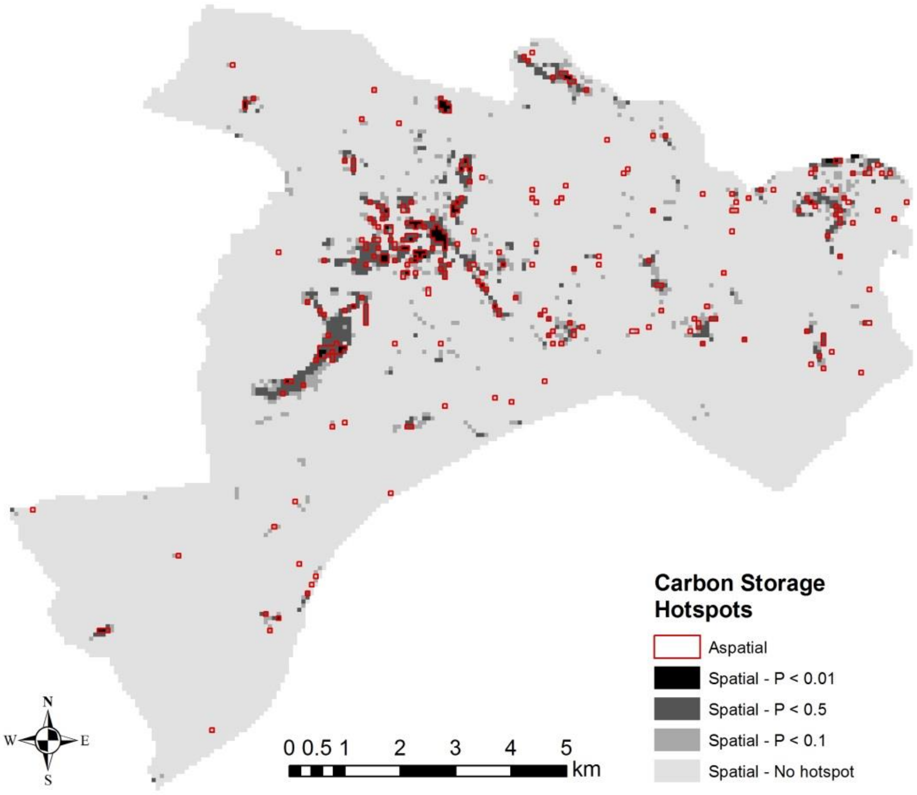

Figure 6.15. Carbon storage hotspots. Aspatial hotspots are outlined in red. Spatial hotspots are shaded in greyscale (Author's own).

Figure 6.16 presents the hotspot patterns for water flow mitigation. The absence of red outlines in the figure demonstrates that there are no significantly strong spatial hotspots. The aspatial hotspots are primarily in wooded areas, but do not map directly onto them. Figure 6.17 presents the climate stress mitigation layer. Table 6.11 shows high percentage overlaps at $p < 0.1$ and $p < 0.5$, but a very low percentage overlap at $p < 0.01$.

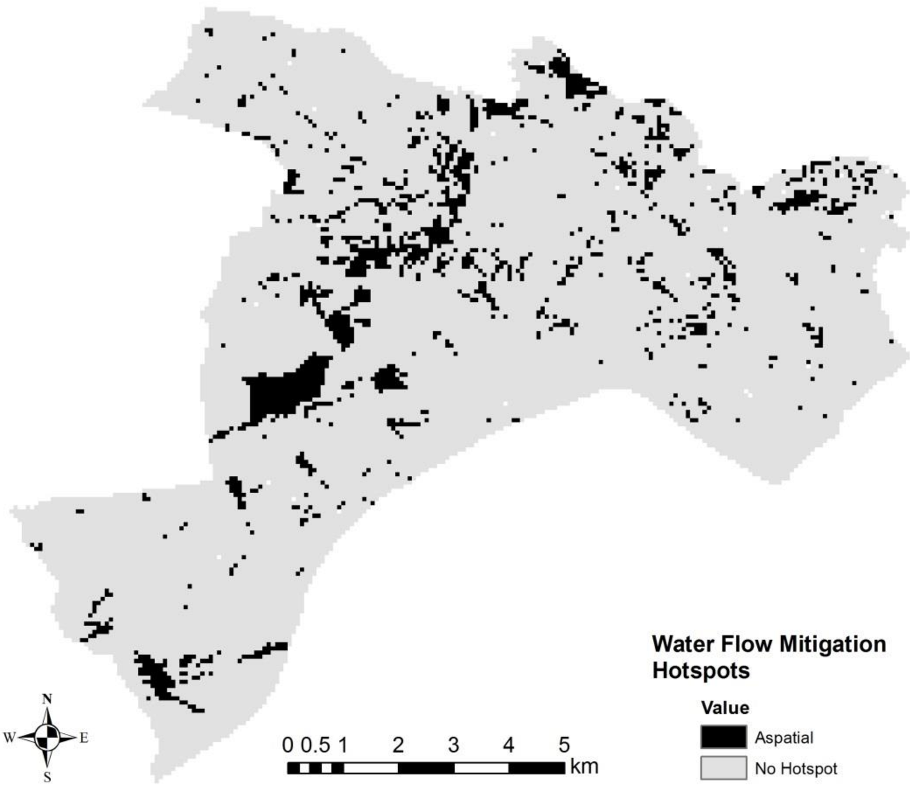

Figure 6.16. Water flow mitigation hotspots. Aspatial hotspots are shaded in black (Author's own).

Figure 6.18 presents the recreation layer. The figure shows large, clearly defined hotspots identifying neighbourhood and district parks across Salford as reflected in Figure 6.8. Table 6.10 shows that recreation has the highest percentage of overlap between aspatial and spatial hotspots, even at $p < 0.01$, the overlap is still over 66%. Figure 6.19 presents the aesthetics layer. The patterns of hotspots are the most diverse here. This is reflected in Table 6.11, which shows that although the aesthetic overlap is higher than carbon at $p < 0.1$. At $p < 0.5$, carbon has the smallest overlap and at $p < 0.01$ there is no overlap. Figure 6.19 reveals that the spatial hotspots map onto the larger wooded areas as described in Section 6.3.1 and shown in Figure 6.9. Conversely, the aspatial hotspots highlight a wider spread of smaller areas distributed across Salford.

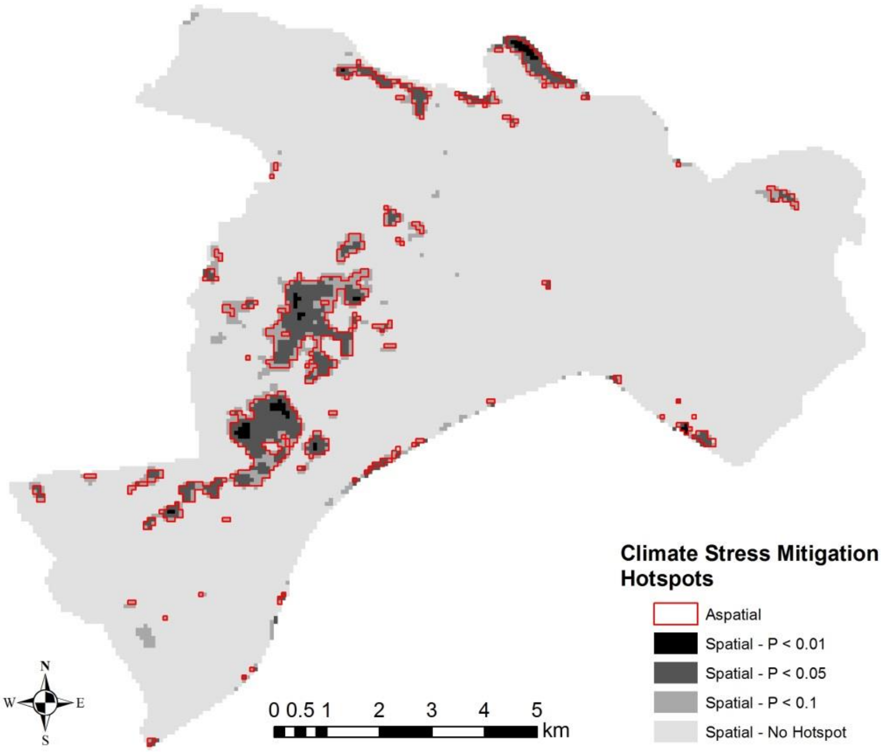

Figure 6.17. Climate stress mitigation hotspots. Aspatial hotspots are outlined in red. Spatial hotspots are shaded in greyscale (Author's own).

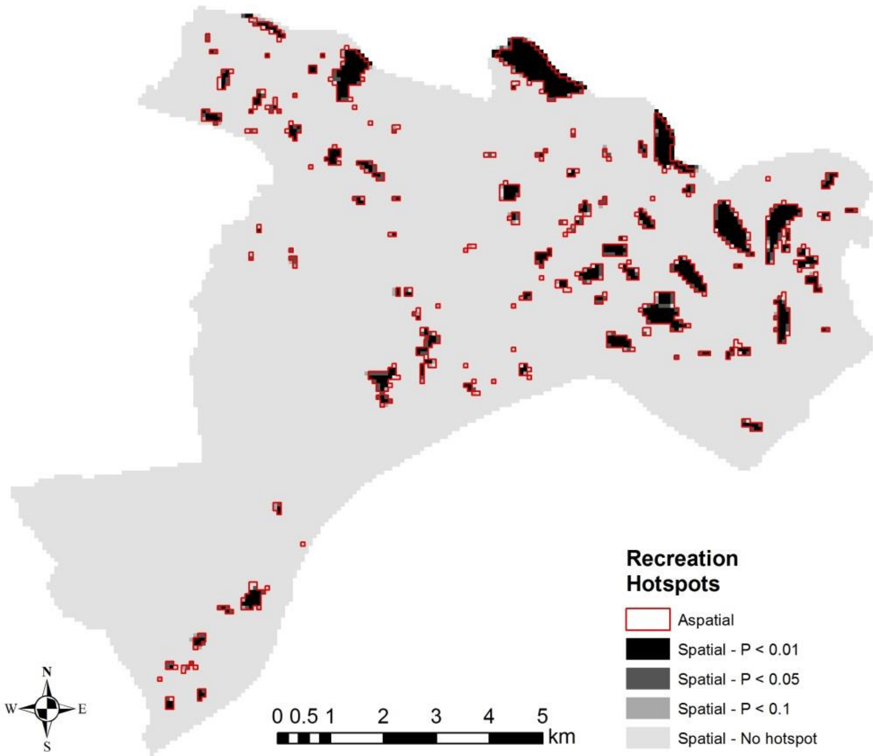

Figure 6.18. Recreation hotspots. Aspatial hotspots are outlined in red. Spatial hotspots are shaded in greyscale (Author's own).

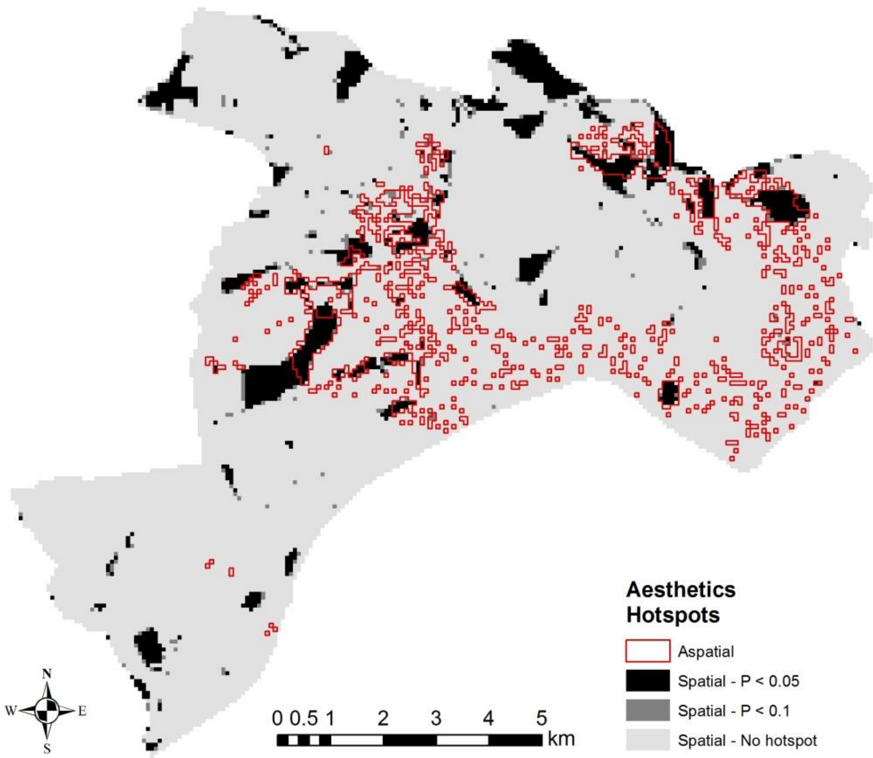

Figure 6.19. Aesthetics hotspots. Aspatial hotspots are outlined in red. Spatial hotspots are shaded in greyscale (Author's own).

Tables 6.12 and 6.13 present information on where the hotspots are by landscape character. As expected, the Woodland and Green or Blue landscape character types perform well for both approaches, although the patterns are not so distinct for the spatial hotspots. For example, agricultural land plays an important role in contributing to climate stress mitigation, potentially related to the distance it lies from the urban centre. The green or blue holds a low percentage of carbon hotspots because it is defined as greenspaces without trees in Chapter 5. Conversely, detached housing has a relatively large percentage. The lowest percentages of hotspots are in semi-detached, terraced and non-domestic characters, although aspatial hotspots show high hotspot coverage for recreation in semi-detached areas.

Table 6.12. Percentage of hotspot area by landscape character - aspatial

Ecosystem Service	Detached	Semi-detached	Terraced	Non-domestic	Agriculture	Woodland	Green or blue
Aesthetic	12.12	7.31	8.15	8.08	9.75	44.15	10.45
Climate	1.95	0.14	0.28	0.84	96.38	36.63	8.08
Carbon	6.69	0.00	0.00	1.11	2.23	20.06	1.39
Water flow	15.53	2.54	1.33	6.89	16.86	47.8	9.06
Recreation	0.86	2.33	0.52	0.52	0.00	30.6	65.17
Total	37.15	12.32	10.28	17.44	125.22	179.24	94.15

Table 6.13. Percentage of hotspot area by landscape character - spatial

Ecosystem Service	Detached	Semi-detached	Terraced	Non-domestic	Agriculture	Woodland	Green or blue
Aesthetic	4.9	3.4	0.5	4.0	9.0	54.0	24.1
Climate	0.4	4.0	0.6	1.5	68.2	22.6	6.4
Carbon	27.1	4.9	1.2	4.0	15.6	42.1	7.0
Recreation	10.6	11.7	4.6	2.0	2.3	28.5	40.4
Total	43.00	24.00	6.90	11.50	95.10	147.20	77.90

6.4. Discussion

The approach applied in this chapter answers the call to improve spatial analyses of ecosystem services by Haines-Young and Potschin (2009) and builds on previous research by authors including Bastian *et al.,* (2012), Burkhard *et al.,* (2012) and Koshcke *et al.,* (2012) by including a novel acknowledgement of spatial influences. Greenspaces are widely recognised as key sources of natural capital, producing required resources for human consumption (Vemuri and Costanza, 2009). The results in this research reinforce this belief, but the spatial methodologies also provide new insights and pose new questions concerning the composition and distribution of these spaces within urban areas (Blaschke, 2006). For example, how does the distribution of building height means affect characterisation in different types, or how does the level of tree canopy fragmentation affect the strength of different land use characterisations? How would changing the landscape alter land use characterisation? Answering these questions would allow development of thresholds to be created for different characterisations, which would then provide a basis for measurements of landscape sustainability, or landscape change scenarios. This research reinforces the work of Whitford *et al.,* (2001) and Petz and van Oudenhoven (2012) who identify that woodlands are of particular importance to services such as carbon storage, water flow mitigation, climate stress mitigation and aesthetic services. Further, large areas of vegetation are also highlighted as of importance to regulating services and as spaces for recreational activities.

Seppelt *et al*., (2010), Eigenbrod *et al.,* (2011) and Haase *et al*., (2014) have all voiced concern over the requirement to provide validation for the data produced. This chapter has addressed this concern through demonstrating methods of validation in Section 6.3.2. The challenge of validating the datasets has been highlighted by Petz and van Oudenhoven (2012) as each service is measured by different means and to different standards. Carbon storage and climate mitigation would benefit from further data collection to improve validation. Improvements to reference datasets would include the facility to report STAR results in geographical regions smaller than LSOAs, which represent relatively large areas, although measurement of surface temperatures and runoff at such a small scale is always going to be challenging (Gill, 2006). Carbon storage, which relates to the presence of trees, may be improved by the addition of low lying shrubbery. However, Chisholm *et al.,* (2006) suggested that this source of carbon storage is relatively small. Conversely, there is potential to include peat areas, which may be significant carbon sinks (Gorham, 1991).

The cultural service survey adapted from Radford and James (2013) could be tailored further to reflect the scale and more homogenous nature of the sample areas studied. In particular, the survey emphasises the functionality of residential areas, not rural or industrial areas. Further, multi-functionality and water features were given weight towards creating high levels of recreational services. This means that while urban parks, quite rightly, produce high values, more natural greenspace with fewer facilities produce lower values. This suggests that there is potential to refine the survey for different types of space to maximise characterisation.

The breakdown of aspatial hotspots closely follows the expected patterns outlined in Section 6.3.1, while the spatial patterns are more complex, potentially revealing more variety in the benefits provided by different green spaces. The outstanding result is that there are no positive spatially derived hotspots for water flow regulation. On closer inspection, this may be expected as the areas with the lowest values are typically of higher elevation and by nature of a small size. This is well demonstrated in Figure 6.3 by the small, lighter shaded areas that represent peaks in the DSM. This means there is less likelihood of clustering. Perhaps more important are the negative hotspots identified by the Getis-Ord Gi* statistic. These areas have the highest levels of runoff and the lowest levels of mitigation, highlighting potential areas of improvement. This is reflected in the other regulating services, although at a smaller scale. Consequently, there is clear potential for analysis of the full range of regulating ecosystem service generation levels.

Acknowledging hotspots in a spatial context has only recently been introduced into ecosystem service research (Zhu *et al.,* 2010; Brown and Raymond, 2014). The comparison between aspatial and spatial hotspots as visualised in Figures 6.15 – 6.19 demonstrates that the spatial approach identifies clusters of high value areas rather than the individual pixels identified by the aspatial approach. In doing so, the spatial approach recognises the influence of the surrounding areas as a complementary method to the simple identification of peak values across the landscape.

Unlike hotspot analysis in more traditional fields of crime mapping and spatial epidemiology, there is value in identifying isolated cells that have high values as these may represent street trees, gardens or allotments, which may be missed by Getis-Ord Gi* such as the aesthetic hotspots representing individual street trees highlighted in figure 6.19. The spatial method provides useful and novel information on the relative significance of clusters present, while the aspatial methods define and highlight outliers. Both are important and the 75 m cell resolution of this research is more than adequate to encapsulate a small urban park. Both approaches are therefore useful and can be used in a complementary fashion, but their application must be based on research objective. An additional benefit provided by the spatial approach is the generation of information on the significance levels of hotspots, which is discussed further in the following chapter in the context of analysing relationships between ecosystem services.

The landscape scale has been further explored to characterise ecosystem service generation by landscape character type, providing some information on the contributions that different land uses make towards the multi-functionality of the landscape (Lovell and Taylor, 2013). Deeper analysis into ecosystem service generation within landscape character types adds to current research that currently focuses on land cover-based analyses by incorporating more information that just surface cover (Chan *et al.,* 2006; Nelson *et al.,* 2009). The landscape character map created in Chapter 5 has proven to be a useful tool in evaluation of service generation at a more 'human scale'. Together, these contribute to Jones *et al.'s* (2012) call to characterise landscape characters and quantify related landscape patterns and ecosystem services. In particular, the work on comparing ecosystem service hotspots against landscape character types highlights patterns in provision when related to different patterns of land cover (Section 6.4). This analysis contributes to Blaschke's discussion on how differing levels of landscape fragmentation can affect levels of environmental processes. The discussion in Chapter 5 showed that semi-detached and terraced land uses were characterised by high levels of fragmentation, which Tables 6.11 and 6.12 show as having the lowest areas of service hotspots.

Incidental communication with local residents during the second field survey operation revealed that people living in areas characterised as 'detached' frequently complained about local problems they experienced from trees such as leaves blocking drains and sunlight, and making footpaths treacherous in wet conditions, roots blocking drains and pollen ruining car bodywork. This raises the issue of ecosystem disservices (Dobbs et *al.,* 2012) and highlights spatial inequalities in the delivery of benefits (or costs) to residents (Hein *et al.,* 2008, Escobedo *et al.,* 2012). Further evidence of this is provided by Tiwary and Kumar (2014), who modelled the impact of greenspaces in urban areas finding that vegetation, contributes to cooling urban temperatures, but also towards increasing humidity and subsequent increased recession of building materials through evapo-transpiration. They also highlight the importance of seasonality within research, which has not been considered here. This example serves as a useful reminder that urban vegetation does not just play a positive role. Research into disservices is an emerging topic, with some recognition of features such as rising hay fever and reduction of the perception safety in urban forestry (Dobbs *et al.,* 2011; Escobedo *et al.,* 2011), and habitats for pests and invasive species more generally (Lyytimaki and Sipila, 2009). Wolch *et al*., (2014) even go as far as to suggest that urban green spaces need to be planned such that residents of lower social and economic standing are not priced out of improved areas as house prices rise and areas become too attractive.

Exclusivity of service generation has not been considered in this research (Fisher *et al.,* 2009). While this bears more relevance to the measurements of cultural services that are more explicitly experienced, a question may still arise as to whether the regulation of water flow or air quality is still an ecosystem service if it occurs in a location that the general public cannot access. In the case study area of Salford, large tracts of land are used for agricultural purposes, and are (apart from public rights-of-way) private property, there are a number of golf courses, which are exclusive to members and industrial land that uses woodland to protect neighbouring housing estates. In terms of the green spaces that are accessible, this research assumes that all potential functions of the green space are present. However, this may not be the case. For example, Van Leeuwen *et al.* (2010) propose that due to the complexity of growing cities, the categorisation of urban greenspaces needs to be rethought to consider the different uses (and potential ecosystem services) that could reasonably be made. Application of the council's greenspace audit has provided a useful first step into categorising the different uses that can be made for different types of greenspaces, but a development of the categorisation including smaller unaudited spaces and potential uses would provide a more useful picture of the potential landscape multi-functionality present.

6.5. Conclusions

A spatially focussed methodology for determining the generation of five ecosystem services across an urban area has been demonstrated in this chapter. Five key ecosystem services have been measured and mapped across Salford and methods of validation have been demonstrated for each. For regulating services, high levels of service generation are found to the west and north of Salford, typically in large wooded areas, while lower values are present to the south and east, near to Manchester city centre. For cultural services, large parks are highlighted for recreational service generation, while urban forests and less formal greenspaces are more important for aesthetic service generation. The validation methods mean that a measure of certainty can be attached to each ecosystem service generation layer, but the validation approaches can be improved through collection of more data or identification of alternative sources of reference data.

Comparison of spatial and aspatial hotspot analysis demonstrates that both approaches can be used in parallel. The spatial Getis Ord Gi* statistic offers useful statistical information on larger, more significant ecosystem hotspots, while the aspatial approach provides information on isolated pixels of high value, which may still be important for cultural service requirements or connectivity studies. The lack of spatial hotspots in evidence for the water flow mitigation service suggests that analysis of negative hotspots may be a useful future direction for evaluating areas of low ecosystem service generation. In terms of water flow mitigation, this approach may contribute to flood risk analysis as coldspots indicate areas where flood risk is at its highest.

7. Spatial patterns of Ecosystem Service Generation

7.1. Introduction

This chapter continues the research conducted in Chapter 6 by evaluating how the landscape mosaic provides a basis for the generation and interaction of multiple ecosystem services. Ecosystem service clusters are created to investigate which elements of the landscape are generating multiple ecosystem services and to what extent. The individual ecosystem service generation layers created in Chapter 6 were used as a basis to examine relationships between multiple overlaying ecosystem services, evaluating the concept that ecosystem service clusters can provide landscape scale analysis of tradeoffs and synergies as well as aligning with current social-ecological systems (Raudsepp-Hearne *et al.,* 2010). Bennett *et al*., (2009) state that bundle analysis of ecosystem services, aggregates areas with similar patterns of ecosystem service generation to create ecosystem service clusters. This has been demonstrated at a national scale by Raudsepp-Hearne *et al.* (2010). For the purposes of clarity, this will be called cluster analysis in this research. The research in this chapter evaluates how adopting a spatial approach to analysing ecosystem service generation patterns can complement and improve on currently used methods. The methodology is discussed in Section 7.2, which is followed by presentation of results in Section 7.3 and discussion in Section 7.4.

7.2. Methodology

7.2.1. Introduction

Figure 7.1 contains the methodology for this chapter and is further discussed in Sections 7.2.2 – 7.2.4. The chapter applies overlap analysis (Chen *et al.,* 2006) to compare spatial association of paired service distribution and relate individual ecosystem service patterns to landscape character types (created in Section 5.8). This is discussed in Section 7.2.2 and represented in the top section of the lowest grey boxes in Figure 7.1. The fact that there are two grey boxes highlights that aspatial (traditional) and spatial methods are evaluated in this research. Characterisation of multiple ecosystem service generation is explored in Sections 7.2.3 and 7.2.4 by creating ecosystem service clusters by grouping areas that contain similar patterns of generation. This is represented in the bottom section of the lowest grey boxes in Figure 7.1.

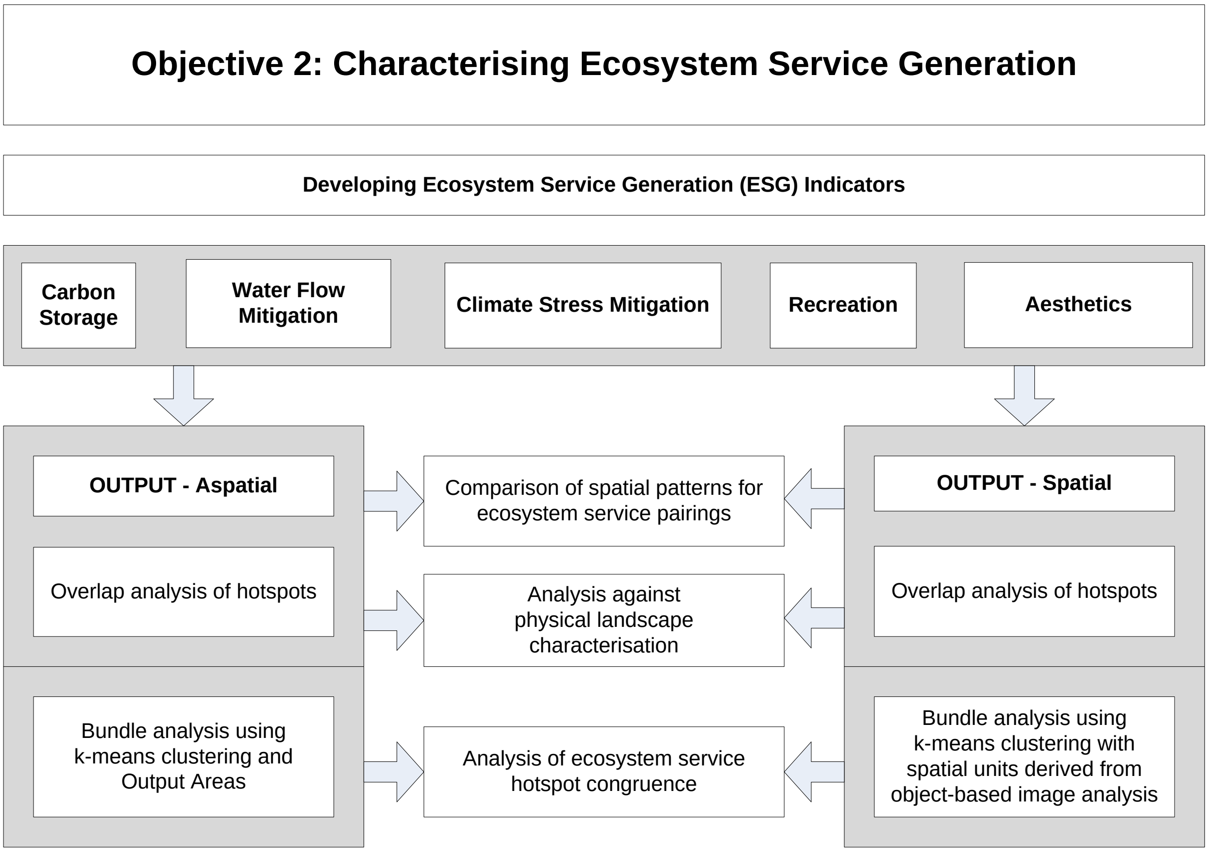

Figure 7.1. Methodology for Chapter 7.The grey boxes indicate themes of analysis. The top grey box encapsulates the ecosystem service generation layers created in Chapter 6. The bottom two grey boxes encapsulate the Aspatial and Spatial methodologies.

7.2.2. Overlap analysis

Measurement of relationships between pairs of ecosystem services for different landscape character types was conducted before analysing trends among multiple ecosystem services. This provides useful preliminary information on ecosystem service interactions (Wu *et al.,* 2013). The hotspot layers created in Section 6.3.3 were individually reclassified to identify hotspot and non-hotspot cells. The hotspots were coded using a 2^n sequence (Table 7.1), for each ecosystem service layer. When layers are summed together, this coding ensures that for any given total, the combination of specific ecosystem service layers can be derived. The reclassified layers were summed to produce a single overlaid map. The values of the cells in this final output indicate the number and type of ecosystem service hotspots present in each cell.

Table 7.1. Ecosystem service hotspot cell recode values

Ecosystem service	Hotspot cell value
Aesthetics	1
Climate stress mitigation	2
Carbon storage	4
Water flow mitigation	8
Recreation	16

Spatial association between pairs of ecosystem service was measured using the reclassified ecosystem service generation layers and two measurements applied by Chan *et al.,* (2006) and Bai *et al.,* (2011). The first measurement calculates the ratio of observed to expected numbers of overlapping hotspot cells. The expected overlap was calculated by dividing the product of the paired hotspot areas by the total research area. This calculates the average area occupied by both hotspot coverages (Chan *et al.,* 2006).This provides information on how well the paired hotspot areas are associated and whether the ecosystem service generation is overlapping more or less than expected. The second measurement counts the number of cells that record a hotspot for both ecosystem service layers. This is expressed as a percentage of the smallest hotspot area. This measurement provides information on the extent to which the smaller coverage is occurring within the larger one, providing evidence for the extent to which ecosystem service generation is occurring in the same place (i.e. potentially drawing from the same natural resources (Egoh, *et al.,* 2008)). High percentages of overlap indicate that ecosystem services are generated from similar areas, identifying potential tradeoffs or synergies. Low overlap percentages suggest that ecosystem services are produced by different processes and may not share or compete for the same natural resources.

7.2.3. Cluster analysis - Aspatial

Aspatial ecosystem service cluster analysis was completed using k-means cluster analysis in SPSS using the mean standardised ecosystem service values per Output Area. The clustering went through 10 iterations with the membership and distance from cluster mean saved as outputs. The analysis was repeated for 3 to 10 clusters as suggested by Vickers and Rees (2007).

There appears to be little consensus for methods used to select appropriate cluster numbers from k-means clustering (Tibshirani *et al.,* 2001). Further, cluster analysis results rely on a researcher's interpretation to derive meaningful results, so validation is often ignored. However, several methods have gained in popularity and provide some measure of integrity to analysis (Jain, 2010). The distance of each cluster member from the cluster centre is the most common method used to determine cluster strength. Short distances suggests strong/tight clusters, while large distances suggest weak, and less well defined clusters (Pham *et al.,* 2005). However, this only considers the distance of a member from one cluster centre and the result ignores clusters that are close to each other. Another commonly used measurement is consideration of the variation in cluster membership size. Often there is a desired minimum cluster size, below which, the cluster is merged with the next closest. In this instance, clusters that do not occupy a reasonable area should be reconsidered.

Evolving from these methods is a range of more complex statistical approaches that have been applied less often in the literature. One of the oldest of these more complex methods is that of determining silhouettes around each cluster (Rousseeuw, 1987). Silhouettes are a ratio of the distance of a member from its cluster mean with that of the next closest cluster mean. They are called silhouettes due to the representation of the distribution as identified in Figure 7.2.

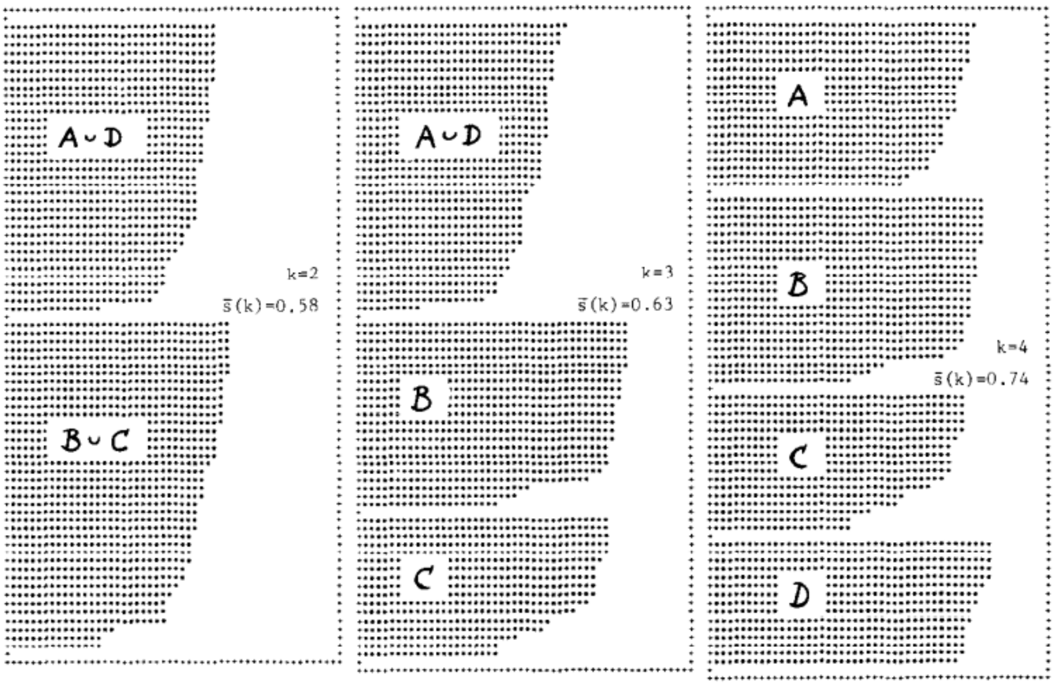

Figure 7.2. An example of silhouettes for 2 – 4 cluster solutions. Rows of dots represent the 'silhouettes' of individual members of a cluster compared to the centre of the cluster (from Rousseeuw, 1987).

Producing a score between 0 – 1, smaller silhouettes imply stronger cluster definition because the member is much closer to its parent cluster than any other. Where the distances are similar, the value rises to nearer 1, indicating a weaker cluster definition. Average silhouette widths can be determined for each cluster and for the overall dataset. In a review of eight validation algorithms, Chiang and Mirkin (2006) found that no single approach provides an optimum answer in all situations, but three methods appear to outperform others: Silhouette width, Least Squares and Least Moduli. This research selects suitable cluster numbers based on the deviation in cluster size from the mean cluster size, average distances from cluster centres and silhouette widths.

After selecting an optimal number of clusters, cluster membership for each area and the strength of that membership were recorded. The distribution of individual ecosystem service values within each cluster were created by calculating zonal means, standard deviations and inter-quartile ranges for each individual ecosystem service. The proportion of landscape character type made up of the ecosystem service clusters (Section 5.10) was calculated to determine the ecosystem service composition of specific landscape character types, and to derive a measure of similarity between landscape characterisation and ecosystem service characterisation. Finally, the similarity in composition of ecosystem services was evaluated for ecosystem service clusters and landscape character types. This provides a measure of validation for conclusions posed by Raudsepp-Hearne *et al.,* (2010) that suggest that ecosystem service clusters (ecological patterns) can act as proxies for land use categories (social/physical). This is described in more detail in Section 7.3.4.

7.2.4. Cluster analysis - Spatial

The spatial cluster analysis approach seeks to demonstrate improvements that may be made in analysis through acknowledgement of spatial influences and measures of association. For this reason, the spatial clustering approach used object-based analysis to develop spatial units that may be more suitable to recording environmentally-based ecosystem service generation data. In growing regions around similar land cover patterns, spatial units are created that are more physically homogenous than administrative Output Areas.

There is an additional processing step compared to the aspatial approach. This first step in object-based analysis is image segmentation into regions that contain similar values, which in this case are patterns of ecosystem service provision. In preparation, the maps of ecosystem service generation (Section 6.3.1) were stacked in ERDAS Imagine to produce a single multi-layered image. The stacked image was converted into an 8-bit image, where numbers were converted from decimal values in a range of 0 - 1 into an integer range of 0 – 255, to run the Image Segmentation tool in ERDAS Imagine. The tool applied a region growing algorithm based on randomly selected ‘seed’ pixels, which were used to initialise the approach. From these seed pixels, regions were grown until a specific threshold of variability is exceeded. The algorithm used by ERDAS performs two steps. 1) Edge detection is applied to segment the raster image into different regions (Baboo and Thirunavukkarasu, 2014), and 2) Minimum value difference is applied to determine whether adjacent regions are merged or not.

The first step is edge detection, which is conducted by considering the values of a pixel compared to its immediate neighbours, for each layer of the image. The difference in values is compared against a pre-defined threshold value. If the difference in values exceeds the threshold, the pixel is considered as an edge pixel. If the difference is under the threshold, the two pixels are aggregated into the same region. As well as considering adjacent pixels, a minimal length variable is also included, which determines the smallest size a region can be. This variable provides a spatial threshold which determines the minimum length of edge pixels in a region. Without this variable, image segmentation would produce too many single pixel regions, which would defeat the object of segmentation. Experimentation was done to amend the thresholds. For example, increasing the edge detection threshold had little effect on the number of segments created (Table 7.2) and where regions were merged, visual analysis against aerial photography shows that segmentation crossed natural boundaries. The values in the table suggest that 385 is the minimum number of segments that can be produced based on changing the edge detection threshold. Changing minimal length thresholds presented similar patterns. For this research, default settings were applied. The edge detection threshold for growing the regions was set at 18 and the minimum length threshold was set at 3. This produces a similar number of segments as OAs in the aspatial approach. Further, in assigning an ecosystem service cluster to each segment, aggregation may be possible at a later stage in the analysis.

Table 7.2. The effects of changing the edge detection threshold on the number of segments produced (other variables set to default).

Edge Detection Threshold	Number of Segments Produced
18 (default)	537
50	404
100	385
250	385
500	385

The second step involves comparison of the values in adjacent regions to determine whether adjacent regions should merge or not adopting a threshold-based approach and using default settings (Minimal Value Difference =15).

The default setting produced 537 different regions. The second stage of processing and the methods for determining cluster numbers follows the aspatial methodology through its application of k-means clustering.

7.3. Results

7.3.1. Ecosystem service generation by landscape character type

The boxplots in Figure 7.3 display the range and distribution of values for each ecosystem service by landscape character. As the data is normalised to a scale of 0 – 1, maximum and minimum values are not included as they would all be the same. Figure 7.3 (A), (B) and (C) present the three residential character types and describe similar patterns in service generation, with generation scores for each ecosystem service increasing as housing gets larger from Terraced to Semi-detached and Detached. For example, values for aesthetic inter-quartile ranges increase from 0.32-0.40 for Terraced to 0.40-0.46 for semi-detached and 0.49-0.57 for detached (Table 7.3).

Table 7.3. Interquartile range values for ecosystem services (columns) by landscape character types (rows).

Landscape Character	Quantile	Aesthetic	Climate	Carbon	Water flow	Recreation
Agriculture	Q3	0.56	0.37	0.10	0.37	0.40
	Q2	0.51	0.33	0.07	0.33	0.36
	Q1	0.49	0.27	0.04	0.27	0.32
Detached	Q3	0.56	0.19	0.20	0.19	0.32
	Q2	0.52	0.13	0.14	0.13	0.29
	Q1	0.49	0.09	0.07	0.09	0.27
Green or blue	Q3	0.70	0.35	0.15	0.35	0.99
	Q2	0.60	0.25	0.05	0.25	0.70
	Q1	0.55	0.16	0.00	0.16	0.47
Non-domestic	Q3	0.40	0.13	0.10	0.13	0.20
	Q2	0.37	0.05	0.05	0.05	0.13
	Q1	0.31	0.01	0.03	0.01	0.10
Semi-Detached	Q3	0.45	0.10	0.10	0.10	0.26
	Q2	0.43	0.05	0.06	0.05	0.24
	Q1	0.40	0.02	0.00	0.02	0.21
Terraced	Q3	0.40	0.04	0.09	0.04	0.19
	Q2	0.36	0.01	0.03	0.01	0.15
	Q1	0.32	0.00	0.00	0.00	0.11
Woodland	Q3	0.95	0.40	0.51	0.40	0.50
	Q2	0.94	0.29	0.34	0.29	0.49
	Q1	0.74	0.18	0.19	0.18	0.43

Non-domestic (Figure 7.3 (D)) and Agriculture (Figure 7.3 (E)) produce similar patterns to the residential areas, with Agricultural areas achieving higher scores in all ecosystem services. Medians for climate and water flow mitigation increase by the largest amount between these two landscape characters (Non-domestic medians: Climate = 0.08, Water = 0.08, Agriculture medians: Climate = 0.32, Water = 0.32). However, carbon storage has similar generation distributions for both character types (median of 0.1).

Woodland (Figure 7.3 (F)) and Green or Blue (Figure 7.3 (G)) character types display different patterns from the more developed character types and from each other, with Woodland favouring aesthetic (median = 0.93 compared to Green or Blue median of 0.60) and carbon services (median = 0.34 compared to Green or Blue median of 0.05), while Green or blue spaces display higher values in recreational services (median = 0.70 compared to Woodland median of 0.48). In both instances, the provision of climate mitigation and water flow mitigation is similar (median values of approximately 0.28, although the inter-quartile range of Woodland is slightly larger at 0.21 compared to 0.18 for Green or Blue). This suggests that different land character types generate services at different levels. In particular, forests produce higher levels of carbon storage and aesthetic, while more open green or blue spaces produce higher levels of recreation services.

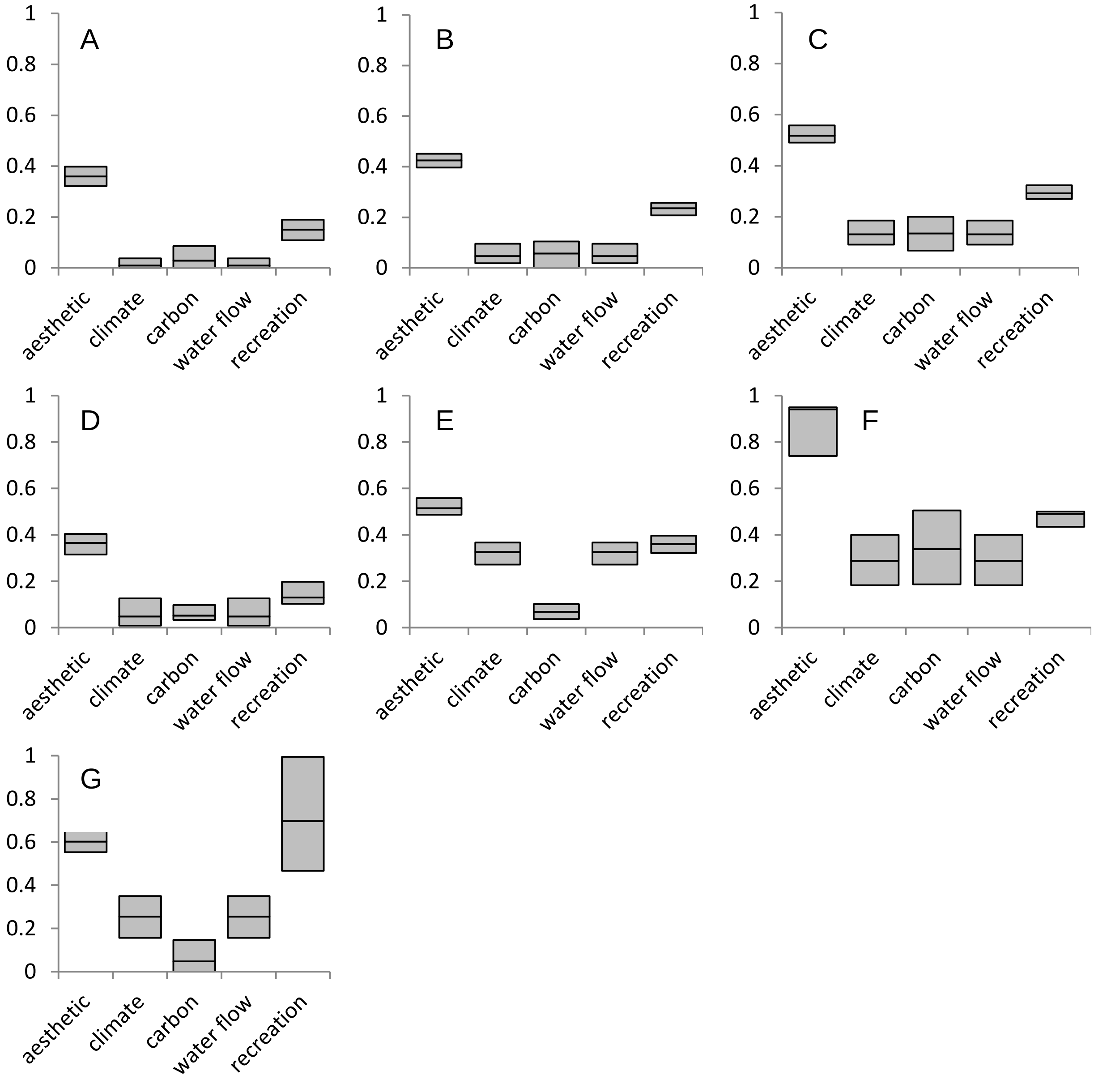

Figure 7.3. Boxplots displaying normalised ecosystem service generation values by landscape character (A) Terraced, (B) Semi-detached, (C) Detached, (D) Non-domestic, (E) Agriculture, (F) Woodland, and (G) Green or blue.

Ecosystem service generation layers are not normally distributed (Table 6.3), so Kruskal-Wallis tests were conducted to measure the difference in distribution of data by landscape character from the land use map created in Section 5.8. The tests found that ecosystem service distributions were significantly different between pairs of character types (Figure 7.4). Shaded rectangles in Figure 7.4 indicate significant differences in specific ecosystem service generation levels within landscape character pairings. Carbon storage service generation levels were significantly different in the fewest landscape character pairs (13 pairs out of a possible 21). This suggests that carbon storage levels are similar (or at least not significantly different across all landscape character types. The pairings of Agriculture-Green or Blue held no significant differences in ecosystem service levels, while the Woodland-Green or Blue pair held only one significant difference in carbon generation. This indicates that they are indistinguishable in terms of ecosystem service generation levels. This is because these landscape character types are characterised by large proportions of green space (as evidenced in Table 5.11 (high PLAND vegetation scores). which Chapter 6 shows is an important source of ecosystem service generation. There is a similar pattern present for Terraced-Non-domestic and Semi-detached-Non-domestic pairings. Although in both cases different services are significantly different. For Terraced-Non-domestic, climate and water flow are significantly different. For Semi-detached-Non-domestic, aesthetic and recreation are significantly different.

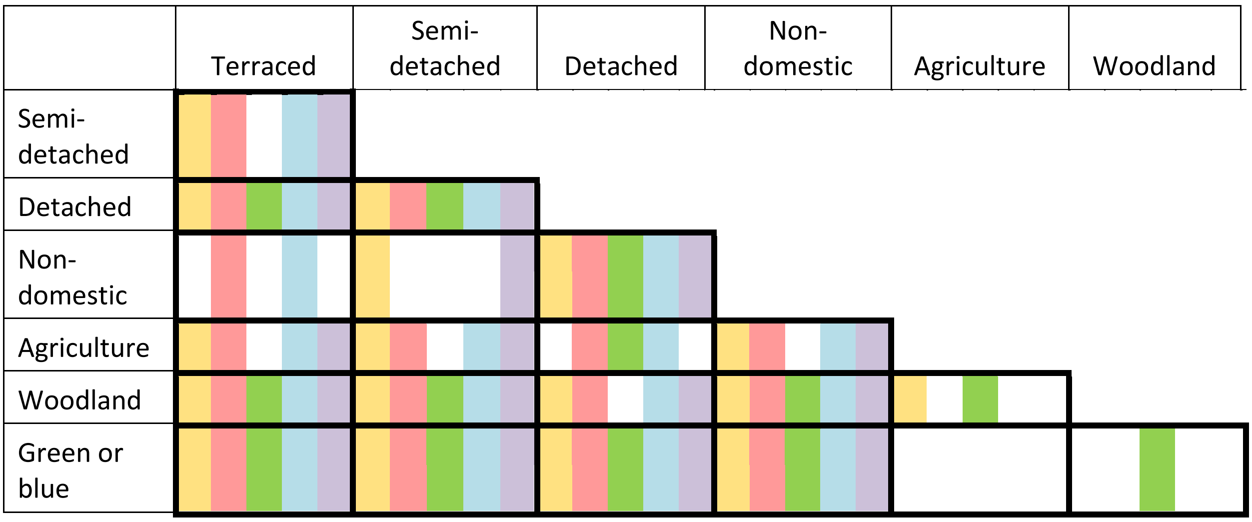

Figure 7.4. Significant differences in ecosystem service generation between landscape character pairs. Shaded rectangles indicate paired character types that displayed significantly different patterns ($p < 0.01$) for: orange = Aesthetics, red = Climate stress mitigation, green = Carbon storage, blue = water flow mitigation, and purple = recreation. White rectangles represent no correlate between ecosystem service pairs.

The Detached landscape character type appears to have the most different patterns of ecosystem services from the other character types, having only three insignificant pairings (white rectangles) out of a maximum thirty. Agriculture is the least different with 13 insignificant pairing. This reflects the fact that detached housing appears to have the most distinct landscape patterns, while agriculture appears to be the least distinct. Terraced, Semi-Detached, Detached and Non-Domestic landscape character types all present significantly different patterns of ecosystem services compared to Woodland, Green and Blue spaces and to a lesser extent, Agriculture. This reflects differences between predominantly urban land uses and predominantly rural or green land uses. Non-domestic areas were significantly different from the Woodland and Green or Blue areas, but had some insignificant pairings with Terraced housing and Semi-detached areas. However, the pattern of services was different for both pairs, with the Terraced having significantly lower water flow and climate mitigation services (Figure 7.3, A and D), while the Semi-detached had significantly higher levels of cultural services compared to Non-domestic land use.

7.3.2. Combining services - Overlap analysis

Pearson's correlation was calculated for each pair of ecosystem services as presented in Table 7.4. Correlations are generally weak across the pairings. The strongest relationships occur between aesthetics and recreation ($r = 0.72$, $p < 0.01$), and aesthetics and water flow mitigation ($r = -0.64$, $p < 0.01$).

Table 7.4. Pearson's correlation of ecosystem services. No correlations were significant at $p < 0.1$.

	Aesthetics	Climate	Carbon	Water Flow
Aesthetics				
Climate	0.55			
Carbon	0.18	0.07		
Water Flow	-0.65	-0.47	-0.17	
Recreation	0.72	0.43	0.11	-0.55

Table 7.5 presents the ratios of observed and estimated overlap between paired hotspots, comparing the aspatial approach and the lowest confidence spatial approach ($p<0.1$). Use of the lowest confidence level matches parameters used in previous research for easier comparison (Bai *et al.,* 2011). All pairings were more overlapped than expected. The expected overlap was calculated by dividing the

product of the paired coverages by the total research area as discussed in Section 7.2.2. The highest ratios of observed: expected were produced for carbon-water and carbon-aesthetics pairings (Table 7.5).

Getis-Ord Gi* produced results that were more overlapped than the aspatial thresholding approach evidence for this is provided by the values in Table 7.5, where the P<0.1 values are higher than aspatial ratios, by between 0.63 and 1.49, indicting a higher level of overlap. This is true for all pairings apart from the carbon-recreation, which has a higher more overlapped ratio for the aspatial analysis (1.19) compared to the p<0.1 (1.14), although these ratios are both close to 1, which suggests that the observed overlap is similar to the expected overlap. Pairings with recreation generally had ratios similar to those expected (all close to 1). All ratios were significant when tested with a chi squared goodness of fit. Water flow values are zero because no significant hotspots were found in the Getis Ord Gi* analysis.

Table 7.5. Ratios of observed to expected shared areas.

	Aesthetic		Climate		Carbon		Water flow	
	Aspatial	p<0.1	Aspatial	p<0.1	Aspatial	p<0.1	Aspatial	p<0.1
Climate	1.70	2.84						
Carbon	5.25	6.06	3.08	3.71				
Water flow	3.22	0.00	2.12	0.00	4.84	0.00		
Recreation	1.39	2.88	1.19	1.14	1.55	2.69	1.56	0.00

Table 7.6 presents the proportion of the overlap as a percentage of the smallest of the paired hotspots. The carbon-aesthetic pairing has the largest overlap in the spatial analysis (62%), while the largest overlap for the aspatial analysis was carbon-water flow (47%). with other carbon pairings also producing high overlaps. Recreation pairings produce the lowest overlaps (8% - 15% for aspatial analysis, and 9% - 30% for spatial analysis. Getis-Ord Gi* produces larger percentage overlaps than the aspatial method.

Table 7.6. Shared area as a percentage of the smallest service coverage.

	Aesthetic		Climate		Carbon		Water flow	
	Aspatial (%)	p<0.1 (%)	Aspatial (%)	p<0.1 (%)	Aspatial (%)	p<0.1 (%)	Aspatial (%)	p<0.1 (%)
Climate	14	29						
Carbon	44	62	19	31				
Water flow	31	0	20	0	47	0		
Recreation	12	30	8	9	10	16	15	0

Table 7.7 presents aspatial and spatial hotspot congruence across Salford. In this research, congruence is defined as extent to which multiple ecosystem service hotspots are overlaid across Salford. Many hotspots in one pixel represents high congruence. The aspatial approach produces the largest area containing at least one hotspot (41.62%). The aspatial percentages are comparable to Getis-Ord Gi* at p<0.1, with approximately 25% of Salford identified as hotspots. This drops to below 5% at p<0.01. Applying the spatial hotspot approach, estimates that 29.84% of Salford contains at least 1 hotspot at the lowest confidence interval, lowering to 22.27% at p<0.05. No areas contain all five service hotspots.

Table 7.7. Hotspot congruence expressed as a percentage of the total study area.

Number of overlapping hotspots	aspatial	P<0.1	P<0.05	P<0.01
0	75.10	77.04	83.77	95.12
1	19.09	17.19	12.63	4.68
2	4.28	3.42	2.63	0.09
3	1.36	1.96	0.82	0.00
4	0.17	0.19	0.03	0.00

Areas of Salford to the north and west are highlighted as of importance to multiple services (Figure 7.5, A and B). However, the aspatial approach (Figure 7.5, A) produces a more speckled map than Getis-Ord Gi* (Figure 7.5, B), where isolated cells have uniquely high values. This may be useful for small green space or street tree identification.

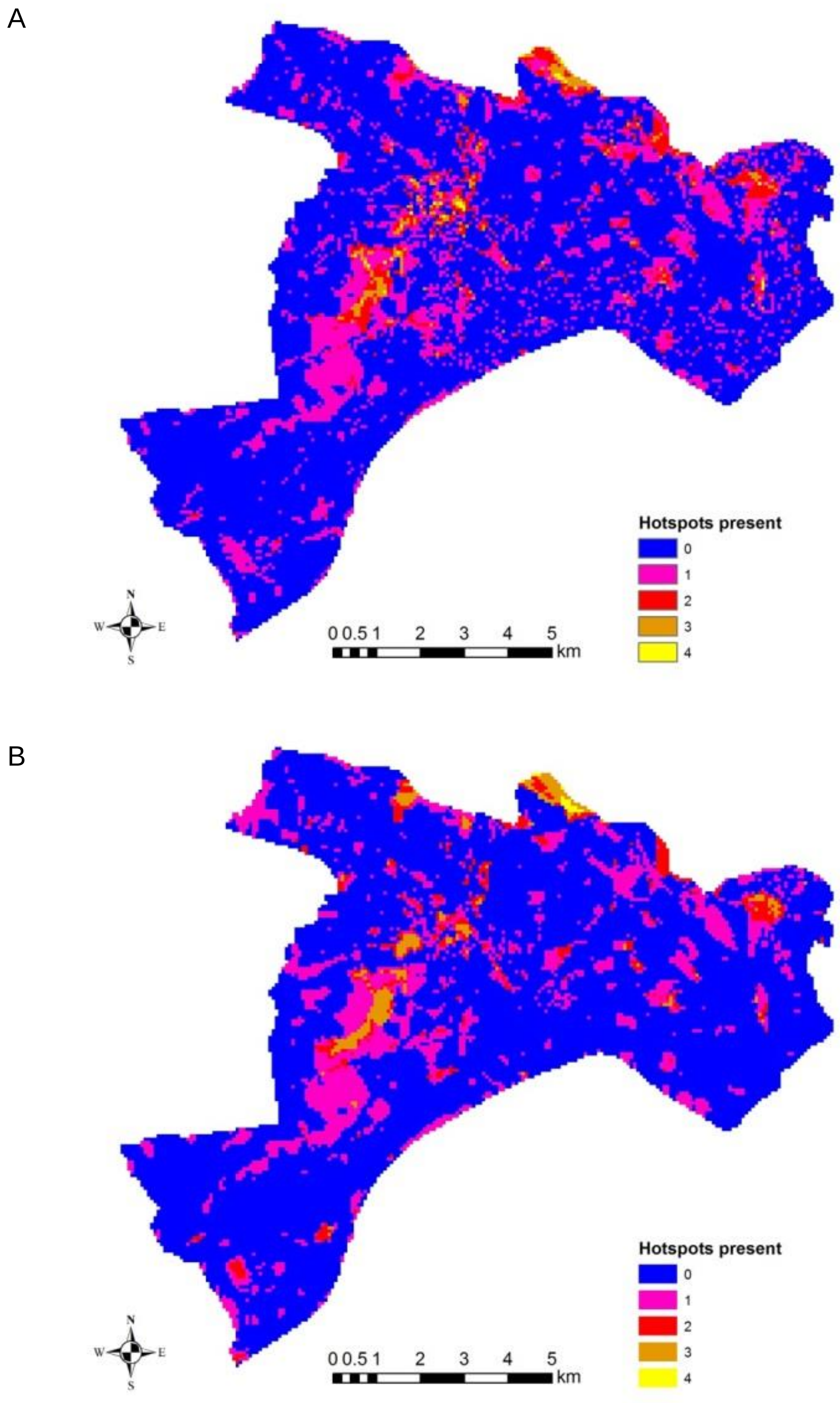

Figure 7.5. Hotspot congruence for (A) aspatial and (B) spatial hotspots (p < 0.1) (Author's own).

7.3.3. Determining cluster sizes

Figures 7.6 – 7.8 display results for deriving the optimum numbers of clusters in both aspatial and spatial approaches. In their methodology for creation of the Output Area Classification, Vickers, Rees and Birkin (2005) suggest that approximately 6 clusters should be used to ensure good visibility between clusters. This is to ensure that there is enough variability represented across the data, but also that clusters are not too similar in composition. Taking this on board, the validation below will adopt a potential range between 4 and 8 clusters.

Figure 7.6 presents the deviation of cluster membership from the mean expected number of members. Optimal values for cluster selection should be low as these represent situations where cluster membership size is similar across clusters. This is more desirable than a high deviation because there is less chance that a cluster will arise that has only a handful of members. The average cluster size reduces as more clusters are added. Figure 7.6 (A) displays high deviations for 4 and 5 clusters, and a relatively high deviation for 7 clusters compared to 6. This leaves 6 and 8 as potential solutions for the aspatial approach. Figure 7.6 (B) displays high deviations at 6 and 7 clusters, leaving 4 clusters as a primary potential solution for the aspatial approach.

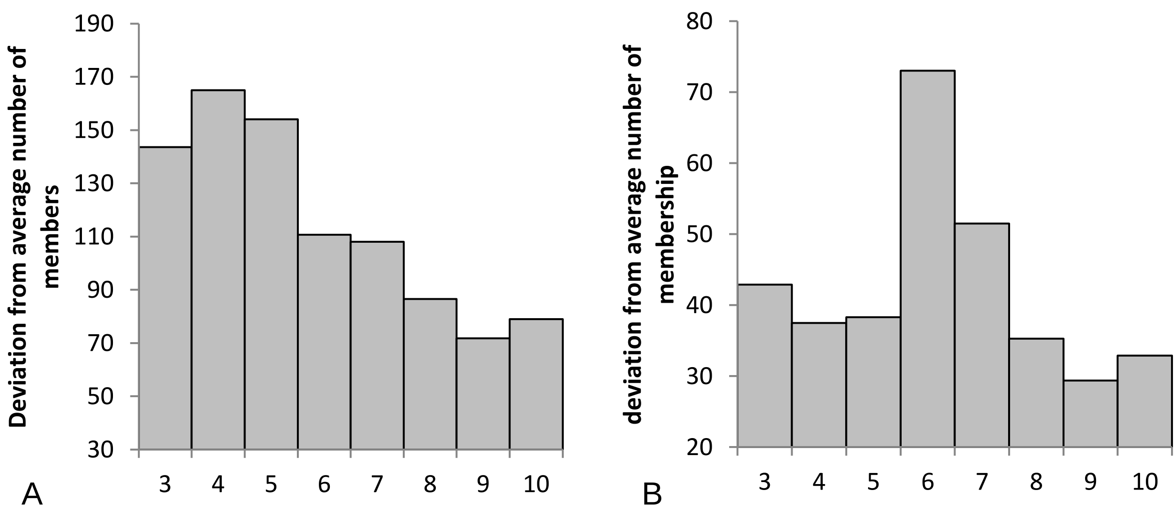

Figure 7.6. The deviation in cluster size from the mean. (A) Aspatial clustering, (B) Spatial clustering.

Figure 7.7 displays the average distance of each member from its parent cluster mean centre for (A) the aspatial and (B) spatial clustering approach. Optimal values should be low as these represent members that have very similar characteristics to the cluster mean centre. Figure 7.7 (A) displays slight peaks for the 5 and 7 clusters, leaving 4, 6 and 8 as potential solutions for the aspatial approach. On the other hand, Figure 7.7 (B) displays higher than expected values for the 6, 7 and 8 cluster solutions while the 4 and 5 cluster solutions offer lower than expected scores and thus are potential solutions for the spatial approach.

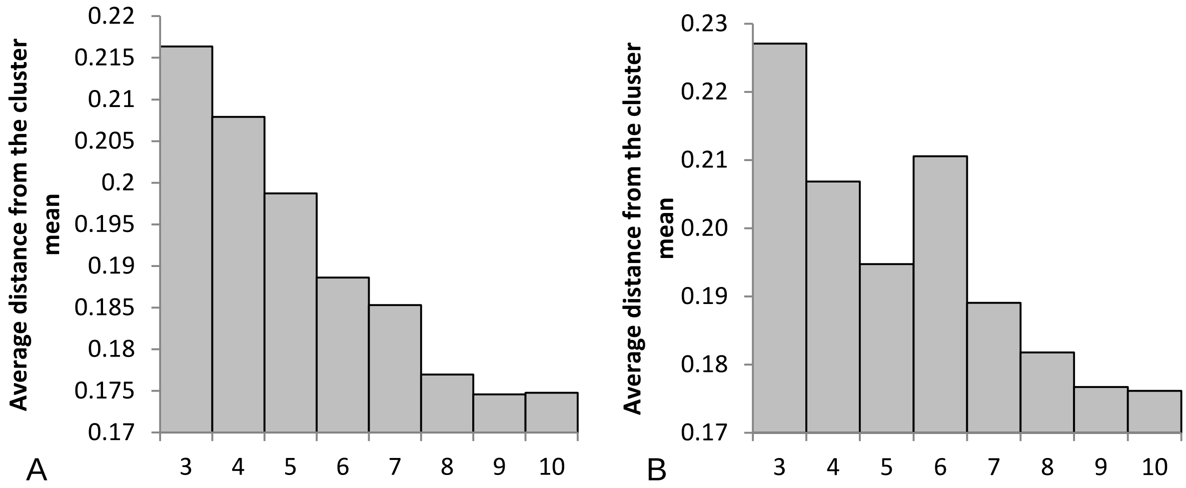

Figure 7.7. Average distances from cluster centres for spatial and aspatial cluster analysis (A) Aspatial clustering, (B) Spatial clustering.

Finally, Figure 7.8 displays the overall average silhouette widths for each cluster number solution. Optimal values should be low as they represent stronger clusters. Figure 7.8 (A) shows that the 6, 7 and 8 cluster solutions perform well for aspatial analysis. Figure 7.8 (B) shows that the 4 cluster solution performs best for spatial analysis.

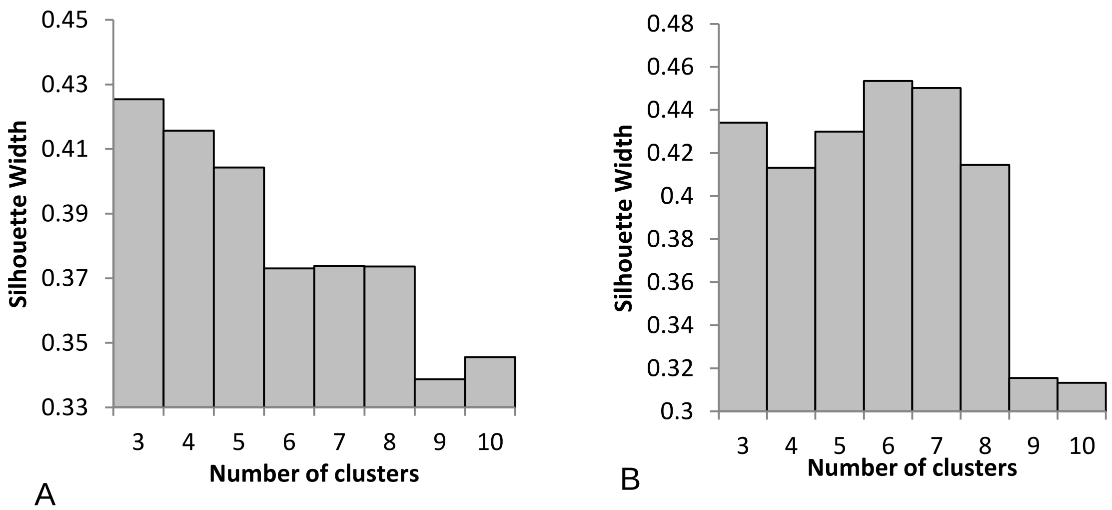

Figure 7.8. Silhouette widths (A) Aspatial clustering, (B) Spatial clustering.

In summary, the aspatial approach offers the 6 and 8 cluster options as the best potential solutions, with little to choose between them. However, Figure 7.8 shows that the overall silhouette width is slightly smaller for the 6 cluster than the 8. This shows that the cluster members are closer to the cluster centres and will consequently be used going forward. The spatial approach appears more definite, with the 4 cluster option performing best in all three tests.

7.3.5. Final cluster solutions

Figure 7.9 and Tables 7.8 and 7.9 display the final clusters for (A) aspatial and (B) spatial clustering. The bar graphs represent the summed mean value for each component of the cluster. Taller bars indicate higher levels of service generation. The aspatial bar graph (Figure 7.9 (A)) displays 6 clusters. Cluster 5 contains the highest potential for service generation, followed by clusters 1 and 6, which are of a similar size. Cluster 1 has a larger proportion of water flow mitigation and aesthetics, while cluster 6 has a more even distribution of service generation across all five services. Cluster 2, 3 and 4 are the smallest and of a similar size to each other. The differences are subtle, with a gradient of decreasing water mitigation and increasing recreation and climate stress mitigation from 2 to 4. Figure 7.9 (B) presents only 4 clusters, but all are of different heights. Cluster 2 is the largest and has a higher proportion of every service available. Cluster 3 is the smallest. In both (A) and (B), water flow mitigation and aesthetics appear to play an influential role in the overall generation levels. Carbon storage appears to be the least influential.

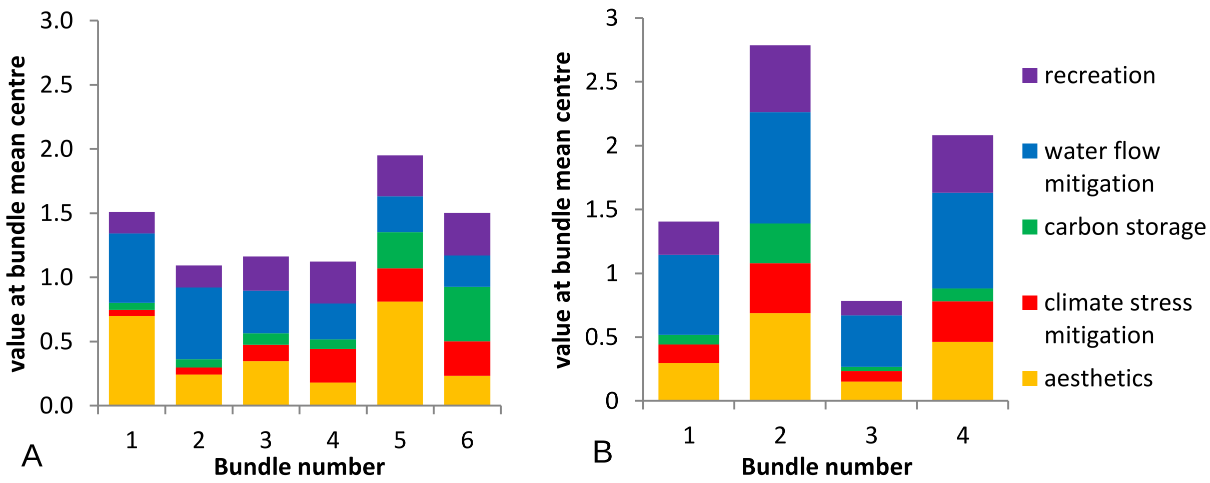

Figure 7.9. Final cluster solutions (A) Aspatial clustering, (B) Spatial clustering. Taller bars indicate higher potential for service generation.

Table 7.8. Aspatial clustering solution – cells present ecosystem service values at cluster mean centres. High values represent high ecosystem service levels (0 – 1).

Ecosystem Service	Cluster number					
	1	2	3	4	5	6
Aesthetics	0.70	0.24	0.35	0.18	0.81	0.23
Climate stress mitigation	0.48	0.55	0.13	0.26	0.26	0.27
Carbon storage	0.05	0.06	0.09	0.08	0.28	0.42
Water flow mitigation	0.54	0.56	0.33	0.28	0.28	0.24
Recreation	0.17	0.17	0.26	0.33	0.32	0.33

Table 7.9. Aspatial clustering solution – cells present ecosystem service values at cluster mean centres. High values represent high ecosystem service levels (0 – 1).

Ecosystem Service	Cluster number			
	1	2	3	4
Aesthetics	0.30	0.69	0.15	0.46
Climate stress mitigation	0.14	0.39	0.08	0.32
Carbon storage	0.08	0.31	0.03	0.10
Water flow mitigation	0.63	0.87	0.40	0.75
Recreation	0.26	0.50	0.11	0.45

7.3.6. Naming the clusters

Following the advice of Vickers and Rees *et al.,* (2007), naming clusters offers a qualitative understanding that reinforces the quantitative measurements. There is no formal method for naming clusters. The cluster names arise from analysis of ecosystem service generation patterns within clusters and across landscape character types. To determine information on the composition of each land character type, Table 7.10 presents the percentage by land cover that each cluster contributes to each character type. Values highlighted in bold indicate dominant clusters. The spatial approach contains a dominant cluster for 6 of the 7 character types, while the aspatial approach only produces 3 dominant clusters, although where dominant clusters do exist they are amongst the strongest, In two cases, Terraced and Agriculture, the aspatial clusters are stronger than the spatial clusters.

Table 7.10. Composition of land character types by service cluster (percent land cover).Rows represent cluster numbers. Columns represent landscape character types. Each landscape character type has values for A = Aspatial clustering, S = Spatial clustering. Bold figure highlight dominant landscape character types (over 50%)

Cluster	Detached		Semi-Detached		Terraced		Non-domestic		Agriculture		Woodland		Green or blue	
	A	S	A	S	A	S	A	S	A	S	A	S	A	S
1	0.4	38.2	1.5	**61.5**	9.9	38.6	5.5	24.6	0.0	17.1	9.9	11.3	11.9	19.0
2	8.9	16.5	43.6	1.4	**61.3**	0.3	**57.6**	7.9	1.5	7.9	3.5	**66.4**	19.0	15.7
3	42.7	5.4	31.9	23.2	25.9	**56.5**	27.6	**56.8**	32.9	19.7	22.6	2.3	23.6	6.6
4	31.0	39.9	21.3	13.9	2.8	4.7	9.3	10.7	**64.5**	**55.3**	13.5	20.0	30.0	**58.7**
5	0.0		0.0		0.0		0.0		0.0		24.8		13.6	
6	17.1		1.7		0.0		0.0		1.1		25.6		1.8	

Tables 7.11 and 7.12 present measurements of similarity between clusters and landscape patterns in terms of ecosystem service generation. A simple measure of absolute difference was used. Similarities were calculated by summing the total absolute differences between each ecosystem service mean value, for each pairing. Small values indicate higher levels of similarity. The tables suggest that linking clustered service generation patterns to landscape character types is not clear cut. Table 7.11 displays aspatial cluster similarities to landscape character types. Clusters 1 and 3 have similarities to residential, non-domestic and agricultural character types with values just below one, with cluster 3 displaying stronger similarities. Cluster 2 has strong similarities with semi-detached, terraced and non-domestic character types suggesting an affiliation with dense urban morphologies. Clusters 4 and 6 have strong similarities to agricultural and detached character types, with cluster 4 having stronger similarities. Cluster 5 has very strong similarities to woodland character types in particular, but also agricultural and detached housing, suggesting an affiliation with character types containing dense vegetation. In general, Green or blue character types are not well reflected in the composition of aspatial clusters. While a clear distinction can be made for urban and vegetated character types, urban morphologies seem to be better modelled. Distinctions can be made between residential and other urban land uses and also within residential neighbourhoods.

Table 7.12 displays spatial cluster similarities to landscape character types. Cluster 1 and cluster 3 display similarities to residential, non-domestic and agricultural character types, with cluster 3 having stronger affiliation to the urban landscape character types. Cluster 2 has no strong similarities to any character type, but large differences between terraced and non-domestic character types, which represent the densest urban forms. Its closest similarities lie with Woodland and Agricultural land. Cluster 4 contains similarities between detached housing, agricultural, woodland and green or blue spaces, clearly associating with the greener parts of Salford.

Table 7.11. Aspatial cluster similarities against landscape character types. Bold figures indicate distinguishing features.

Landscape Character Type	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Semi-detached	**0.83**	**0.79**	**0.54**	0.80	1.21	1.03
Detached	**0.83**	0.91	**0.46**	**0.63**	0.86	**0.86**
Terraced	**0.89**	**0.75**	**0.63**	0.90	1.44	1.13
Agricultural	**0.86**	1.00	**0.56**	**0.52**	**0.73**	**0.79**
Non-domestic	**0.85**	**0.72**	**0.58**	0.85	1.38	1.08
Woodland	1.19	1.59	1.09	0.99	**0.45**	1.17
Green or blue	1.12	1.42	0.98	0.86	0.91	1.10

Table 7.12. Spatial cluster similarities against landscape character types. Bold figures indicate distinguishing features.

Landscape Character Type	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Semi detached	**0.82**	1.95	**0.79**	1.27
Detached	**0.79**	1.60	**0.95**	**1.05**
Terraced	**0.91**	**2.18**	**0.69**	1.50
Agricultural	**0.89**	1.18	**1.01**	**0.66**
Non-domestic	**0.87**	**2.11**	**0.63**	1.44
Woodland	1.44	1.15	1.64	**1.04**
Green or blue	1.31	1.33	1.42	**1.04**

7.3.7. Aspatial cluster names

Drawing together the information from Tables 7.10– 7.12 together, cluster 1 is dominated by semi-detached housing and has similarities with many of the urban morphologies indicative of **suburban neighbourhoods**. Cluster 2 has high proportions of semi-detached, terraced and non-domestic land use suggesting a higher density of **urban land use.** Cluster 3 does not dominate any of the land uses as it has a relatively high representation in all landscape characters, although it has strong similarities with agricultural lands and detached housing. Consequently, this can tentatively be called **rural-urban living.** Cluster 4 dominates agriculture and detached housing and represents the **urban fringe.** Cluster 5 is only present in woodlands and green or blue spaces and has its strongest association with woodlands, describing **urban forests.** Finally, cluster 6 has a strong presence in woodland and detached land uses with its strongest similarities for detached and agricultural land uses suggesting **leafy suburbs.** The final cluster solution is mapped out in Figure 7.10, where it becomes obvious that the suburban neighbourhoods and leafy suburb clusters could easily be merged with urban land use and urban fringe respectively to enhance the visualisation of the clusters.

7.3.8. Spatial cluster names

Cluster 1 dominates urban land forms, but semi-detached housing in particular suggesting that **suburban neighbourhoods** would also fit well here. Cluster 2 dominates woodland land uses without featuring strongly in any others. Although it does not bear high levels of similarity with any land use, woodland and agricultural lands are the closest suggesting that these areas are **urban forests.** Cluster 3 dominates terraced housing and non-domestic urban land uses and to a lesser extent, semi-detached housing suggesting that this is a cluster of **urban land use.** Finally, cluster 4 dominates agricultural land, green or blue spaces and detached housing indicating **greener living.** The final cluster solution is mapped out in Figure 7.11. The broad pattern of clusters is similar to that of Figure 7.10 and all four clusters are well represented across Salford. While landscape features that are delineated by the OAs in Figure 7.10 make features such as urban forests clearer, the more ambiguously shaped features in Figure 7.11 as derived by object-based analysis allow features to be captured that would cross OA borders, which produces results more appropriate for ecological study.

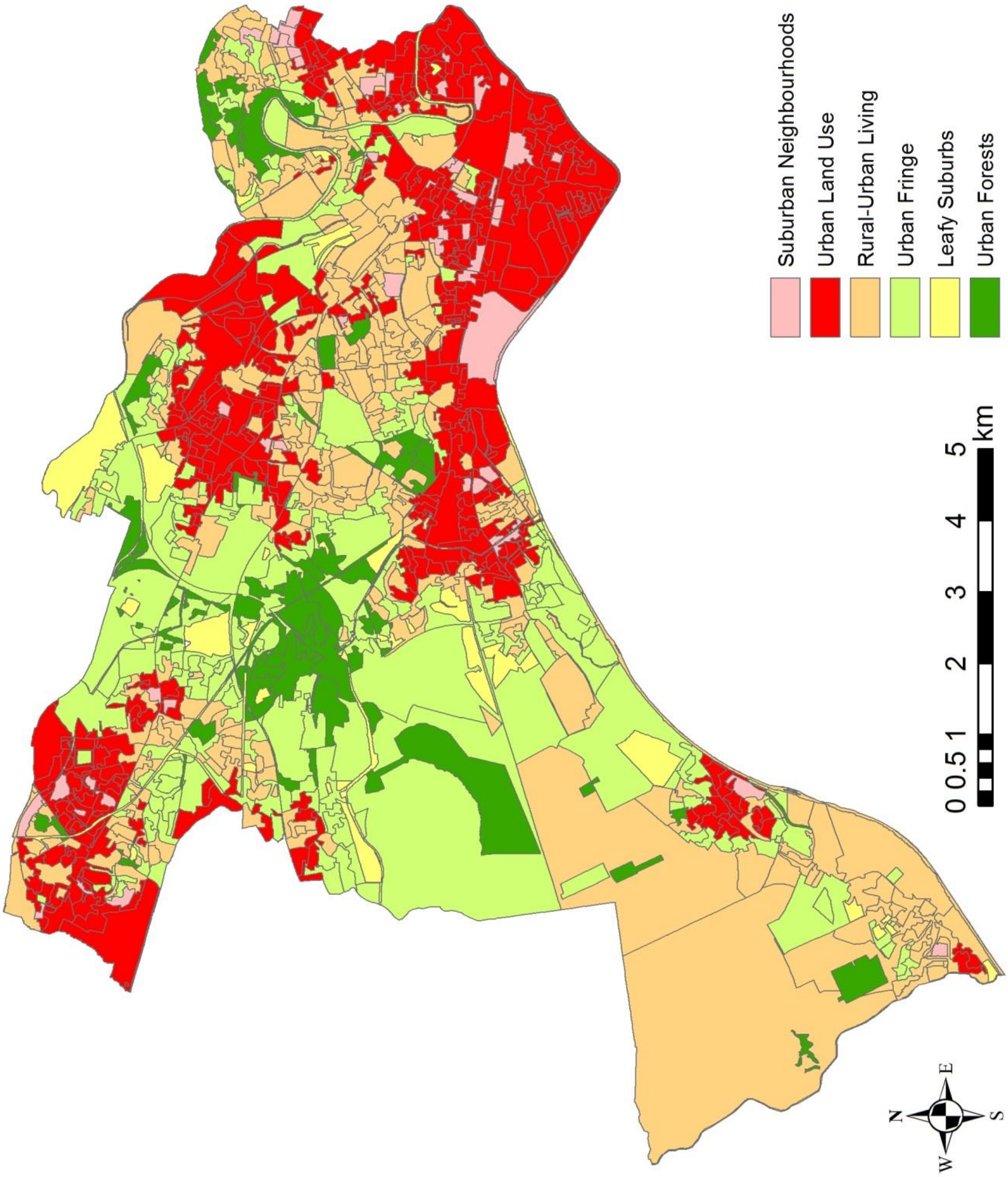

Figure 7.10. Geographical distribution of ecosystem service generation clusters - Aspatial approach (Author's own).

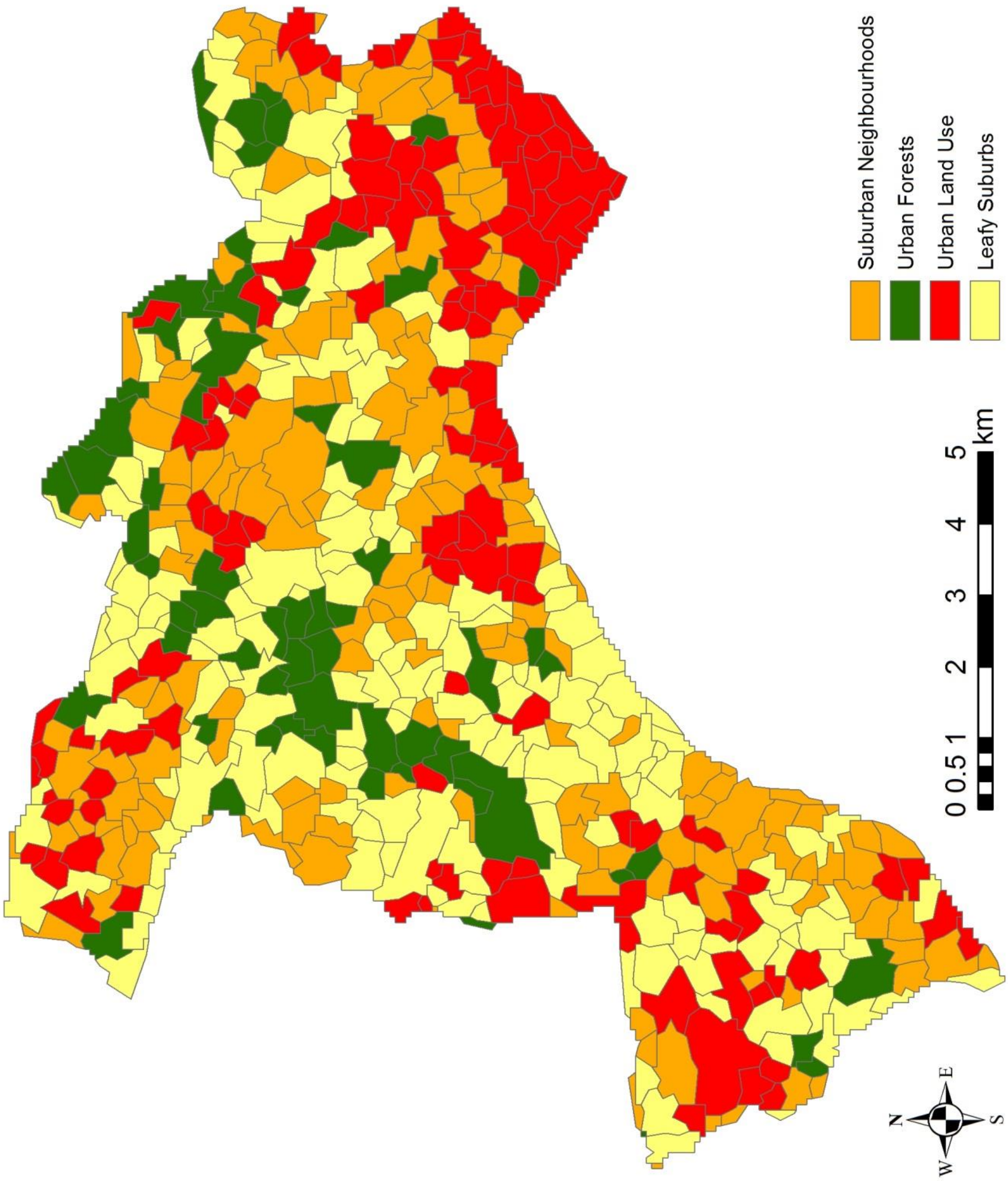

Figure 7.11. Geographical distribution of ecosystem service generation clusters - Spatial approach (Author's own).

7.3.9. Analysis of clusters

Figures 7.12 and 7.13 display box plots of the distribution of individual ecosystem service values in each cluster. While the boxplots in Figure 7.13 are all different, similarities can be discerned between mean values of the Urban Land Use cluster and Rural-Urban Living. Although carbon storage levels are expectedly low in urban clusters, water flow mitigation is high, possibly due to the position of these areas within the catchment. Aesthetics quality and water flow mitigation levels appear to play an influential role in discerning which cluster an OA falls into, as the other service levels tend to vary less between services.

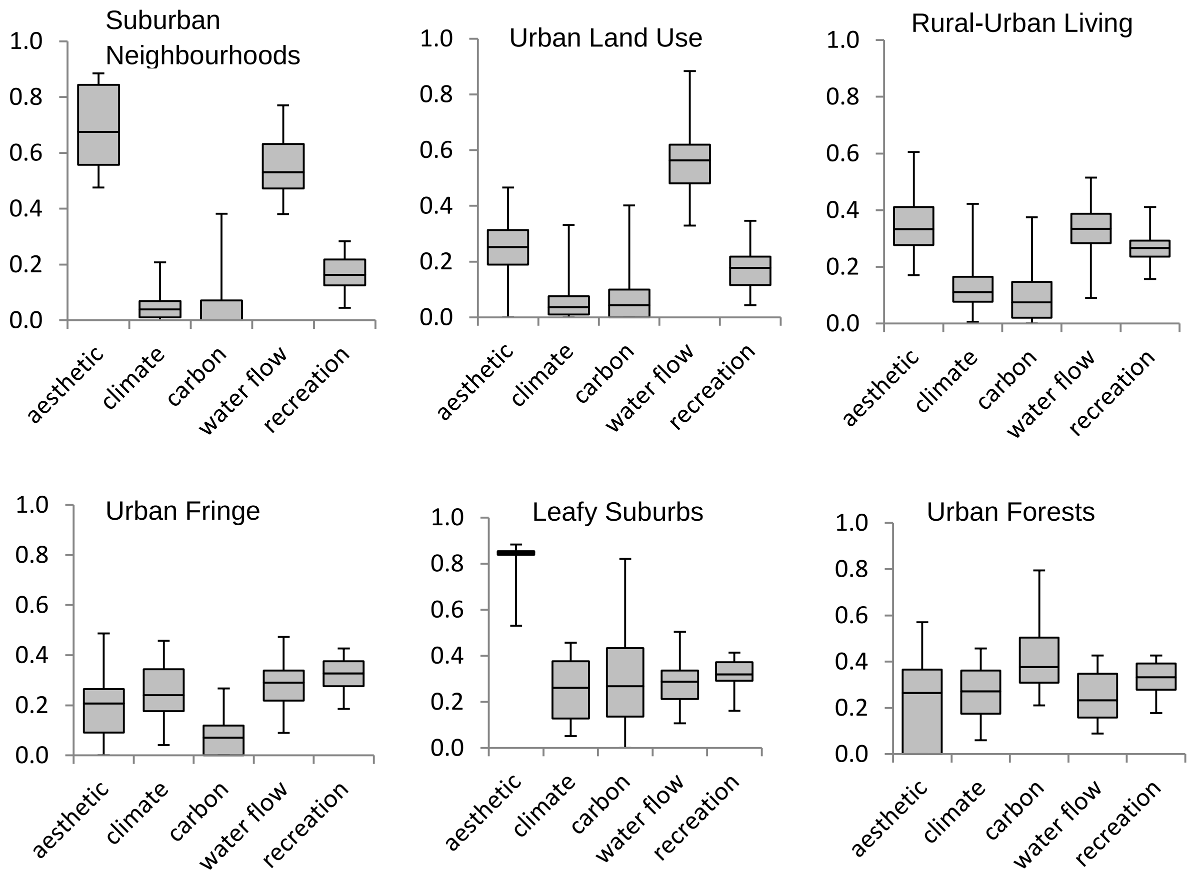

Figure 7.12. Box plots of the ecosystem service values in each cluster for aspatial bundling

On the other hand, the spatial approach shown in Figure 7.13 displays a similar trend in ecosystem service generation mean values across the clusters, with the difference being the magnitude of service generation levels. A distinct hierarchy can be visualised with Urban Forests presenting the highest levels, followed by Leafy Suburbs, Suburban Neighbourhoods and finally Urban Land Use. The fact that the trends in service generation are the same across clusters suggests that the top two producing clusters: Leafy Suburbs and Urban Forests are areas to encourage the conservation of and maintenance of current service levels, while the Urban Land Use and Suburban Neighbourhoods are areas to consider options for improving service generation levels.

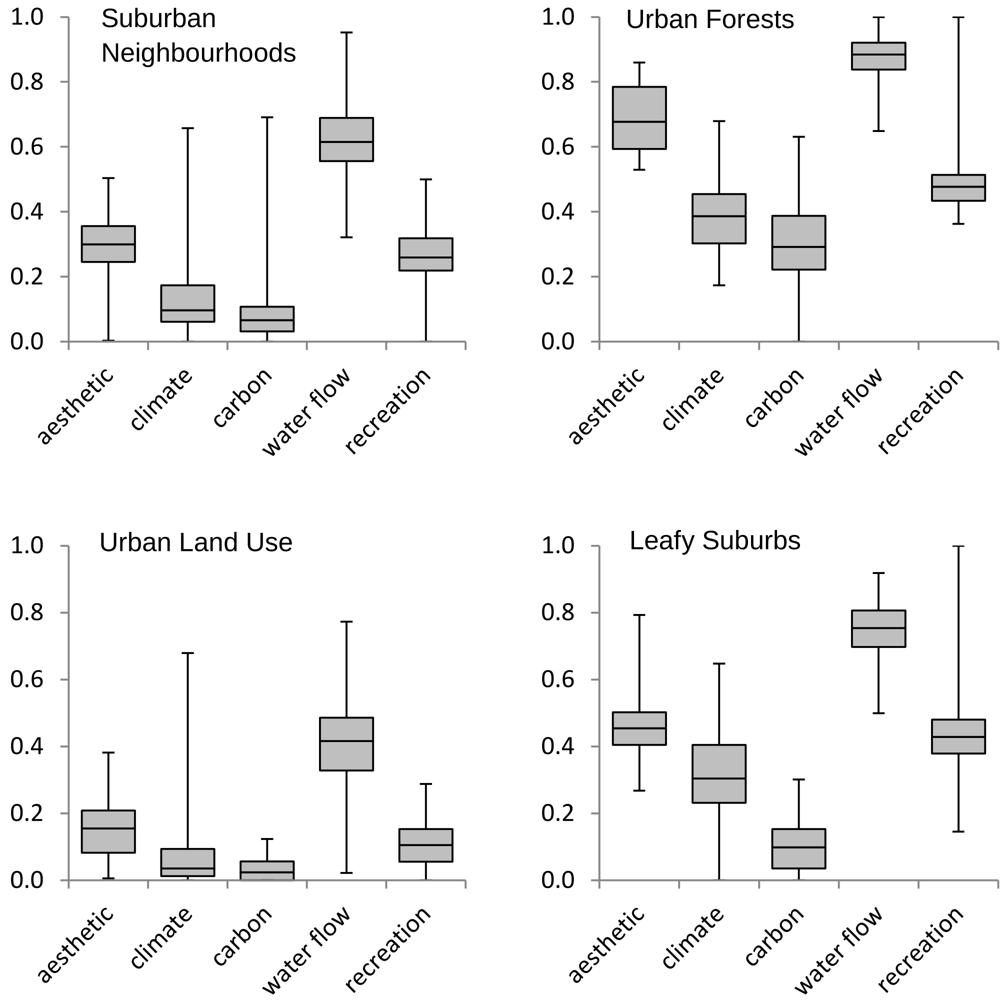

Figure 7.13. Box plots of the ecosystem service values in each cluster for spatial bundling

7.4. Discussion

7.4.1. Landscape multi-functionality

The results presented in this chapter show that the ecosystem service layers present different spatial distributions of generation across the different landscape mosaics of Salford. This is reflected in low correlations between service pairs (Figure 7.2). This points to the fact that the factors contributing to the generation of each service are different enough that they can all be included in the study with reasonable confidence that double counting is not occurring too frequently (Boyd and Banzhaf, 2007). Measuring hotspots at different significance values provides information on how tightly clustered the hotspots are. For example, the overlapped areas shared by recreation and carbon remain the strongest hotspots at $P<0.01$, despite being among the smallest areas at $P<0.1$. This suggests that these areas are among the most robust. On the other hand, services paired with aesthetics typically present larger areas of hotspots at $P<0.1$, but drop away to zero at $P<0.01$ suggesting a low level of resilience or tolerance.

High overlaps between regulating services in Tables 7.5 and 7.6 can be accounted for by the fact that they are measured by similar biophysical properties of the vegetation. The major difference between the generating levels of the two services is the impact of urban areas. The two cultural services present relatively low overlap values for both approaches, due to the methods of indicator creation and identification of isolated street trees in the aspatial approach. The patterns suggest that there are between 12% and 30% hotspot overlap (Table 7.7). These areas are the large urban parks to the north of the area, which present the highest opportunity for multi-functionality. The five urban landscape character types (terraced, semi-detached, detached, non-domestic and agriculture) show a smaller variation in service generation that the green and blue spaces and woodland. It is expected that this is because the greener landscape characters are typically unlikely to be as pure in description as the other land cover types. Where agriculture typically suggests single practice land use of crop growing or pasture, the wider description of green and blue spaces incorporates parks, gardens, cemeteries, tow paths, allotments etc. (Wang, 2009). The comparison between cultural services for the woodland and green and blue character types is also stark and draws on the perceived attraction to trees and forests as well as the multi-functionality of green spaces, which can be used for a wide range of team and individual recreational pursuits (Sherrouse *et al.,* 2011). The attraction of non-wooded green spaces also lies in the perceived safety of open spaces (Wolfe and Mennis, 2012), while the cover presented by forests also provides a greater distancing from urban sights and sounds, enabling a heightened sense of solitude and peace (van Herzele and Wiedemann, 2003). The patterns of regulating services between the two are similar suggesting a balance between small woodlands and larger open green spaces.

7.4.2. Cluster Analysis

This research has evaluated the spatial patterns of multiple ecosystem services through the application of two methods. Overlap analysis of hotspots has defined multifunctional hotspots and cluster analysis to define ecosystem service clusters across the entire landscape of Salford. Evaluation of aspatial and spatial approaches suggests that both approaches have created reasonable clusters. However Figure 7.9 (B) demonstrates that the spatial approach has produced clusters that are more distinct in terms of differing service generation levels. This represents differing levels of ecosystem services, more readily presenting a hierarchy of service generating units across space. The spatial approach provides further benefits by creating more homogenous service generation units through the use of object-based creation. This means that the clusters are stronger and more different. This is emphasised in Tables 7.11 and 7.12, where the higher values in Table 7.12 (spatial) indicate more difference between clusters than the aspatial approach (Table 7.11). Previous research has found strong links between land use and ecosystem service cluster patterns (Raudsepp-Hearne *et al.,* 2010; Martin-Lopez *et al.,* 2012). However, this research suggests that patterns are not as clear cut as previously suggested. This research further presents the first attempts to produce bespoke spatial units for characterisation of ecosystem clusters, which has been shown to improve characterisations in previous research (Jellema *et al.,* 2009). Characterisation of land uses provides a subjective description to regions of the urban landscape mosaic that have been clumped together (Vickers and Rees, 2007). This does not necessarily need to be scientifically robust, but the categorisation applied in this thesis does follow land use categories used in UK national databases and published literature.

The importance of multifunctional landscapes has gained recognition in academia and it underpins the concept of sustainable landscapes as an alternative approach to the ecosystem services (Blaschke, 2006; O’Farrell *et al.,* 2010). Sustainable landscapes focus on the multifunctional properties (social, biophysical, economic, cultural etc.) attached to a unit of land and how the landscape mosaic affects the capability to produce goods and services and the resilience to changing circumstances (O’Farrell and Anderson, 2010). This effectively grounds the ecosystem services in physical space and while there may be issues with ecosystem services flows that cross boundaries between landscapes, it could be argued that the majority of ecosystem service research is already doing this (Termorshuizen and Opdam, 2009).

7.4.3. The influence of greenspaces

The influence of larger greenspaces and vegetation as houses get larger is highlighted by the overall increase in service generation from the densest terraced housing to the most dispersed detached estates as shown in Figure 7.3. Despite the fact that the levels of service generation for the residential and non-domestic character types is similar, Figure 7.4 shows that when paired, the patterns are nearly all significantly different. This is largely due to the increased variance within the non-domestic character type. In particular, the detached housing is very different to the other urban characters, but the distribution of the carbon storage service between terraced, semi-detached and non-domestic appears to be difficult to distinguish. This suggests that the distribution of urban tree canopies is statistically different in areas of detached or large residential housing. This statement is as far as the conducted research can go other than to suggest that this offers a higher level of carbon storage. To improve this conclusion, a closer study of residential neighbourhood characteristics is required. Studies have shown that the presence of open greenspaces and trees raises house prices due to perceived benefits including access to green space and improved privacy (Cho *et al.,* 2008, Wolfe and Mennis, 2012).

van Leeuwen *et al.* (2010) state that urban greenspaces are sites of multifunctional ecosystem service generation. Results from hotspot analysis in Chapter 6 and the cluster analysis in Chapter 7 reinforce this statement because higher numbers of ecosystem services and higher ecosystem service values have been found in the larger urban greenspaces. This notion of multi-functionality is one that is repeated in the literature, with calls to consider multifunctional landscapes (Brandt, 2003). To demonstrate the importance of greenspaces in generation of ecosystem services, the aspatial and spatial hotspot areas derived from Figure 7.5 were overlapped with SCC audited 2 ha+ greenspaces. Over all, the SCC greenspaces overlap by approximately 30% with the aspatial (36.7%) and spatial hotspots (29.5%) and together the common greenspaces are identified in Figure 7.14, which highlights the major urban parks and gardens in Salford (shaded green).

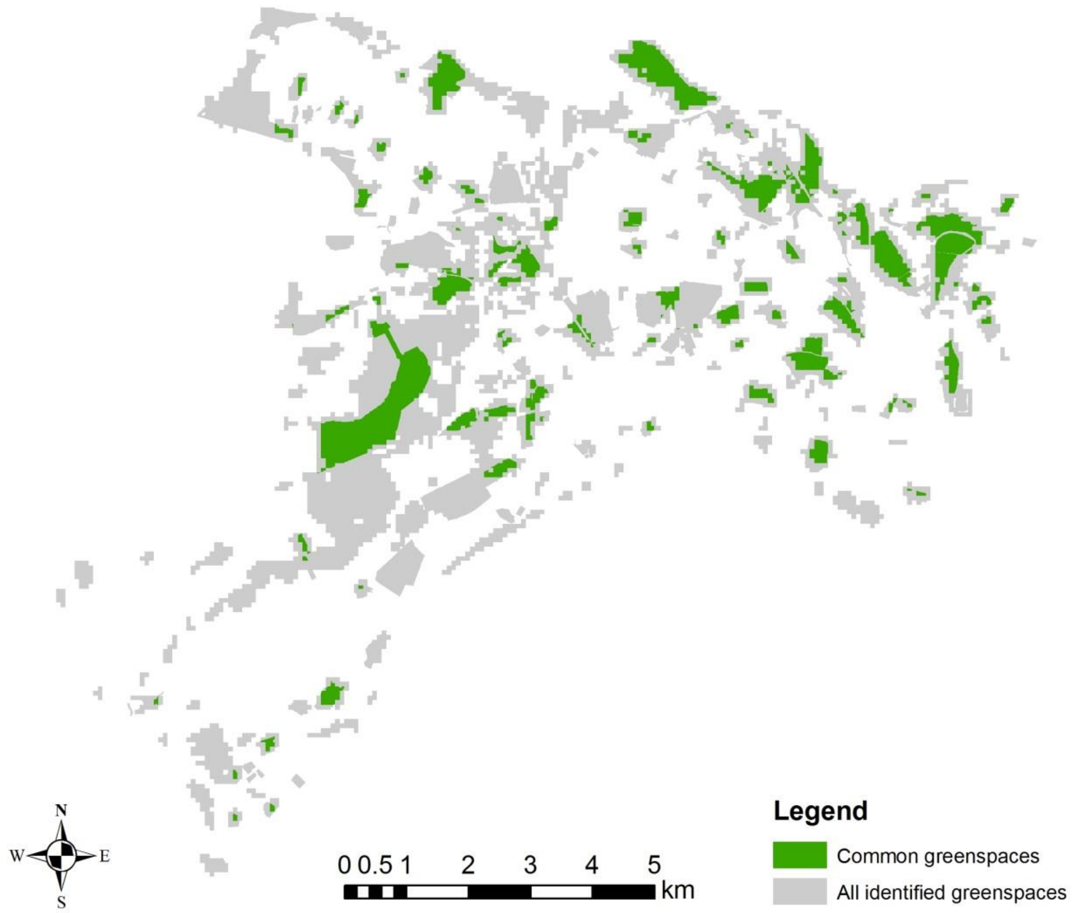

Figure 7.14. Greenspaces as identified using three approaches; from the SCC greenspace audit and from aspatial and spatial hotspots created in chapter 6 (shaded grey). Areas shaded green are highlighted in all three approaches (Author's own).

7.4.4. Ecosystem services and human well-being

Creating clusters across a landscape offers an opportunity to evaluate potential links with present social-ecological systems already in place (Bennett *et al.,* 2009). Both spatial and aspatial approaches produce cluster compositions that relate to underlying landscape characteristics, although the aspatial approach produces a higher ambiguity for the clusters that produce medium levels of services. Comparison between approaches used in the cluster analysis suggests that the spatial approach produced clusters that were more different from each other and that clustered better onto the landscape character types, reinforcing work by Raudsepp-Hearne *et al.* (2010) who make more explicit links to land use categories. The naming of the clusters was more intuitive for the spatial than aspatial, although this may be because the final solution produced a smaller number of clusters. Within each spatial cluster the ratios of service generation between ecosystem services remained constant. On the other hand, the aspatial clusters display different ratios within their structure, potentially due to the heterogeneity of the landscape underpinning them.

Administrative areas such as OAs used in this research provide useful spatial units for collecting social and economic data, but their value for ecological and environmental data collection may be called into question as they are not created with these factors in mind (Briggs *et al.,* 2008). OAs must contain a certain number of households. This means that prominently green areas may have their characteristics blurred by urban development. On the other hand, they do provide the opportunity to explore patterns that can be compared against social and economic data and determine patterns in supply of services to different populations (Deas *et al.,* 2004). In particular, Comber *et al.* (2012) find inequality in the perception that different ethnic groups have of public greenspaces and a related lack of use by minority groups in Leicester. Daw *et al*. (2012) further suggest that the ecosystem service concept creates winners and losers from different groups within a community with regards to who receives benefits and who may experience costs. The spatial approach to cluster analysis is novel to ecosystem service research and has offered a method of producing regions that are ecologically homogeneous. Although social data becomes harder to format in these boundaries, it is by no means impossible and characteristics can be inferred by data fusion methods such as dasymetric mapping or other data fusion methods discussed in Chapter 4 (Mennis, 2003; Weng, 2012). Research in this area is not yet mature.

A final consideration is that of management strategies. The maximum potential levels of services generated as highlighted in the results section cannot all be achieved at the same time and prioritisation must take place. This may be different between region and community (McPhearson *et al.,* 2014). It may also be forced by designing vegetation structures for specific purposes. For example in the formation of Sustainable Drainage Systems, may not optimise the aesthetic or recreational qualities of the landscape as a priority but do focus on maximising water-based services (Scholz *et al.,* 2014).

7.5. Conclusions

This research chapter has developed themes of ecosystem service generation by considering spatial relationships between different ecosystem services. The research has revealed that spatial patterns between ecosystem services are not equally distributed across the landscape. This can be modelled by analysis of the landscape mosaic of land covers and land uses and provides a physical grounding to otherwise ethereal concepts. This means results can be more easily quantified and presented to audiences across a range of academic and practical fields.

The spatial methods demonstrated here are novel to ecosystem service research. Spatial hotspot analysis introduced in the previous chapter is explored further here. Further benefits highlighted include analysis of hotspot significance, which means that differing levels of priority can be identified. Cluster analysis has presented a method to characterise ecosystem service generation in a fashion that mirrors landscape characterisation. Emerging patterns are not clearly attached to landscape character types as suggested in previous literature, but this is largely due to the different features being mapped. This is demonstrated in the comparison between aspatial and spatial methodologies. The object-oriented approach to deriving the spatial clusters creates spatial units that are more appropriate for ecological indicators as they do not directly consider patterns of human activity. This means that patterns offer better homogeneity and stronger characterisation. This enriched understanding of the landscape can highlight areas of specific importance due to their generation or vulnerability.

A large body of research has already been completed on the supply or generation of natural capital and ecosystem services. This is largely because measurements can be easily made and validated through quantitative analysis of proxy data formed through specific biophysical properties of the landscape. However, less quantitative research has been conducted for the demand for natural capital. A key component of the ecosystem service definition across all its evolutions is that it must be of benefit to human beings. This is something of a subjective concept and consequently fits well into social and cultural studies. However, there is a current lack of research undertaken by cultural geographers (Leyshon, 2014) and often this research suffers from a lack of cohesion between supply and demand. Previous research has typically focused on population centres (Nedkov and Burkhard, 2012) or observation points in National Parks (Baerenklau *et al.,* 2010) as indicators for service demand. Typically this has been measured using Euclidean distance measurements from population centres. While this may be a suitable and valid approach for bio-physical processes such as regulating services, for more tangible benefits, accessibility plays a much more influential role.

Figure 7.14 presents evidence that currently audited urban greenspaces play an important role in the generation of ecosystem services. Consequently, to provide a more comprehensive analysis of ecosystem services, these spaces provide a useful context for analysis of physical access to ecosystem services discussed in the next chapter. As this provides a baseline level of ecosystem service consumption analysis, further research will be conducted into the impacts of more peripheral urban greenspaces. Consideration of cultural service accessibility is further analysed by considering line of sight as a measure of accessibility based on literature discussed in Section 3.5.2.

The research in Chapter 8 focuses on accessibility of ecosystem services by considering an approach whereby physical accessibility is measured through a two dimensional route network and a visibility approach utilising three dimensional viewshed. This considers the impact of the topography of the landscape as well as the density, shape and form of features on the landscape, in particular trees and buildings which provide positive and negative barriers as well as observation points. The results of which can be used in conjunction with those presented in Section 6.3 to determine features such as supply and demand and carrying capacities.

8. Evaluating physical and visual accessibility to urban greenspaces

8.1. Introduction

Close proximity to urban greenspaces provides physical and mental health benefits and contributes to human wellbeing (Velarde, *et al.,* 2007; Lee *et al.,* 2009; Sander and Polasky, 2009). Many of these benefits can be identified and evaluated using an ecosystem service framework (Sections 2.3 and 2.4). This framework places an emphasis on human consumption of ecological functions to convert them into services and benefits to humans (MA, 2005). The human context is reflected in current UK guidelines produced by Natural England, which focus on increasing accessibility to local urban greenspaces (Natural England, 2010). The Access to Natural Greenspace Standard (ANGSt) recommends that humans should live within certain distances of greenspaces in order to enjoy the benefits produced there. The benefits listed by Natural England in their report (2010) include reduction of stress, contact with nature and physical exercise which can all be considered cultural ecosystem services (see Figure 2.3).

ANGSt guidelines have been adopted by councils across the UK to evaluate local provision of safe and accessible greenspace (Natural England, 2010). However, ANGSt guidelines, while stringent, also recommend using local standards. This flexibility allows councils to create their own standards relevant to specific local geographies, but it poses challenges when comparing provision of greenspace between different urban areas. These standards also neglect the contribution that informal urban green spaces and street trees make for enhancing wildlife connectivity and recreational opportunities (Jim, 2013; Rupprecht *et al.,* 2014). Finally, they do not consider the importance of vegetation visibility for reducing stress and maintaining contact with nature (Hauru *et al.,* 2012). For example, urban forests, reduces urban disturbance by acting as green barriers (Yang *et al.,* 2009). This increases the perception of being closer to nature, which can alleviate mental ill-health (van Herzele and Wiedemann, 2003).

The research in this chapter addresses research objective 3, (Section 2.6.3): *Evaluating physical accessibility and visibility to aesthetics and recreational cultural ecosystem services*. In developing new insights for physical accessibility to greenspaces, this chapter revises current methods to include transport routes to access (Barbosa *et al.,* 2007) and multiple access points to urban greenspaces (Comber *et al.,* 2012). This study contributes to the body of research by evaluating composition of the surrounding accessible landscape for individual households. This incorporates previously ignored unaudited greenspaces in assessment of the urban environment. This includes the space that is physically accessible and the space that can be viewed at different observation heights across Salford. Finally, these patterns are assessed against a standard measure of social and economic deprivation to determine whether the two concepts are spatially related to socio-economic patterns.

First, levels of ecosystem service accessibility are evaluated using the current accessibility standards and methods used by Salford City Council, against methods using network analysis, viewshed analysis and ANGSt guidelines derived from the literature (Section 3.6). Second, evaluation is made of the contribution of smaller greenspaces towards ecosystem service access within physically accessible areas surrounding individual households. Third, the impact of changing observation height is evaluated by analysing changes in visible landscape composition from ground floor to second floor and also from taller tower blocks across Salford. Finally, relationships with the IMD are explored.

8.2. Methodology

The methodology applied in this chapter is outlined in Figure 8.1 and is described in the following section. The chapter is broadly split into two separate methodologies which occupy the top half of Figure 8.1: a two dimensional network analysis using the local road structure and walking speeds and driving limits, discussed in Section 8.2.1, and a three dimensional viewshed analysis incorporating a bare earth digital terrain model and height features, from trees and buildings, described in Section 8.2.2. The bottom half of Figure 8.1 lists methods used to evaluate land cover composition and socio-economic patterns. These are further discussed in Section 8.2.3.

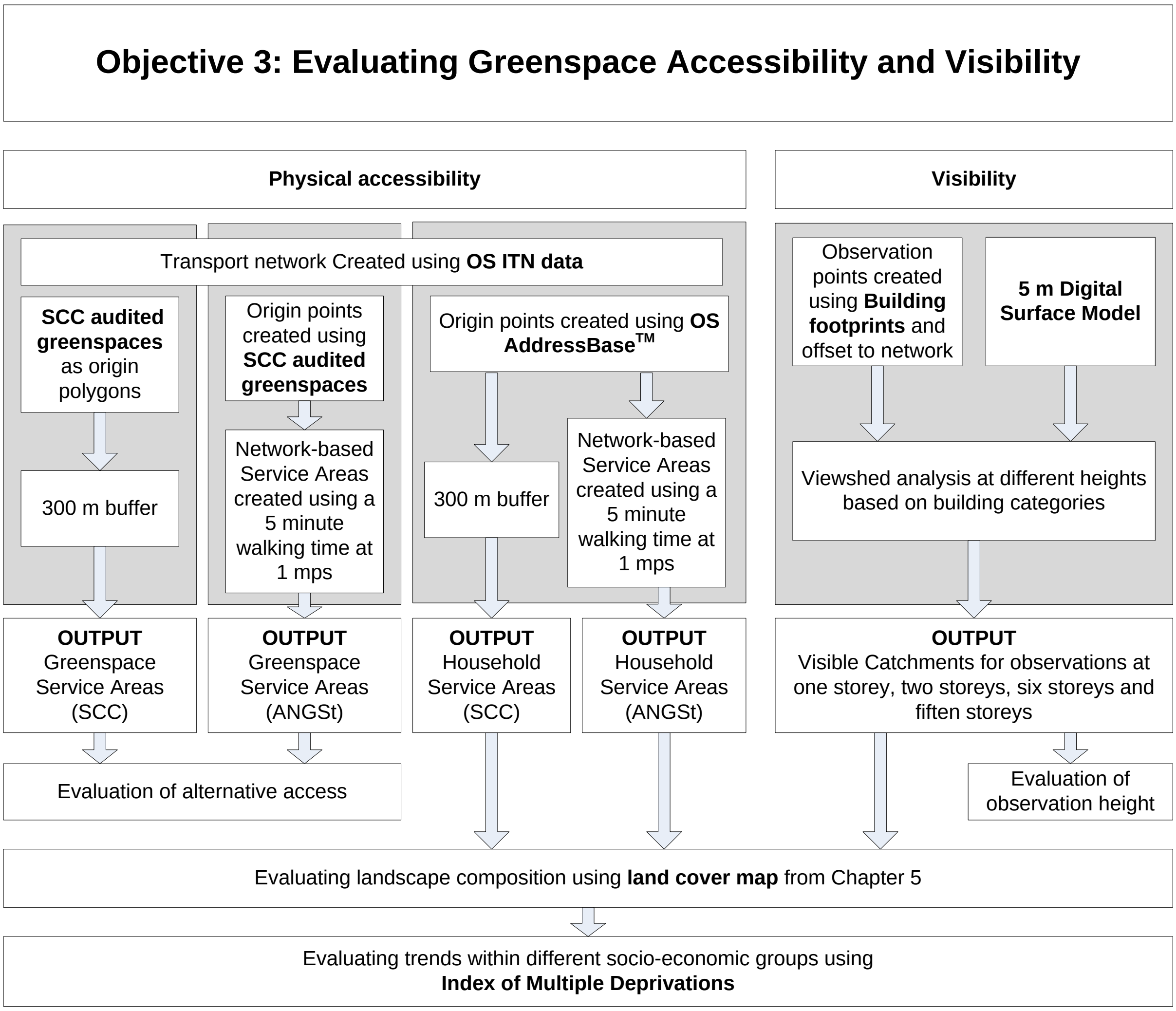

Figure 8.1. Cartographic model of methodology for Chapter 8.

8.2.1. Network Analysis

Network analysis is used to measure physical distance, as justified in Section 3.6.1 and presented in the top left-hand section of Figure 8.1. Two approaches to network analysis were applied to answer the research questions outlined above. The first approach provides information on access levels to greenspace and ecosystem services, as well as identifying where access is lacking. This was achieved through measurement of ‘service areas’ grown out from greenspace access points along transport routes to derive maximum areas of access. The second approach provides information on the composition of accessible land surrounding individual residences. This appreciates the value of greenspaces that fall outside the ANGSt guidelines (greenspaces less than 2 ha) and that are not included in current greenspace accessibility assessments. This was achieved through creation of service areas surrounding residences to determine the landscape composition.

8.2.1.1. Pre-processing

Greenspace access points for the first network analysis approach, were manually created for each greenspace larger than 2 ha and audited by SCC (Figure 3.5). Access points were identified using aerial photography and a 1:25,000 Scale Colour Raster Ordnance Survey map and digitised onto a separate dataset in ArcGIS 9.3 (total access points = 404). This provides a more realistic solution than using greenspace centre points, which assume equal access from all directions and can be a large distance from a greenspace boundary. Figure 8.2 presents the example of Buile Hill Park. The red point represents the geographical centre of the park. In some locations, this is more than 350 m from the park perimeter. This equates to a maximum walking time of five minutes and fifty seconds to reach from the edge of the park, making it technically inaccessible from outside. Alternatively, using the whole polygon as an access point assumes that he park can be accessed anywhere across its boundary. This overestimates accessibility because fences and walls often surround urban greenspaces.

Figure 8.2. Greenspace entrance points (yellow) around the perimeter of Buile Hill Park, Salford (green). The park centroid is shaded in red. (Landmap; The GeoInformation Group 2007)

Digitising individual access points has highlighted how public parks designed for use by local populations have more access points around their perimeter, effectively enlarging their areas. District and Neighbourhood Parks have the largest average number of access points (5.2) (Table 8.1). Less formal and less managed Local Natural Greenspaces have fewer points of access (1.2 on average), effectively shrinking their size in terms of physical access.

Table 8.1. Descriptive statistics for greenspace access points.

SCC Audited Green Space Type	Number of access points	Average Number of access points
District and Neighbourhood Parks	39	5.2
Golf Courses	6	2.7
Sports Pitches	129	1.6
Local Natural Greenspaces	123	1.2
Woodland	70	1.0
Cemeteries	7	0.7
Allotments	25	0.6
Total	**399**	**1.7**

Household origin points for the second network analysis approach were represented using AddressBase^{TM} data points from Ordnance Survey (OS) as described in Section 4.2.9, under the assumption that each address represented a household. Populations were estimated using the Office of National Statistics average value of 2.3 people per household in Salford at the 2011 census (ONS, 2013). The 2013 AddressBase data was laid over the 2006 building height dataset described in Section 4.2.4. Points that did not lie within a corresponding building footprint were removed from the dataset to create a 2006 address dataset, although buildings demolished between 2006 and 2013 have not been included.

8.2.1.2. Network creation

The spatial threshold in this research was defined by Natural England's ANGSt guidelines (Natural England, 2010). ANGSt recommends that everyone, wherever they live, should have accessible natural greenspace of at least 2 hectares in size, no more than 300 metres (5 minute walk) from home. The network dataset was created in ArcGIS 9.3 using the Network Analysis extension. OS Integrated Transport Network (ITN) data, as described in Section 4.2.8, was used as the transport route data. Default connectivity settings were applied under the assumption that walking was the only method of travel, which did not account for other specific transport obstacles (one-way systems, traffic lights etc.). A walking speed of 1 m/s as recommended by ANGSt was used. This means that vertex length (m) could be used for route impedance values. Locations beyond 300 m of the point of interest were deemed to have no access.

8.2.1.3. Service areas and buffers

Service areas represent the total area of accessible space, either from greenspace access points or from individual residences. Service areas were derived using the Network Analysis extension in ArcGIS 9.3. Service area analysis calculates the length of every journey along the network from the origin point based on a predefined distance threshold (ESRI, 2008b). The outer boundaries of these journeys are then joined together around the origin point to create a polygon that defines the area within which it is possible to travel the defined distance. This is called a service area. For this research, the origin points were the greenspace access points for the first approach and households for the second approach; the distance threshold was set to 300 m. As the research is only concerned with residents walking along a network, impedance factors along the network such as one-way systems and speed limits were not considered.

Traditional methods used by local councils employ Euclidean (straight line) buffers around points ignoring route information. SCC use a 300 m buffer to replicate a 500 m threshold, citing a 40% reducing in Euclidean distance to compensate for passage along a non-linear route (SCC, 2006). This research replicated the SCC approach by creating service areas around origin points using Euclidean 300 m buffers. This approach creates service areas that are circles and which therefore represent the largest area within which it is possible to travel 300 m.

8.2.2. Viewshed analysis

Visible accessibility used viewshed analysis as described and justified in Section 3.6.2. Building centroids were used as observer points because OS AddressBase data used in the network analysis (Section 8.2.1) includes overlapping points where a single building has multiple addresses. The building centroids were offset onto the closest vertex of the OS ITN road network. This simulates a person standing in the middle of the street or at the front of the building. This was done because the observer points are within features (buildings) that extrude from the surface of the earth. This means that when viewshed analysis is completed, the view is often the inside of the building. This is because the observer points actually lie underneath the DSM. This is a particular problem for buildings with a large footprint. The viewshed analysis used in this study required observation points with related height information. The analysis is based on a 5 m DSM, described in Section 4.2.3.

Viewshed analysis was completed in ArcGIS 9.3 using the 3D Analyst toolkit. The input surface was the DSM and input observer points were the offset building centroids. Viewshed analysis calculates which DSM pixels can be seen from an observer point to create a grid of visibility. This is repeated and aggregated for each observer point to produce a grid of pixels whose value represents the number of observer points that can see that pixel. Pixels with a value of 0 are not visible.

For changing observer heights, a number of assumptions were made. Firstly, the eye level of the average person is 1.6 m from the ground (Bin *et al.,* 2008). Secondly, a typical room is 3 m high (la Rosa, 2011). Finally, the top 3 metres of a building comprise unoccupied roof space (Bin *et al.,* 2008). Observer height was categorised to model different viewpoints of Salford (Table 8.2). The first two rows of Table 8.2 represent 99% of residential dwellings. Categories for taller buildings were derived from the national building classification (Geoinformation group, 2012). The classification includes a building class called tall flats, which are typically 6 – 15 storeys. The third and fourth rows of Table 8.2 present the observer heights to be used for these taller buildings, which are present in areas of Salford such as Salford Quays and around the University of Salford.

Table 8.2. Observer heights used in viewshed analysis

Height of building	Observer height (m)
Ground floor	1.6
First floor	4.6
6 storeys	16.6
15 storeys	43.6

Observer heights were used to simulate an observer being a) stood up from the DSM surface and b) stood on different floors of a building. Observer heights were used to increase the height of the observer point above the DSM. Final viewshed outputs were created as raster grids. The value of each cell was the number of observers it could be observed by.

8.2.3. Relating accessibility and visibility to landscape and socio-economic factors

To determine how accessibility is related to the landscape mosaic, the results from Sections 8.2.1 and 8.2.2 were assessed against the land cover map created in Section 5.5. For simplicity, land covers were aggregated to form a Green/Not green land cover map. Green is represented by the aggregation of trees, vegetation and water. Not Green is represented by aggregation of impervious, mixed, buildings, bare earth and peat. Although bare earth and peat land cover types can make up part of an urban greenspace area, these have not been included in the Green category because there are many instances where these land covers appear without adjacent vegetation or trees and would not constitute a greenspace. Further experimentation could focus on how the distribution of bare earth and peat could contribute to aesthetic value.

Patterns of accessibility were assessed against the Index of Multiple Deprivations (IMD) as a standard measurement of relative deprivation across the UK. Regions inside and outside ANGSt service areas, and inside and outside SCC service areas, were compared with the overall IMD index and the individual domains of deprivation.

8.3. Results

8.3.1. ANGSt greenspace accessibility

Based on a 2006 – 2007 survey monitoring greenspace standards by ward in Salford, SCC identify that, 49.3% of addresses are located within a 300 m straight line of target greenspaces (SCC, 2011). This falls short of their Strategic Development Plan (SPD) target of 76%. This compares to 30.8% of addresses within the ANGSt catchments when applying a 300 m network approach, which replicates the ANGSt guides. Figure 8.3 presents the spatial distribution of greenspace access service areas for both guideline thresholds. In terms of area, 19% of Salford is within ANGSt service areas, while 76% lies within SCC service areas. Figure 8.4 and Table 8.3 present the percentage of addresses with greenspace access by administrative ward in Salford. Darker shaded areas represent wards with a higher percentage of accessibility. Distribution of access is uneven. Clarendon in the centre of Salford has the most accessibility, while Pendlebury, Kersal and Little Hulton to the north and Cadishead to the south also have high accessibility. Conversely, central and south eastern wards have low accessibilities. Ordsall in the south east has the lowest accessibility. Correlations with the index of multiple deprivation (IMD) are weak and insignificant for both service area types (ANGSt, r = 0.1; SCC, r = 0.23).

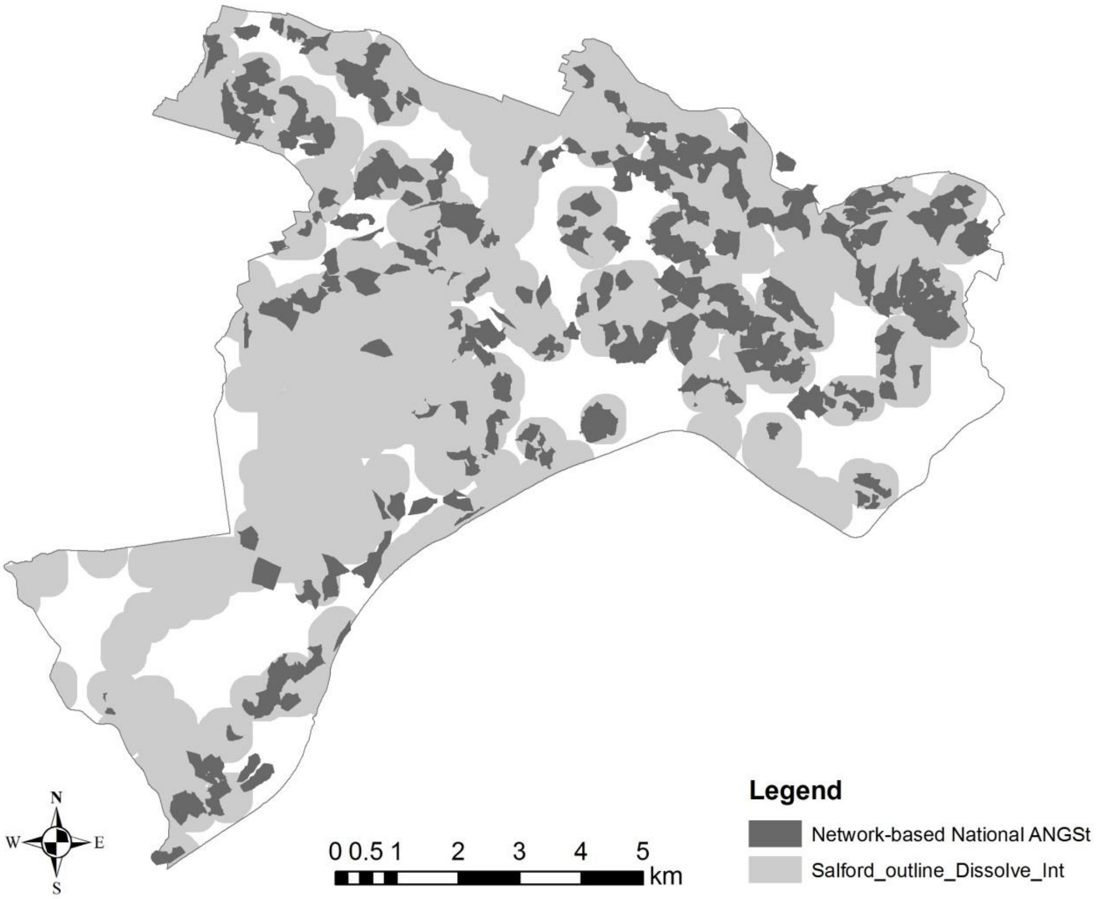

Figure 8.3. SCC Service Areas (Light grey) and ANGSt Service areas (Dark grey) (Author's own).

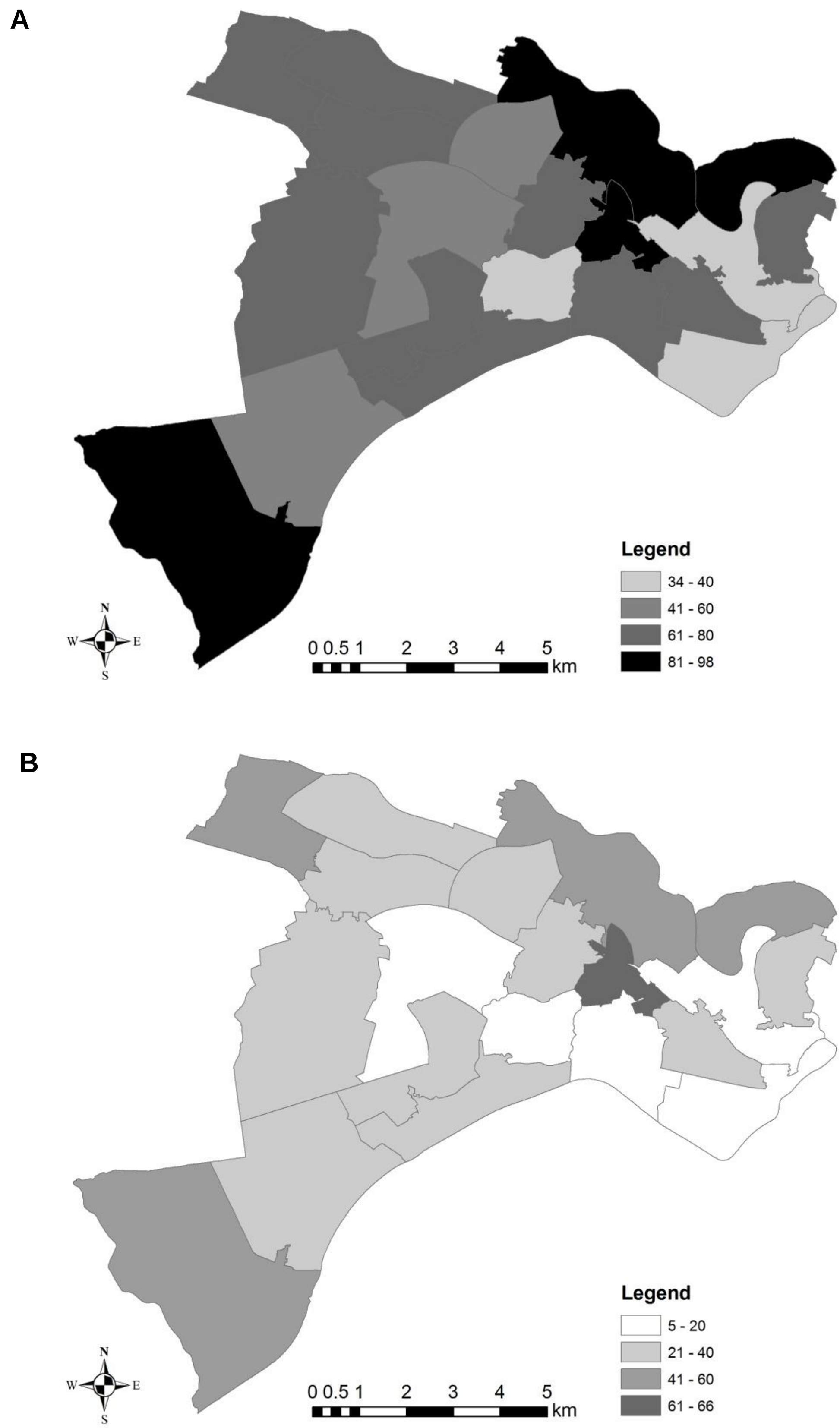

Figure 8.4. Percent of addresses inside (A) SCC service areas and (B) ANGSt service areas by ward (Author's own).

Table 8.3. Percentage of addresses within accessibility guidelines based on SCC service areas and ANGSt service areas for The Accessible Natural Greenspace Standard (ANGSt) and the Salford City Council (SCC) guidelines.

Ward Name	ANGSt (%)	SCC (%)
Broughton	39.0	72.9
Walkden South	30.4	70.5
Irwell Riverside	15.4	34.5
Walkden North	27.5	63.6
Kersal	47.1	84.9
Irlam	22.8	47.6
Winton	29.3	71.0
Swinton South	35.9	61.4
Eccles	16.8	37.7
Pendlebury	47.1	86.7
Claremont	65.8	97.6
Boothstown and Ellenbrook	22.8	65.1
Weaste and Seedley	16.1	67.1
Ordsall	5.1	36.4
Langworthy	36.0	62.4
Swinton North	36.5	58.0
Barton	25.4	75.7
Worsley	18.9	55.0
Cadishead	43.4	93.4
Little Hulton	48.6	75.2

Table 8.4 presents the percentage of population resident in each of the urban land use (derived in Chapter 7) that has access to 2 ha greenspaces and lies within either the SCC service areas, or network-based ANGSt service areas. Green and Blue spaces and Trees are not included due to the absence of residents in these areas. For the character types specifically designated as residential, between 32% and 39% of addresses are within ANGSt service areas, with Terraced housing areas having the highest percentages. However, of the residential landscape character types, Terraced housing areas have the lowest percentage of addresses within SCC service areas, while Detached areas have the highest percent of addresses within SCC service areas.

Table 8.4. Percentage of addresses with physical access to an ecosystem service by land use. Values in the table represent the mean average of percentages by OA.

Land use	Average percent of addresses inside National ANGSt service areas (%)	Average percent of addresses inside SCC service areas (%)
Agriculture	32.1	80.8
Non-domestic	20.0	59.2
Detached	36.8	85.4
Semi-detached	32.3	76.7
Terraced	39.6	70.2

Physical and visual accessibilities to audited greenspaces are presented in Figures 8.5 to 8.7. Figures 8.5 and 8.6 present the density of potential physical accessibility for the SCC service areas (Figure 8.5) and ANGSt service areas (Figure 8.6), where darker green areas represent lower density access. Figure 8.7 presents the most visually accessible 2 ha greenspaces from a ground floor observation. Relationships between level of accessibility present distributions that have no correlation ($n = 116$, $r_s = 0.045$, $p > 0.1$). Figure 8.6 emphasises the high population density and relative lack of greenspace in the east of Salford. The most visible greenspaces (Figure 8.7) tend to be wooded areas more widely distributed across the centre of Salford.

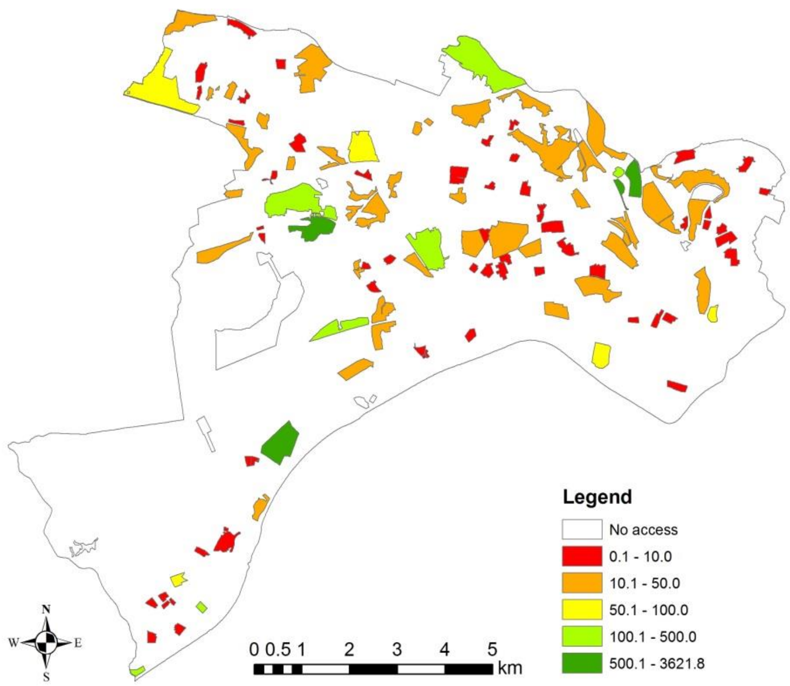

Figure 8.5. ANGSt greenspace physical accessibility based on the ANGSt service areas. Values are hectares per 1000 population. Population is based on an estimation of 2.3 people per address (ONS, 2014) (Figure is Author's own).

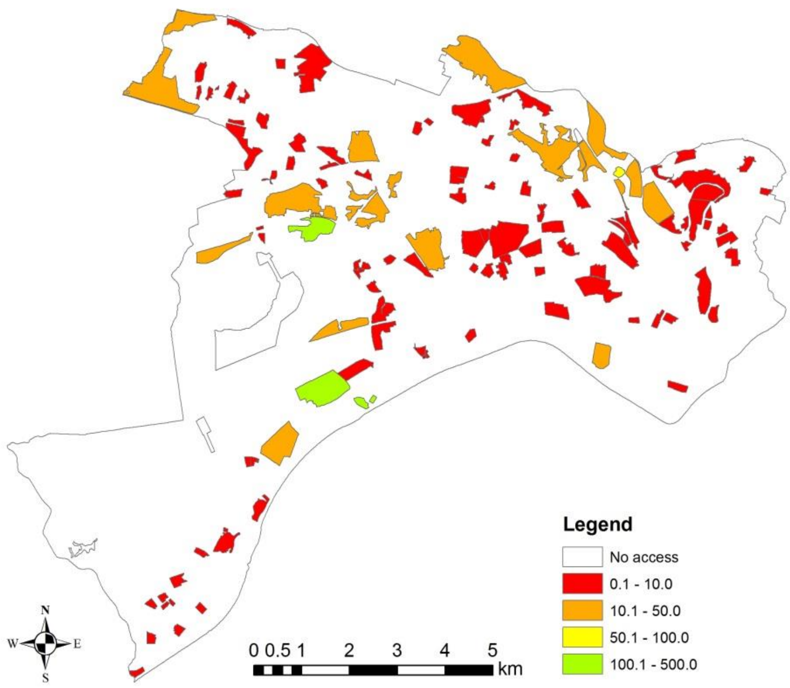

Figure 8.6. SCC greenspace physical accessibility based on SCC service areas. Values are hectares per 1000 population. Population is based on an estimation of 2.3 people per address (ONS, 2014) (Figure is Author's own).

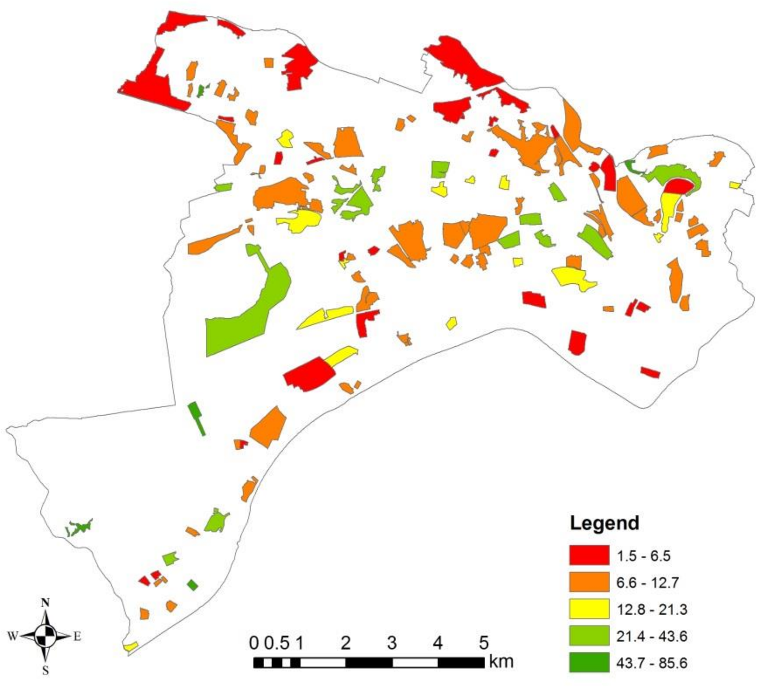

Figure 8.7. 2 ha greenspace visibility. Values represent the average number of observers that can see the greenspace based on 100 m^2 cell-level observation counts (Author's own).

8.3.2. Residential landscape composition

This section considers greenspaces unaudited by the local council, but identified using the land cover map created in Chapter 5 to gain an understanding of the contribution that these greenspaces make to overall access to nature. These include wide areas of physically inaccessible agriculture as well as informal greenspaces such as brown field sites and roadside verges. Figure 8.8 presents the coverage of physically accessible land in green, based on residential network-based service areas, the visible land from the ground floor in red and areas that are physically and visibly accessible in yellow. Just under a quarter of Salford is neither visible nor accessible for the population (Table 8.5) although 42% (shaded yellow) is accessible and visible for at least part of the local population. The yellow area represents a 55% overlap in physical and visual coverages and highlights the fact that more land is visible (red) than physically accessible (green).

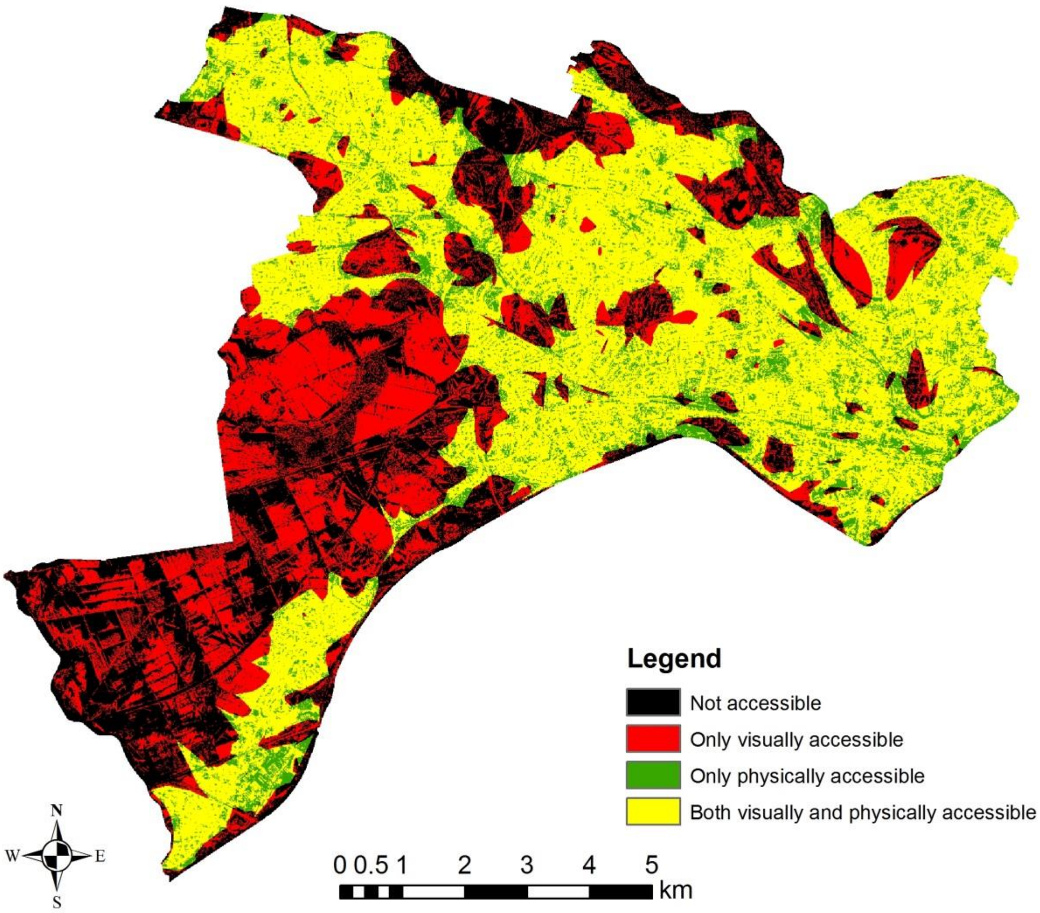

Figure 8.8. Accessible landscape: red only visually accessible, yellow only physically accessible, green accessible both visually and physically (Author's own).

Table 8.5 Accessibility statistics by area of Salford across the top row (km^2), and percent of Salford's area across the bottom row

	Not Accessible	Physically Accessible	Visible	Accessible and visible
Area (km^2)	23.6	51.4	62.6	40.5
Percent	24.3	52.9	64.5	41.7

Table 8.6 separates physically accessible and visible landscape into Green and Not Green as described in Section 8.2.3. Just under a third of Salford's physically accessible land is Green (15.1 km^2 out of a total of 51.4 km^2), while the rest is Not Green (36.6 km^2). More of Salford's visible landscape is Not Green (36.3 km^2 out of 64.5 km^2) compared to Green (27.7 km^2).

Table 8.6. Area (km^2) of physically accessible and visible greenspace across Salford. The columns represent the area of land classified as Green and Not Green using the land cover map created in Chapter 5

	Green (km^2)	Not Green (km^2)
Physically Accessible	15.1	36.3
Visible Ground floor	27.7	35.0

Table 8.7 presents the percentage of physically accessible and visible Green space by network-based household service areas and household service areas created using Euclidean 300 m buffers. The table shows that visual access to green space is much higher than physical access. Buffered household service areas contain a larger proportion of greenspace than network service areas for all buildings regardless of where they are. In all cases, buildings located outside accessibility service areas have access to the lowest proportions of greenspace.

Table 8.7. Mean percentage of greenspace physically accessible or visible for buildings outside and inside different accessibility service areas.

	ANGSt	SCC	View at ground floor
Inside network	19.2	34.1	50.8
Inside buffer	18.2	30.8	46.6
Outside all	15.9	19.5	43.8

Buildings located within the 300 m network have access to the highest proportion of greenspace. Mann-Whitney statistics suggest that buildings located inside and outside the accessibility service areas are significantly different ($p < 0.01$) (Table 8.8). However, as the population is very large ($n = 103005$), effect sizes have been calculated. Effect sizes describe the magnitude of difference between two groups (Coe, 2002). This is commonly used for very large data samples, which are likely to produce high significance values and statistical scores even if populations appear to be very similar. This is because statistical measures are often based on absolute differences or ranked values. Very large datasets are likely to have a large number of small differences, which can impact on the significance as evidenced in Table 8.8 The effect size for outside/inside ANGSt service areas is small indicating that the variance is explained by the population size rather than the population values. However, the effect size for inside/outside SCC service areas is 0.41, which is just below a medium effect size (Cohen, 1988). This means that the differences between populations within SCC are more likely to be different than populations within ANGSt service areas populations, which are less likely to present significant differences. In real terms this means that populations located inside SCC service areas are more likely to be able to see and access a higher percentage of greenspace, whereas being located inside or outside ANGSt service areas presents less of a pattern.

Table 8.8. Mann-Whitney statistics and accompanying effect sizes ($p < 0.01$)

	Inside/outside ANGSt guides		Inside/outside SCC guides	
	Mann Whitney U	**Effect size**	**Mann Whitney U**	**Effect size**
Proportion green	1273701607	0.11	1708383733	0.41

8.3.3. The impact of changing observation heights

The distribution of buildings by height category across Salford is presented in Figure 8.9. There are high densities of one and two storey buildings across the majority of Salford apart from the South West region, which is predominantly occupied by agriculture. Taller buildings (6 storeys plus) are typically found towards the east of Salford, near Manchester city centre and Salford Quays in the south east. However, clusters of taller buildings are also present in central urban areas such as Eccles and Swinton.

Relating building height to the physical service areas, a larger percentage of taller buildings (6 and 15 storeys) are outside the physical service areas including almost 60% of all 15+ storey buildings (Table 8.9). On the other hand, only 9.5% of single storey and 14.7% of two storey buildings were outside. Approximately half of the buildings inside SCC service areas were also inside the more stringent ANGSt service areas, although the proportion for six storey buildings was closer to a third.

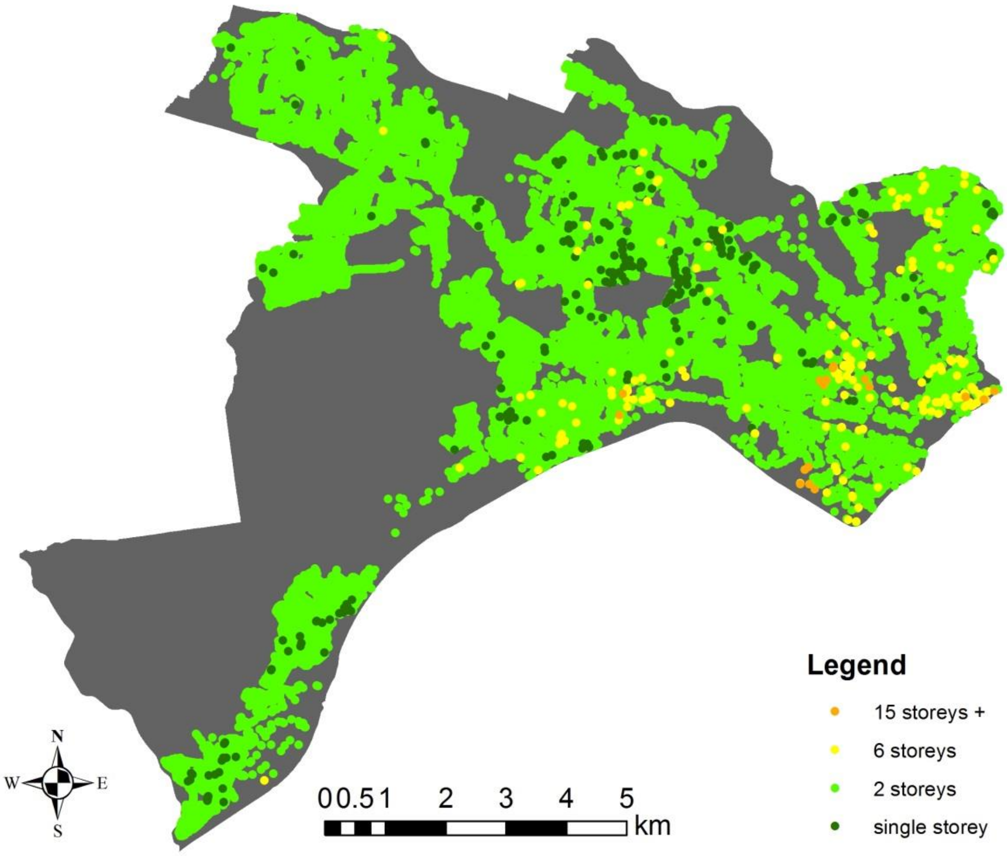

Figure 8.9. Building heights across Salford (Author's own). This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown (2015).

Table 8.9. Number of buildings of different height located inside and outside of SCC and ANGSt service areas. Percentages are calculated by building height.

Building Heights	Outside all service areas		Within SCC service areas		Within ANGSt service areas	
	Number	%	Number	%	Number	%
Single storey	42	9.5	259	58.3	143	32.2
Two storey	5761	14.7	22845	58.1	10713	27.2
Six storey	87	43.1	83	41.1	32	15.8
Fifteen storey	13	59.1	6	27.3	3	13.6

Single and two storey buildings are highly correlated and 6 and 15 storey buildings are highly correlated, but other pairings are not, suggesting a clear separation between shorter and taller buildings (Table 8.10). This is reinforced by the visibility distributions in Figure 8.10, which also show that visibility increases with observation height. This is because barriers become easier to overlook. For shorter buildings, which cover most of Salford, the highest visibility occurs largely in wooded areas across a West-East transect. For taller buildings, greenspaces surrounding the river Irwell to the East are highlighted as being more visible.

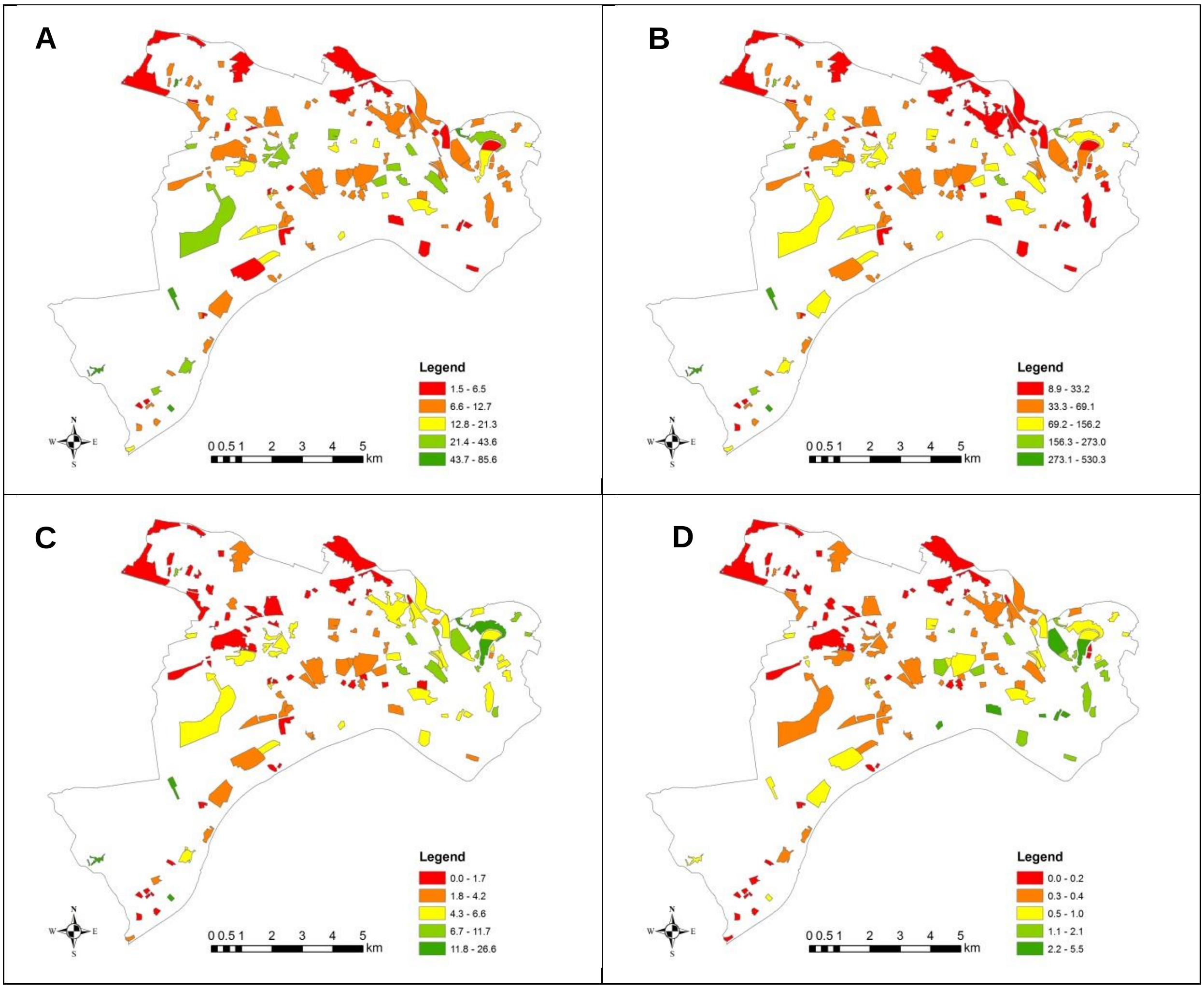

Figure 8.10. Visibility of Salford City Council audited 2 ha greenspaces at (A) ground floor level, (B) 2nd floor, (C) 6th floor, and (D) 15th floor. Values are the average number of observers that can see the greenspace based on cell-level observation counts (Author's own).

Table 8.10. Spearman's rank correlation for different view heights. All correlations significant at p <0.01.

	Single storey	Two storey	Six storey
Two storey	0.90		
Six storey	0.51	0.46	
Fifteen storey	0.32	0.24	0.79

Gaining an extra storey from the ground floor increases the area of Salford that can be seen by approximately 10% (Table 8.11). This increases the percentage of visible Green to 34.5%. From lower observation heights (one and two storey), more Not Green than Green can be seen. Higher observation points better reflect the 50/50 proportions of Not green and Green across Salford. There are only a small number of buildings of 15+ storeys (total = 19), but observers at the top storey of these buildings can observe 18.0% of Salford.

Table 8.11. Area (km^2) of total greenspace visible at different observation heights.

Building Heights	Green		Not Green	
	Area	%	Area	%
Ground floor	27.7	28.5	35.0	36.0
Second storey	33.5	34.5	39.7	40.8
Sixth storey	18.1	18.6	17.7	18.2
Fifteenth storey	8.6	8.8	8.9	9.2

Table 8.12 presents a further breakdown of land cover elements accessible both physically and visually from different heights. The breakdown of 'Green' land cover contains similar proportions of water and trees, but more low-lying vegetation can be observed than physically accessed (27.3% compared to 11.0%). As observation height increases, proportions of land cover for single and two storey observations remain constant as the height difference is relatively small. Conversely as the observation height increases to six storeys, the proportion of mixed land cover decreases, while the proportion of visible buildings increases. The height increase from six to fifteen storeys presents the greatest change, potentially due to the fact that the fifteen storey buildings are clustered to the east of Salford (Figure 8.9). Here, the proportion of vegetation reduces from 28.6% to 20.6%, while the proportion of trees increases from 18.9% to 23.3%. Further, while the overall proportion of Not

Green has increased, most of this is composed of buildings. Across the range of heights, proportions of bare earth visible remain relatively stable at approximately 4% of the total view, while impervious surfaces experience a slight increase, rising from 12.7% to 14% of the total view.

Table 8.12. Percentage land cover accessible within residential service areas and visible at different observation height. Values in each cell represent the percentage of a given land cover type (column) that is physically accessible and visible from a given observer height (row).

Access	Trees	Buildings	Water	Peat	Vegetation	Bare Earth	Impervious	Mixed
Physically accessible	17.2%	15.1%	0.7%	0.0%	11.0%	2.5%	17.8%	35.6%
Ground	16.8%	11.4%	0.8%	1.7%	27.3%	3.8%	12.7%	25.5%
2^{nd}	16.3%	10.2%	1.1%	1.6%	29.2%	3.9%	12.6%	25.1%
6^{th}	18.9%	13.3%	1.8%	2.0%	28.6%	4.2%	13.0%	18.2%
15^{th}	23.3%	18.5%	2.4%	0.6%	20.6%	3.9%	14.0%	16.8%

8.3.4. Accessibility and deprivation

Table 8.13 presents median values for socio-economic characteristics across Salford and Mann-Whitney statistics for populations inside and outside ANGSt and SCC service areas. Overall, the most deprived people live in locations that are outside ANGSt and SCC service areas. This is indicated by lower IMD values in the third column of Table 8.13. The least deprived residents live within SCC service areas, but outside the ANGSt service areas. Breaking down the Index of Multiple Deprivation (IMD), this trend exists for income, employment, health, crime and environment. However for the Education and Barriers dimensions of the IMD, the least deprived locations are outside all the guides. Mann-Whitney statistics suggest that socio-economic categories are significantly different for locations that are inside and locations that are outside the ANGSt service areas, apart from income and employment dimensions (shaded grey in Table 8.13). These relationships are similar for locations that are inside SCC service areas and locations outside SCC service areas except the education dimension also presents higher p values ($p > 0.05$). This suggests that the distribution of these dimensions is similar for both populations. However, in all cases, the effect sizes are very small, which indicates that the large population size may be exaggerating significance.

Table 8.13. Median values for IMD and Mann-Whitney statistics with effect sizes. For the IMD columns, lower values are more deprived. Areas shaded grey are significant at p < 0.05.

IMD Component	Median values			Inside/outside ANGSt service areas		Inside/outside SCC service areas	
	Inside network	Inside buffer	Outside all	Mann Whitney U	Effect size	Mann Whitney U	Effect size
IMD Overall	6547	6987	5828	1140317029	0.01	1173551501	0.03
IMD Income	8231	8528	7645	1119621098	0.00	1140898020	0.01
IMD Employment	6882	7381	6121	1132365271	0.00	1138223075	0.00
IMD Health	2678	2963	2238	1197739060	0.05	1239859132	0.07
IMD Education	8441	8639	8736	1114028052	-0.01	1130863977	0.00
IMD Barriers	17668	17285	17900	1087836348	-0.03	1051638870	-0.06
IMD Crime	6527	6681	5370	1134909719	0.02	1245660669	0.08
IMD Environment	13809	14573	12256	1143992495	0.01	1242326831	0.08

8.4. Discussion

Access to greenspace is important for urban residents as a means to enhance and maintain physical and mental health (Natural England, 2010). In the UK, ANGSt guidelines have been created for local councils to use as benchmarks for determining physical accessibility to a range of urban greenspaces. These guidelines have been incorporated into a number of local council greenspace assessments, but the guides are arbitrary and measurement definitions are vague. The guidelines also do not consider observer visibility across a landscape, which may contribute to a resident's cultural ecosystem service requirements. Further, the ANGSt guidelines only consider greenspaces above 2 ha. This is a large area when considering potentials for retrofitting into existing urban areas (Barbosa *et al.,* 2007).

The research presented in this chapter has assessed the physical accessibility of Salford as a representative UK city, based on current greenspace accessibility guidelines, taking into consideration transport routes as well as access points to those greenspaces. This study additionally considered the impact of greenspaces smaller than 2 ha and how they may positively impact on physically and visually accessible space in the city. Finally, this chapter presented the contribution that visibility across a 3D landscape may have on analysis of urban greenspace accessibility.

8.4.1. Accessible greenspaces

The results presented in Section 8.3.1 show that the more relaxed SCC methodology and service areas produce a 50% rise in the population with access to greenspace. However, the difference in potential greenspace accessibility increases from 19% to 76% of Salford (Figure 8.3), meaning that SCC service areas cover almost 300% more area. This suggests that the positioning of 2 ha greenspaces across Salford is sufficiently close to urban populations that a large increase in accessible space relates to a relatively small increase in population with access. This difference can largely be explained by the approach taken by SCC to use the whole greenspace polygon as a unit compared to the use of individual points of access in the ANGSt network approach, which is arguably more realistic (Comber *et al.,,* 2008; Higgs *et al.,,* 2012). The results found in section 8.3.1 can be used to determine not only how popular parks might potentially be, but also the impacts of changing distance thresholds. This information can then be use to tailor guidelines to suit the unique geographies of individual cities. Alternatively, by considering a standard level of accessibility (e.g. percentage population), comparisons can be made between urban areas and national averages. Analysis of how patterns change when distance thresholds change would also provide information on the sensitivity of physical accessibility distances and assist in optimising a more scientifically robust measurement.

There is an underlying assumption that people will travel to the closest 2ha greenspace. Dallimer *et al.,* (2012) suggest that this may not be the case as personal motivations and differences in greenspace facilities may mean that people are willing to travel further for a better park. In this case, further research could usefully focus on actual visitor numbers. Further investigation into the nature of greenspaces would assist in improving this analysis, as would determining local perceptions of specific greenspaces in order to better capture and maintain local character as well as better understanding how people use different greenspaces in different ways (Seaman *et al.,* 2010).

A major critique of the 3D visual analysis is that it has been conducted under the assumption that green (and blue) spaces are attractive, while developed, built-up spaces are not. This does not take into account attractive architecture or landscape maintenance. For example, Gospodini (2001) demonstrates that historical and architectural components of urban structures are valuable assets for defining a city's unique character and the form that they take can inform and encourage tourism and recreation activities. The actual nature of those greenspaces and what might make them unique features in the landscape is ignored, although larger urban greenspaces have been linked in Chapter 6 and Figure 7.14 as major producers of ecosystem services. Van Leeuwen *et al.,* (2010) emphasise the importance of multifunctional urban greenspaces, but clearly, some green land uses may only be suitable for certain activities. This means that the closest greenspaces may not be the most desirable for residents. For example, the above research includes four golf courses, which comprise 180 ha of the accessible greenspace. Spaces such as golf courses are used for a single recreational purpose and are exclusive to paying members (Fisher *et al.,* 2009), but are also becoming increasingly recognised for their conservation value in rapidly urbanising areas (Hodgkinson *et al.,* 2007).

Public parks have proven to be among the most physically accessible greenspaces (Table 8.1), particularly in more deprived areas towards the east of Salford (Figure 8.5). Here, higher building (and population) densities reduce the greenspace ha per 1000, increasing potential density of use. However, Moseley *et al.,* (2013) warn that this is likely an overestimate particularly when considering areas where government health initiatives are in place. Further, Villaveces *et al.,* (2012) and Chong *et al.,* (2013) demonstrated that perception of greenspaces in more deprived areas is related to higher levels of psychological distress due to safety concerns. This means that it is likely that fewer people are using urban greenspaces in more deprived areas. This influences patterns and scales of use, particularly when considering the probable health, fitness and activity levels of different demographic groups (van Holle *et al.,* 2014). By identifying the patterns of accessibility across Salford, the information derived in Section 8.3.1 can be used to develop decision support tools similar to that of Laing *et al.,* (2009) who integrate physical accessibilities and digitally rendered visualisations of greenspace into a GIS database which also included spatial, ecological and park attribute information.

As mentioned in Section 8.2.1.2, the walking speed used in this research is slower than 1.34 mps (3 miles per hour), which is used more commonly in the literature (Browning *et al.,,* 2006). As this walking speed is a third faster, service areas are larger and more houses have access. This is modelled in Figures 8.11 and 8.12, which compare the increased walking speeds with the 1 mps used in this study.

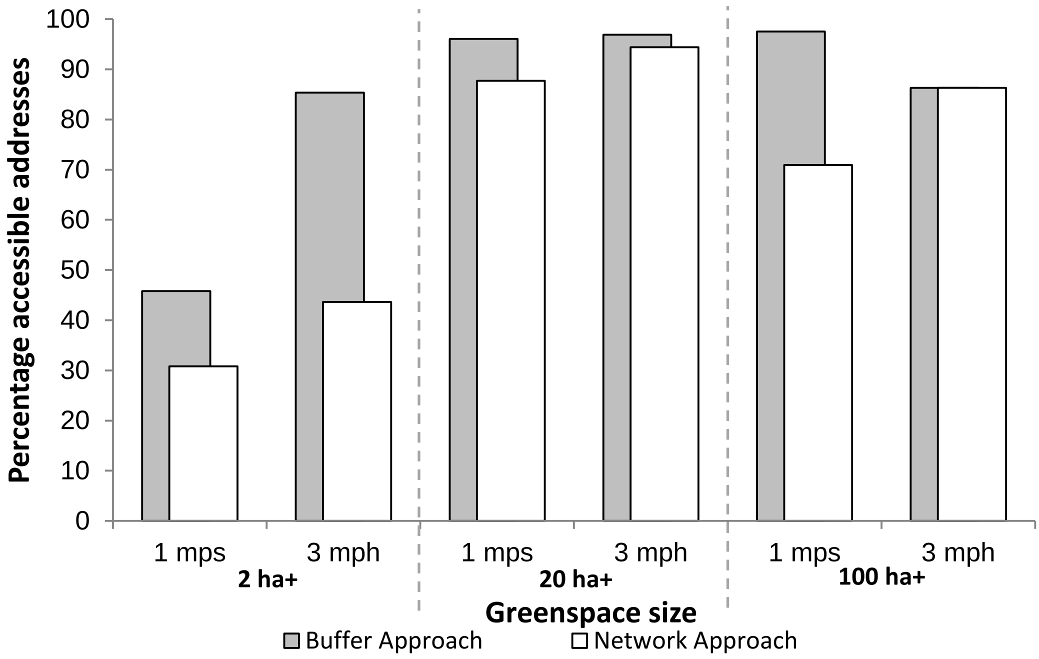

Figure 8.11. Percentage of addresses falling within accessibility service areas at walking speeds of 1 mps and 1.34 mps using the SCC-audited greenspaces and applying ANGSt and SCC service areas.

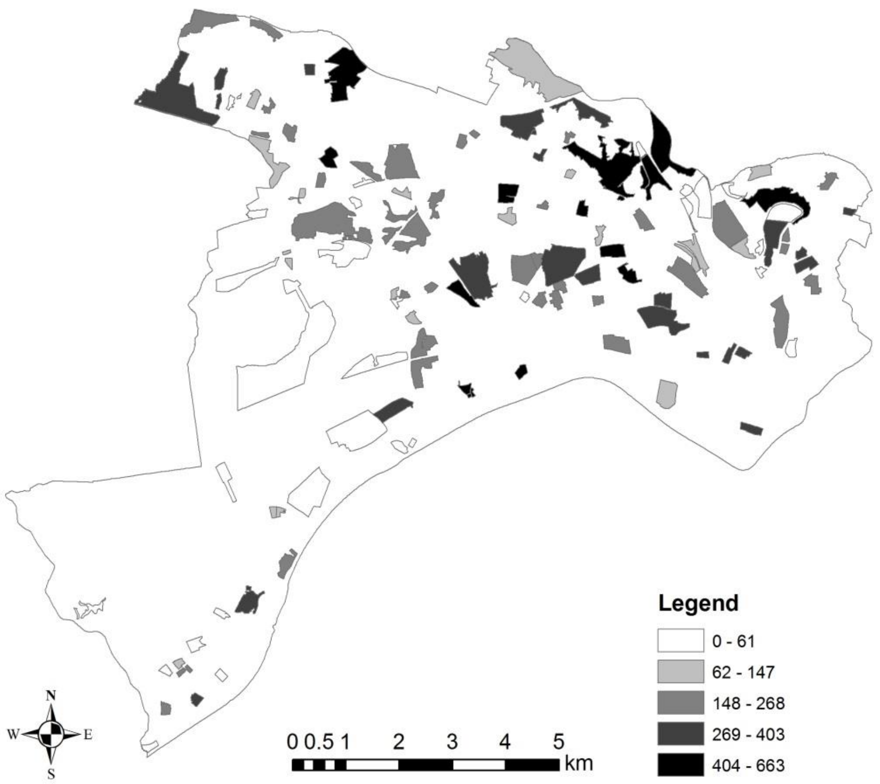

Figure 8.12. Increase in accessible population when walking speed is increased from 1 mps to 1.34 mps using SCC audited greenspaces (Author’s own).

The bars in Figure 8.11 show that at 1 mps, SCC service areas increase percentage accessibility by 15% and at 1.34 mps by 44.5%. An increase in speed from 1 mps to 1.34 mps using ANGSt service areas increases the accessible addresses by 12.8%. There is a difference of 54.5% accessible housing when comparing a 1 mps network-based service area approach against a 1.34 mps SCC buffered service area approach, which equates to either 30.8% or 85.3% accessible addresses. This is represented spatially in Figure 8.12, where shading represents the changes in accessibility as walking speed increases from 1 mps to 1.34 mps. Road speed limits were also trialled, but are not relevant to ANGSt service areas.

8.4.2. The accessible landscape

Residents living in locations outside any of the accessibility service areas (Tables 8.5 and 8.6) experience a lower percentage of greenspace in their local service areas. However, those living within SCC service areas tend to have a higher percentage of accessible greenspace than those within the ANGSt service areas. This highlights that the contribution made by smaller unaudited greenspaces is unevenly distributed, but also highlights that residents within ANGSt service areas live closer to large greenspaces, without other greenspaces nearby. Van Herzele and de Vries (2012) highlight that view of urban greenspace from households directly relates with perceptions of happiness and neighbourhood greenness. This is a particular issue in Britain, where traditional, formal Victorian and Edwardian parks created within urban centres remain as large greenspaces, despite the surrounding urban areas that degrade as development continues at the outskirts (O’Reilly, 2013). Larger service areas based on SCC buffer zones will also incorporate more of the audited greenspaces than the smaller network-derived ANGSt service areas. The visible landscape follows intuition, with buildings within ANGSt service areas having the largest proportion of visible greenspace and those outside all guidelines having the lowest, although these values are generally much larger than the physically accessible spaces.

8.4.3. Impact of height

More of Salford is visible than physically accessible, and patterns of accessibility are unrelated. As view height increases, views get wider as expected, but generally also greener as evidenced by Figure 8.10. Further, the proportion of trees rises in comparison to lower lying vegetation as observer height increases, which can have a therapeutic and mentally restorative effect on residents (Lee *et al.,* 2009, Tsunetsugu *et al.,* 2013). However, only a small proportion of the buildings residents live on the higher floors and can therefore appreciate the views. The proportion of buildings also increases when compared to mixed land cover. As many of the taller buildings are in higher density urban areas, views tend to be less green, although a high percentage of woodland and buildings are visible. This is because they are defined as the extent to which an observer can see acting as ‘Green or ‘Not Green’ walls. This effect is diminished as observer height increases and the observer is increasingly looking over and down on the green barriers. Integration of house prices would introduce a useful development to this analysis, which would also tie results to hedonic pricing analysis. For example, Cavailhes *et al.,* (2009) find that high house prices are directly related to local urban greenspaces and in particular urban greenspaces that can be seen from the property. They find that local greenspaces that cannot be seen do not appear to contribute to house prices. As an alternative approach to observer visibility, the viewshed analysis used in this research could be applied to ventilation analyses following methods by Yang *et al.,* (2013) who also use sky-view factors and green-proportion indices to determine ventilation in urban areas in relation to urban morphologies. In particular, further analysis of the green and grey ‘walls’ of trees and buildings could be useful. Future research could seek to disaggregate this data to individual household viewsheds. This would require specialised programming skills and a high powered computing facility. This branch of research would produce a house by house analysis comparing physical and visual accessibilities to better determine how what a resident can see compares to where they can go.

A final issue with the viewshed analysis is that it does not give any weighting to distance. In effect, the observer can see forever, or until they reach the edge of the surface model (Bishop *et al.,* 2004). However, Yang *et al.,* (2009) found that the impact on view also depended on the size of the trees and the distance they were away. Figure 8.9 shows that all of the 15+ storey buildings are located towards the east of Salford, near the city centre and while visibility is enhanced from the top floor, the physical accessibility has not been considered from any point it the building other than from the ground floor. Living 15 storeys up, would take time to leave the building itself, before even travelling across the ground to get to an urban greenspace. For example, based on the recommended maximum step rise of 220 mm (Scott, 2005) a typical storey includes 13 steps, a 15 storey building would include 195 steps. If each takes a second to traverse a single step, the ANGSt guides would leave only 1 minute and 25 seconds of travel time from the base of the building.

8.5. Conclusions

This chapter has considered the accessibility of greenspaces using physical and visual methods and considering service areas of accessibility around audited greenspaces as well as individual residences. Inequalities of demand have been outlined by consideration of two methods of physical analysis. Network analysis is more conservative in its estimates of accessibility than Euclidean buffering, but is also more realistic in its consideration of access points and routes of travel. The changes in population with access are smaller than expected due to the distribution of the population. Increasing building heights generally increases the quality of the view as more greenspace is revealed. Further, the distribution of visible greenspaces shifts towards the east of Salford as view height increases. Further improvements can be made through the use of complex programming to develop viewsheds for individual buildings. However, this does represent a significant increase in processing powers.

This chapter has provided new insights into measuring access to greenspaces. In doing so, the visual access measurement provides opportunities for developing greater insights into cultural service access. In particular, the relationships between recreation, which by its definition involved immediate physical contact, and aesthetics, which includes the psychological and social benefits of green views. Visibility analysis is also particularly useful for consideration of demographics that are less mobile and less able to physically access green spaces. Underlying themes revealed in Chapters 5 to 8 are drawn together in the following Chapter. Links are made between ecosystem services and the underlying landscape, flows and relationships between generation and service accessibility and relationships between ecosystem services and human wellbeing.

9. Discussion

The discussion in this chapter returns to the original aim of the thesis (Section 2.6) to critically assess how well it has been achieved. The research aim was primarily borne out of a requirement to address the neglect of spatial patterns in ecosystem service analysis as raised by Haines-Young and Potschin (2008). The aim is as follows:

"To develop a new body of knowledge that focuses on how multiple ecosystem services are generated and consumed within a complex three dimensional urban landscape mosaic".

The discussions in this chapter critically review the extent to which a new body of knowledge has been created, how well it deals with mapping ecosystem services, relationships between ecosystem services, and trade-offs and synergies in ecosystem service flows.

The research contained in this thesis has built on these platforms, using a habitat approach as outlined by Potschin and Haines-Young (2013) (Section 2.3). Interpretations of the landscape have been developed, which are based on objective, remotely sensed imagery. These align with interpretations relating to generation and consumption of a range of ecosystem services in urban areas. The new body of knowledge stated in the aim builds on current ecosystem service assessments to incorporate spatial dimensions to analysis. This has created new observations, produced new questions to ask of ecosystem services and provided some answers to current questions.

9.1. Relationships between ecosystem services and the landscape

Landscape ecology in general and landscapes in particular are a natural platform for ecosystem service measurements as they are traditionally related to ecological measurements (Forman, 1995). Their physical definition carries additional benefits of being easily communicated to a range of audiences (Termorshuizen and Opdam, 2009). Consequently, ecosystems and landscapes are gaining in popularity both in academic research and in professional practice. Evidence for this is provided by their position in the UK government's Natural Environment White Paper (Defra, 2014) and National Planning Policy Framework (NPPF), (DCLG, 2012). Although ecosystem services are not central to these documents, Daily *et al.,* (2009) state that increasing availability and access to ecosystem service information can promote the credibility of ecosystem services for more successful integration into UK policy.

At a practical level, programmes such as the UKNEAFO (2014) are making significant contributions towards making the ecosystem approach through the ecosystem services framework operational. At a broad level, the research presented in Chapter 6, 7 and 8 can make a useful contribution to the ecosystem services tools for decision support, presented in the UKNEAFO (2014). This is demonstrated through a rapid and transferable method of measuring the generation and accessibility to ecosystem services. This process is made easier by alignment of the research outlined in this document with conceptual and methodological decisions made by the UKNEA. More specifically, research objective 2 contributes to this operationalising call by considering how ecosystem services can be measured using properties of the landscape. The research in Chapter 6 also considers the different spatial patterns for each ecosystem service and has demonstrated that regulating and cultural ecosystem services can be measured using patterns of landscape composition. The validation results from Chapter 6 (Section 6.3.2) suggest that regulating services provide stronger representations than cultural services. This trend is well documented in the literature (Fisher *et al.,* 2009; Raudsepp-Hearne *et al.,* 2010; Plieninger *et al.,* 2013) and producing cultural service measurements at the landscape scale remains a challenge. In following the UKNEA (2011) and UKNEAFO (2014), this research has developed quantitative measurements of environmental settings as a proxy for cultural services that can be used in parallel with current qualitative approaches.

9.1.1. Landscapes

The classification and characterisation of the landscape created in Chapter 5 is central to the modelling and analysis of the ecosystem service generation and accessibility in Chapter 6, 7 and 8. Consequently, the decisions made at this point have had the largest impact across the rest of the research. The classification of the landscape has proven to be a suitable and relevant basis for the measurement of ecosystem services in Salford. However, it is recognised that different test sites may contain different land covers of importance. For example, coastal cities may experience different patterns of ecosystem services resulting from the larger influence of the coast as a source of ecosystem services. For example, Marshall *et* *al.* (2012) cite the importance and fragility of beaches as a dynamic source of ecosystem services. Consequently, a scoping exercise of the test site would be recommended.

The discussions on the remote sensing imagery used (Chapters 3 and 5) have highlighted the balance that has been struck between the pixel size of the image (i.e. the level of spatial detail that can be achieved from the image) against the radiometric resolution of the image (i.e. the number of electromagnetic bands recorded) as discussed (Weng, 2012). This research chose imagery that favoured the wider applications available from a wide radiometric resolution by sacrificing the spatial detail. Of particular importance is the thermal infra red band, which has been a key input for the Bareness Index in the land cover classification (Zhao and Chen, 2005) and the climate stress mitigation generation layer (Chen *et al.*, 2006).

Sensors do exist that have a smaller spatial resolution, or a wider selection of radiometric bands. Wentz *et al.* (2014) state that the additional complexity would be useful for extract different types of urban features composed of different materials. For example, hyperspectral sensors have the capability to measure thousands of spectral bands (Thenkabail *et al.,* 2004; Heiden *et al.,* 2012; Hermosilla *et al.,* 2012), but this radiometric complexity is not required for this research because the use of spectral indices requires specific bands common to other sensors. Further, the spatial extent covers a smaller area; the availability of imagery is not as global as Landsat. These factors restrict the flexibility and generalisation of the method to other research sites and would change the fundamental approach taken to classify the landscape. Instead, this represents an interesting future branch of research, which could follow the call by Weng (2012) to fuse the results of multiple datasets together. This could work in a hierarchical fashion, whereby dense urban areas are targeted by the broader classification and fused with the more complex remote sensing information. This would have applications beyond ecosystem service research which could include urban heat island research (Memon *et al.* 2009), mapping urban morphology (Heiden *et al.* 2012), and improved extraction of bare earth land uses (Bannari *et al.*, 2006).

This thesis has outlined methodologies for creating models of ecosystem service generation and accessibility at the city-scale in urban areas via patterns of the 3D landscape mosaic. This type of analysis has previously only been completed at national and county level (Burkhard *et al.,* 2012; Koschke *et al.,* 2012). The landscape characterisation in this research (Chapter 5) satisfies research objective 1 by providing a suitable anthropocentric context for ecosystem service measurements. This has been coupled with a recognition from the literature cited in Chapter 2 that errors may arise from attempting to directly relate landscapes and ecosystem services together under the assumption that specific land covers/land uses generate specific ecosystem services (Termorshuizen and Opdam, 2009; Raudsepp-Hearne *et al.,* 2010; Burkhard *et al.,* 2012). Previous land use characterisations used in urban ecosystem service research have concentrated mainly on land uses dominated by the built environment, or consider research sites larger than single cities. For example, Tratalos *et al.,* (2007) use city centre, an inner suburb and inner suburb characterisations, while Raudsepp-Hearne *et al.,* (2010) and Egoh *et al.,* (2008) use national land use characterisations. However, the land use characterisation in this research also recognises the importance of land uses dominated by greenspace. This has involved manipulation of boundaries designed for collation of administrative, social and economic data (Output Areas), but in doing so, arbitrary boundaries are removed. This therefore provides a more effective arrangement of geographical boundaries for wider environmental analysis (Jellema *et al.,* 2009). Further, the method produced in Chapter 5 can be repeated quickly as it requires little manual interpretation.

By characterising OAs in Chapter 5, not only can a level of urbanisation be approximated, but levels of potential demand and accessibility can be inferred. A decision was made to attribute a single landscape character type to each Output Area. This was chosen to more easily communicate results and clarify patterns at a more general level, following the approach of studies by Comber *et al.,* (2012) and Higgs and Langford (2013). For example, the smallest OAs which represent the highest population densities are typically characterised as Terraced housing and Semi-detached housing land use (Table 5.10). They have the smallest levels of ecosystem service generation (Tables 6.12 and 6.13) and are often home to the most economically deprived members of society (Lee and Murie 1999). These results provide evidence for the concept of environmental justice (Pearce *et al.,* 2010), where the least deprived residents have the resources necessary to ensure that they have access to desired amenities and distance from undesired amenities. This is further demonstrated in Section 8.3.4, which shows that the most deprived people tend to live furthest from urban parks.

An alternative approach would have been to define key land character type characteristics and attribute a less certain membership to each Output Area, following similar methodologies to Sebari and He (2013). This would allow improved modelling of OA characterisation, and enhance the uniqueness of each OA. This would also allow more information to be used to analyse patterns in service generation and allow more than one landscape character type to appear in each OA. However, this adds complexity to analysis, which complicates presentation of results and can blur patterns and may be challenging to create in a scientifically robust fashion. Chapter 7 offers a third option of object-based spatial unit that is more explicitly tied to land cover patterns (Blaschke, 2006). This has assisted in developing ecosystem service characterisations that do not have to compromise spatial boundaries and that are not constrained by households. This means that the characterisations are theoretically stronger and can be disaggregated into component administrative boundaries to better derive the composition of these socio-political units (Jellema *et al.,* 2009). This method of generating bespoke spatial units suitable for environmental (ecosystem service generation) and socio-economic (ecosystem service consumption) indicators contributes to the research aim by offering a common spatial platform to conduct ecosystem service research at the city-scale.

9.1.2. Ecosystem services

Previous characterisations of ecosystem service and landscape have been shown to be highly correlated (Ericksen *et al.,* 2012; Raudsepp-Hearne *et al.,* 2010). However, Chapter 6 has shown that these correlations are complicated by a large amount of ecosystem service variation within land use character types. This is evidenced by the boxplots in Figure 7.4 and histograms in Figures 5.16 – 5.20. Woodland and Green and blue spaces present more variety in service generation while the shorter boxplots suggest that land uses characterised by larger urban proportions are less variable (Figure 7.4). The exception to this is agricultural land use, which is characterised by landscape uniformity. Figures 5.16 - 5.20 show that agriculture and terraced housing show the strongest clusters. Further evidence is provided in Figure 9.1, which presents the average number of overlapping hotspots by landscape character types (applying a spatial approach). Ecosystem services that have the largest number of overlapping hotspots belong to the Woodland and Green and blue spaces. Apart from a general trend of urbanisation (indicated by land use character types) linked to hotspots, there is a marked increase from densely urbanised residential and non-domestic areas up to greener human activities. Trees play an integral role in the provision of ecosystems service generation (Dobbs *et al.,* 2014), and consequently produce high levels of hotspots. This is further demonstrated in Chapter 6, which presented trees as integral to carbon storage, water mitigation and aesthetics service generation. Trees are also integral to forming green barriers to obscure urban views as demonstrated by changing observation heights in Chapter 8 (Table 8.11).

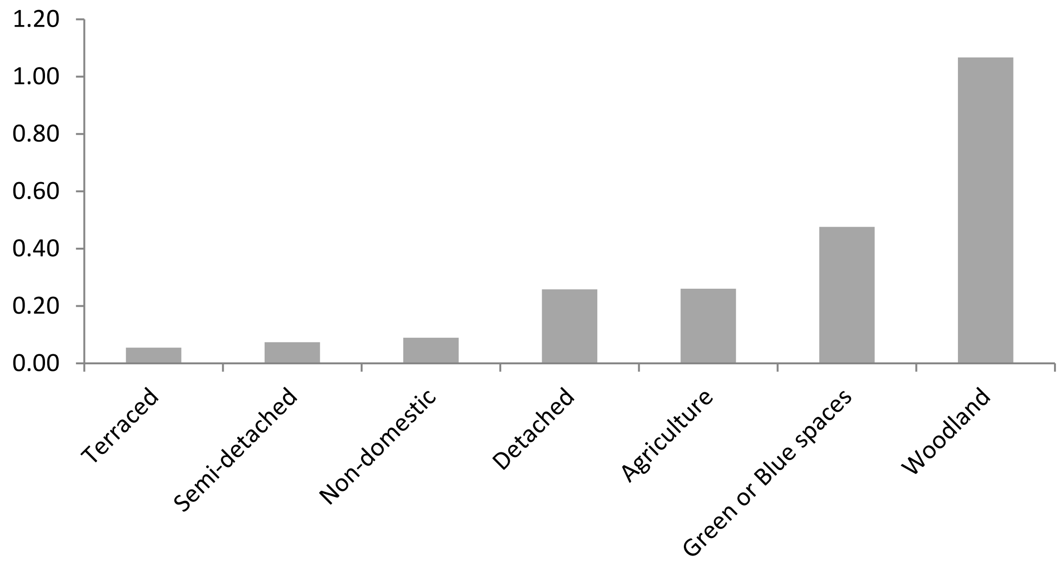

Figure 9.1. Average number of congruent hotspots by landscape characterisation (applying the spatial approach).

Analysis of service generation against land uses under research objective 2 (Section 6.3.3, Section 7.3.1 and Section 7.3.4) has demonstrated that in general, as urbanisation activity increases, ecosystem service generation decreases. This reinforces results found by Alberti (2005) and Kroll *et al.,* (2012) who focussed on relationships between ecosystem service generation and the composition of the landscape mosaic across the urban-rural gradient. Ecosystem service generation hotspots create similar patterns but climate stress mitigation is best represented in agricultural areas, while carbon storage is well represented in detached residential areas. Further, analysis of the number of overlapping services against land use (Section 6.3.3), reinforces the trends of environmental quality against the urban rural-gradient found by Luck and Wu, (2002) and Kroll *et al.,* (2012).

Research objective 3 of the research aim provides a novel perspective for approaching accessibility to ecological hotspots. By integrating visual and physical analysis together and by focussing on a desire for access to ecosystem services, a more informed picture is produced that better incorporates cultural services (van Herzele and Weidemann 2003). For example, aesthetics and recreational services, while both are cultural services and following the UKNEA, both rely on specific environmental settings; they should be perceived using different approaches. Recreation tends to demand immediate access and physical activity and use of the space. Aesthetics *may* also do this, but this is not a necessity and in some cases wider vistas from further away can offer more value than close up experiences (Sherrouse *et al.,* 2009). Consequently, consideration of visibility has a large part to play in how we think about cultural services. This is echoed and may be relevant for local councils, who place emphasis on provision of accessible, open and safe greenspaces (SCC, 2006). Within this context, the results found in Chapter 8, under research objective 3 only provides one side to the story. What is not known is how sustainable this is. How much activity can a specified area of greenspace withstand before the benefits it supplies are eroded? Conceptually, this depends on the activities occurring and the management regime in action. One direction of research has focused on the concept of ‘emergy’, which is the calculation of energy flows through a system (Huang *et al.,* 2011). This provides a useful measurement of how sustainable an area is, but as units of measurement are joules, this makes interpretation and communication with wider audiences challenging.

Added height information allows visibility studies to be calculated across a landscape as evidenced in Section 8.3.3. In particular, the research in Chapter 8 emphasises the importance of tree heights in defining visibility as a proxy for aesthetic services and develops work by van Herzele and Weidemann (2003), who considered concepts of space and perceived distance from urban areas as important for relieving stress. However, the research in Chapter 8 does not include the height of shrub layers, which can often form more of a solid green barrier than trees (Bartie *et al.,* 2011). This may be useful information for further consideration of the ecosystem service of noise buffering, where Daltrop *et al.,* (2012) found that dense hedges reduced noise levels the most, while the largest broad leaved trees scattered sound down into the shadow zone increasing sound levels.

In line with the research conducted under research objective 3 on the potential demand for greenspace in Chapter 8, analysis of how the resource is destructively consumed would provide a useful balance. Further, consideration of the destructive rate of different activities would assist in the management of greenspace use in urban activities. Along a similar vein, Zhang *et al.,* (2010) created two models to measure urban development and waste recycling capacities in four Chinese cities. Focussing on resource flows, they argue that high development can be buffered by high environmental carrying capacity and only when the balance is in favour of the resource consumption is there a problem. In this instance, the results of objectives 2 and 3 (implemented in Chapters 7 and 8) provide an alternative approach to discern supply and non-destructive demand for ecological resources and in particular cultural ecosystem services.

The research considers accessibility as a proxy for consumption; however Chapter 8 only considers the services that Bagstad *et al.* (2014) call provisioning services. i.e. those that directly provide a benefit rather than mitigate adverse affects. For the services chosen in this study, the focus is on aesthetics and recreation. These have been highlighted as among the most important services and have received less academic attention. As an alternative, other studies have focussed on different measures of demand and consumption. For example, Boyd and Banzhaf (2007) discuss the potential for economic accounting as a standardising measure, while Burkhard *et al.* (2012) consider a matrix of supply, demand and budgeting based on standardised scoring of spatial indicators. These measures are useful, and are anticipated to be complementary to the research in this thesis, which directly relates where services are generated to where the potential beneficiaries reside. This creates a simple, but direct metric for potential human well-being. Future research may focus on augmenting the results in Chapter 8 with more subjective community-based or public participatory approaches, following methods applied by Greg *et al.,* (2014), Raymond *et al.,* (2009) and Alessa *et al.,* (2008).

A further limitation lies in the fact that the analysis in Chapter 8 does not consider the exclusivity of landscape. Some areas of greenspace are unavailable to the general public as they belong to private companies or are located in inaccessible places.

Other greenspaces may require specific membership or ownership. Private gardens are a good example of this (Barbosa *et al.*, 2007). Another example returns to that of golf clubs cited by Hodgkinson *et al.,* (2007). Golf courses represent 11.8% of Salford's greenspace by area (Table 3.2). These spaces typically require membership gained by payment, which can exclude certain members of society. Traditionally, many golf clubs have had restrictions on female members, producing further exclusions. Exclusivity of use is not only formally enforced, but can be informally defined. Minority community perceptions and use of urban greenspace presented by Comber *et al.* (2008) and Byrne (2012) demonstrate that certain ethnic minority groups may feel less inclined to use public greenspaces as they are perceived to already be owned by more dominant cultures.

The research contained in this thesis is designed for UK urban centres. Salford has been selected as a typical urban centre and has presented a range of land uses typical of other major UK centres. However, the configuration of these features is not typical of a traditionally modelled urban area. Instead Salford can be visualised more as a sector of a larger urban area (Greater Manchester). This means that assessment of patterns is challenging and rural-urban transects would have to be measured from West to East. The methods are untested in newer urban centres; however, analysis of different urban areas would provide a useful comparison. For example, in reaction to organically 'grown', unplanned post-industrial cities (Douglas *et al.,* 2002), greater thought has been given to plan newer urban centres and eco-towns to minimise energy consumption and promote healthier living (Barton, 2009). Testing these different urban areas would provide interesting insights into how pre-ecosystem services and pre-ecologically sympathetic spatial planning has indirectly affected the patterns and flows of ecosystem services. This also means that careful definition of different areas by land use will theoretically allow for easier characterisation using the models in this thesis. Alternatively, analysis of other post-industrial urban centres such as Leeds or Sheffield may provide useful validations of the model. Further, the analysis has not been tested in rural areas, where the land cover map and selected land use character types would not be detailed enough to encapsulate a representative rural landscape mosaic (Kroll *et al.,* 2012).

9.2. Cultural Ecosystem services

By considering cultural services as products of environmental settings as recommended by the UKNEA (2011), Chapter 6 has offered an approach to quantitatively measure aesthetics and recreational services. However, use of the land cover classification in isolation has proven to be less suited to cultural service measurements. This is reflected in the validation results in Section 6.3 and reinforces Jackson and Palmer's (2015) claim that cultural ecosystem services are largely defined by the fact that they are not easy to measure and consequently neglected. This research only measures ecosystem services based on properties of the physical landscape and has given no consideration to other methods of measurement. This therefore demonstrates an epistemic limitation that affects some ecosystem services over others. However, cultural service measurements have proven challenging for other approaches. For example, the more traditional use of economic measurements have been proven to be useful for standardising measurement between service generation levels and also between supply and demand (Boyd and Banzhaf, 2007; TEEB, 2010), but have suffered extensive criticism for reducing and simplifying nature down to a dollar value, effectively removing human values from the ecosystem service concept (Jackson and Palmer 2015). The introduction of locally-sourced, volunteered data demonstrates that cultural service generation measurements would benefit from more local scale, qualitative research methods and suggests that a place-based approach would be appropriate here to involve local communities and stakeholders to gain a more realistic picture of the uniqueness of each neighbourhood (Potschin and Haines-Young, 2013).

The shortfalls in use of landscape-based measurements featured in this research have in part been addressed by augmenting environmental measurements with landscape photography to enhance the aesthetics layer (Section 6.2.2.5).This has introduced a novel contribution to the research aim and attempts to answer calls voiced by Blaschke (2006) and Norton *et al.,* (2012) to combine objective and subjective measurements. This remains a key issue that Blaschke (2006), suggests must be overcome for the ecosystem service concept to be viable. The integrative approach applied in Chapter 6 has assisted in enriching the aesthetic service generation layer, but further experimentation is required to optimise methods and more comprehensively validate measurements. This could include more in-depth analysis of the geotagged information attached to individual photos (as Brabyn and

Mark, 2011), and visual analysis of individual photograph composition, which would assist with identification of the local character (De la fuente de Val *et al.,* 2010; Qiu *et al.,* 2013). Alternative approaches for enhancing cultural service measurements have included photo survey methods involving public perception and volunteered information in the form of public participation mapping, which has achieved some success in the literature (Chen *et al.,* 2009; De la fuente de Val *et al.,* 2010; Salesses *et al.,* 2012). These new sources of data are gaining in popularity as scientists are developing methods to mine data from this vast resource, although there are still concerns over the quality, coverage and management of such datasets (Elwood *et al.,* 2012; Mitchell *et al.,* 2013).

As further evidence in favour of the integrative approach, Tengberg *et al.* (2012) found that relating one benefit to one cultural ecosystem service was not possible. To manage the more complex and blurred relationships between cultural services, an integrative approach was preferred. They cite a parallel between cultural ecosystem services and valuation of heritage sites, where intangible benefits are expressed as economic assets, although the approach taken also takes underlying drivers which may result in multiple heritage values that may conflict with each other. Alternatively, Norton *et al.,* (2012) and Raymond (2009) combine GIS-based physical property analysis with a user survey of experiential qualities or community mapping workshops to derive additional information. This is a natural direction for the research presented in Chapter 8 which already provides a robust and objective GIS-based platform for more locally collected subjective data to be attached.

The lack of cohesion between physical and social scientific methods is an issue that Raymond *et al.,* (2009) suggest needs to be addressed to fully appreciate ecosystem service measurements. To this end, Jackson and Palmer (2015) have responded to the call for human geographers to engage with the ecosystem services concept. In their discussion, they argue that the focus should be shifted from economic or environmental measures, which view nature as a stock for generating ecosystem services (as in this research). They see this view as too simplistic and unable to answer questions relating to how the unique character of a place or community can impact on the generation and consumption of ecosystem services in otherwise environmentally and economically similar landscapes. This aligns with a place-based approach to ecosystem service assessment (Haines-Young and Potschin, 2012). Jackson and Palmer (2015) suggest that an understanding of socio-cultural interconnections between nature and humans is required before an understanding of the biophysical relationships. This includes recognition of changing perspectives borne out of changing circumstances within and between different communities. In the context of this research, this could enlighten how differing local perspectives of urban greenspaces can affect how they are generated and consumed. This shift in focus adds a layer of complexity to ecosystem service research that is required to provide a more comprehensive assessment of ecosystem services and more meaningful human-centric interpretations of sustainability, but may be challenging to align with current economic and environmental research and current methods of presenting and communicating results for planners and decision makers.

9.3. Characterising ecosystem service flows

The research detailed in this analysis is only concerned with a static measurement of ecosystem services, effectively measuring a snapshot in time. Costanza *et al*., (1997) stated that the value of ecosystem service research lies in the ability to assess changes in flows within an ecosystem. The methods can be used to generate change over time analysis by repeating analysis over multiple times (Dallimer *et al.,* 2011; Shi *et al.,* 2012). For example, Kreuter *et al.* (2001) conduct temporal analysis for a changing land use in St. Antonio, Texas using data from the older Landsat MSS satellite. They used land use as the sole proxy for ecosystem service measurements, but do consider how developments in urban sprawl can be theoretically neutralised by parallel ecologically positive land use changes. For short time scales, this could provide some interesting results in terms of annual changes in ecosystem service flows. For longer timescales, research could turn to a focus on how land use change over years and decades has changed ecosystem service generation and accessibility. A limiting issue here resides in the acquisition of datasets required for analysis. The broad land cover data should be relatively simple to acquire because the new Landsat 8 satellite was launched in February of 2013 (NASA, 2013) adding to a catalogue of data over 40 years old. Up-to-date building data can be acquired from the Ordnance Survey (Ordnance Survey, 2015a). This includes building footprints and more recently building heights. Collection of tree survey data is available from Bluesky International Ltd (2015), who are continuing to improve the national tree map. Potentially, the most challenging dataset to receive regular updates from is the Greenspace audit, owned by the local council. This data has been collected by a number of agencies and is likely to be updated only when deemed necessary. However, having completed this research, it would be possible to create a bespoke greenspace audit using additional methods and considerations as those used in the creation of the cultural services field survey (Appendix A).

Consideration of how ecosystem service generation (Objective 2) coincides with accessibility or visibility (Objective 3) contributes to research on this statement, relates directly to the research aim and can be demonstrated by the results produced in Chapters 6, 7 and 8. Research conducted by Burkhard *et al.,* (2012), created twinned matrices relating land cover properties to their capacity to produce ecosystem services using a ranked scale from 1 – 5. By overlaying the matrices, they produced an ecosystem service budget matrix, which identified land cover types that produced deficiencies or abundances of different ecosystem services. Similarly, Syrbe *et al.,* (2012) developed spatial units for provisioning, consumption and connection of ecosystem services. The results in Chapter 6 and Chapter 8 can be used to develop Burkhard's and Syrbe's approach by producing spatial tables of ecosystem service budgets. Tables 9.1 and 9.2 provide a demonstration of how the methods and data created in this thesis could recreate similar analyses. Table 9.1 presents an initial demonstration, which considers ecosystem service generation levels against accessible services within distance thresholds from individual residences and inaccessible services outside the distance thresholds. The table shows that ecosystem services scores increase in locations inside SCC and ANGSt boundaries. The results are largely to be expected because these locations are closer to large urban greenspaces. However, the one surprising result is that climate stress mitigation generation decreases within ANGSt boundaries compared to outside. This suggests that these locations are closer to large urban greenspaces, but still relatively close to built-up development.

Table 9.1. Average ecosystem service scores for populations inside and outside physical accessibility thresholds form individual residences.

Ecosystem service	Outside SCC	Inside SCC	Outside ANGSt	Inside ANGSt	Overall
Aesthetics	0.44	0.56	0.47	0.51	0.52
Recreation	0.25	0.37	0.29	0.36	0.33
Carbon	0.02	0.04	0.03	0.04	0.03
Climate	0.22	0.23	0.24	0.15	0.22
Water Flow	0.56	0.68	0.64	0.65	0.64

Table 9.2 provides an additional perspective to observe relationships between generation and consumption of ecosystem services by focusing on the spatial associations of different ecosystem service hotspots against accessibility boundaries. Overlap analysis was completed following the methodology detailed in Section 7.2.2. The results in Table 9.2 show that the overlap of physical accessibility and urban greenspaces/hotspots is lower than random chance. This means that accessible areas are not generally the areas of highest generation. This is to be expected as areas of demand are characterised by urban development and consequently are not greenspaces, but the table does highlight that the relationships for deriving access to ecosystem services are similar across all three approaches for deriving access.

Table 9.2. Overlap analysis of physically accessible spaces (5 minutes' walk from residence) against 2ha+ greenspaces audited by SCC, and those derived via Getis-Ord Gi and value thresholding. The first five rows are measured in km^2*

Areas	SCC	Spatial	Aspatial
Household service areas	51386150	51386150	51386150
Greenspace service areas	16118600	18194700	19812225
Shared service areas	4762125	4195975	5568700
Unshared coverages	24922725	23412775	20422525
Total area of site	97189600	97189600	97189600
Observed/Estimated overlap ratio	0.31	0.28	0.27
Percentage of smallest area (%)	9.3	8.2	10.8

Burkhard *et al.,* (2012) use service providing units and service consuming units, linked together with service transportation units. By using accessibility as a measure of consumption, this research consolidates the consumption and transport into a single measure. While Burkhard's method allows for measurements of supply and demand inequities, this can also be conducted in this research by considering addresses outside of accessibility areas. However, this has been done under the assumption that people are willing to travel 5 minutes only. Consideration of perceptions of access and more physically active residents ensures that the estimates produced here are 'worst case' scenarios'.

A similar analysis of accessibility would be useful, but would require a library of viewsheds for each individual building, which demands huge resources in terms of time and computer processing power. An additional complication, which requires further research is the use in this study of rigid access thresholds (Bonaiuto *et al.,* 2003). For example, the perception of neighbourhood greenness researched by Stronegger *et al.,* (2010) and Kondo *et al.,* (2009) was a key driver in differing recreational patterns. Improving accessibility threshold measurements would help to produce more realistic scenarios. However, this requires further streams of behavioural and survey data, which may be complex to collect and integrate (Paracchini *et al.,* 2013). Future research could focus on characterising accessibility as the third component in parallel with ecosystem service generation and land use. As discussed in Chapter 8, this would involve developing the viewshed analysis to consider individual households. The characterisation would then hold information on proportions of addresses within physical service areas and those within visible thresholds. Potentially this could even include socio-demographic characteristics. Development of this third characterisation would present a unique perspective on trade-off analysis which would consider relative differences and index values.

In identifying potential maximums of ecosystem service generation in Chapters 6 and 7 and consumption in Chapter 8, this research has taken a useful first step in developing understanding of ecosystem service flows. Trade-off analysis is a key outcome of ecosystem service research as it focuses on the balances of service flows across space and time (Rodriguez *et al.,* 2006). This is a popular theme for many ecosystem service studies as it emphasises dynamic relationships (e.g. Chisholm. 2010; Willemen *et al.,* 2012; Gret-Regamey *et al.,* 2012). However, many other studies that claim to analyse trade-offs are in fact only studying the congruence of supply and demand. For example, research developed by Willemen *et al.,* 2012 demonstrated how the index-based value of one service (arable farming) can reduce as another service (habitat) value increases, but without proof that the two are related. Chisholm (2010) present this concept more convincingly with economic tradeoffs in values between carbon services (forestry) and water services (fresh water treatment) in dollar value. To develop the research in Chapters 6, 7 and 8, subsequent steps towards trade-off analysis must consider how services are produced (i.e. whether they make passive or active use of natural resources. For example rival ecosystem services draw destructively from natural resources required by other ecosystem services, decreasing their generation capability and increasing value due to lack of supply (Johnson *et al.,* 2012).

The results in Chapter 7 demonstrate that a high overlap of services or high levels of multiple services does not necessarily indicate a high level of synergy, but it does highlight the potential is present for these services to flourish in the same location. For example, regulating services typically depend on a property of the landscape to counter a perceived threat, whether it is air pollution or flood waters. This is backed up by Chisholm, (2010) who found that regulating services generally positively influence the landscape through simple existence and consequently are more likely to be clustered together with other regulating services (Chisholm, 2010). For example, carbon storage, climate stress mitigation and water flow have synergistic patterns of generation (represented in this research by high overlaps of hotspots in Tables 7.4 and 7.5. This is reinforced by results identified by Wu *et al.,* (2013) and Escobedo *et al.,* (2011). For example, Wu *et al.,* (2013) find synergies with carbon storage, soil retention and habitat conservation, while Escobedo *et al.,* (2011) note that the capacity of a woodland to reduce surface runoff is not affected by its capacity to reduce urban temperatures or capture fine particulate matter. Further, the actual consumption of these services does not require active participation by people meaning that potential for other services is not diminished.

Cultural services offer more of a challenge as they are by their nature experiential (Norton *et al.,* 2012). The diverse associations made with aesthetics and recreation also infer a wide range of activities. This research has only considered landscapes that can provide for the most popular in Salford: walking, sports, cycling. For recreation, consumption demands physically local activity, which takes up physical, visible and aural space in the landscape. This can reduce generation of services such as peace and tranquillity. On the other hand, cultural services are created from surrounding environmental settings (UKNEAFO, 2014). Landscape capacities are less tangible and more related to conflicting human activity rather than ecological capacity. TO develop this aspect of research, methods such as scenario analysis are necessary to determine how these patterns change under different conditions (Eigenbrod *et al.,* 2011, Petz and Oudenhoven, 2012). This would further determine how landscape patterns derived in Chapter 5 affect ecosystem service generation and also which services are the least resilient.

9.4. Ecosystem services and human well-being

Human well-being lies at the core of the ecosystem service framework as a means of determining the value/worth of a service and is key to making ecosystem services relevant and applicable in decision making processes (Potschin and Haines-Young

2008; Kline, 2009). Human well-being spans a range of social, psychological and physical factors (Pacione, 2003; Vemuri and Costanza, 2009). The MA (2003) identifies five broad areas that need to be fulfilled to maintain well-being, shown in Table 9.3. The first column lists main categories of human perception. The sub-categories on the right have been selected by the MA for their relationships to ecosystem services. Many of the sub-categories listed in Table 9.3 are provided by services that are not solely produced by ecosystems. This highlights that while ecosystem services do contribute to human well-being, other external components are also required. This is made more complex because different individuals, communities and cultures have different views on what produces human well-being (Comber *et al.,* 2008; Byrne, 2012). For example, security can be provided through design of the built environment, residential housing and legal limits for development and transport (Villaveces *et al.,* 2012).

Table 9.3. Components of human well-being (from MA, 2003).

Categories	Sub-categories
Security	a safe environment resilience to ecological shocks or stresses such as droughts, floods, and pests secure rights and access to ecosystem services
Basic material for a good life	access to resources for a viable livelihood (including food and building materials) or the income to purchase them
Health	adequate food and nutrition avoidance of disease clean and safe drinking water clean air energy for comfortable temperature control
Good social relationships	realization of aesthetic and recreational values ability to express cultural and spiritual values opportunity to observe and learn from nature development of social capital avoidance of tension and conflict over a declining resource base
Freedom and choice	the ability to influence decisions regarding ecosystem services and well-being

Basic materials for maintenance of well-being that include food and fuel are produced by ecosystems, but after transportation and extensive refinement could arguably no longer be termed ecosystem services. Health is strongly connected to ecosystem service provision although regulation of water quality flow is still largely managed through traditional urban drainage systems (Nordeidet *et al.,* 2004). Good social relationships and freedom of choice reflect the generation of cultural ecosystem services. Objective 2 contributes to these concepts by presenting cultural ecosystem services as environmental settings to encourage social interactions to take place. However, these settings are not critical to those social interactions and similar areas may produce similar results. To develop this further would require a place-based approach that considers the uniqueness of local character (Haines-Young and Potschin, 2011).

Urban environmental quality (UEQ) is a useful tool for spatial scientists for understanding how the physical landscape relates to human well-being, both in quantitative and qualitative measurements (Brown, 2003; Nichol and Wong, 2005; Li and Weng, 2007). The lack of a rigid UEQ definition means that any form of measurement is awkward and easily critiqued (van Kamp *et al.,* 2003). van Kamp *et al.,* (2003) conduct a literature review on UEQ and quality of life. While they do not arrive at a single definition for UEQ, a generalised description incorporating well-being and satisfaction being achieved through physical, social and symbolic characteristics of the environment is noted. Similarly Nichol and Wong (2005) do not explicitly define UEQ, but they acknowledge that it is composed of natural and human factors occurring at different spatial scales. This lack of definition can be addressed via application of the ecosystem service framework. Despite the history of semantic disagreement over the nuances of ecosystem services, Chapter 2 demonstrated that a consensus has been achieved, with significantly more clarity than UEQ. By fitting the ecosystem service within UEQ, classification and measurement of UEQ indicators can be made through evaluation of multiple ecosystem services. Specifically, the mapping methods derived in this thesis under objectives 1 and 2 (Chapters 5 and Chapter 6) tie services to the physical landscape, which also allows easier and more sophisticated mapping of processes. This then allows a disaggregation of measurements within UEQ through hotspot analysis (Section 6.3.3) and bundle analysis (Section 7.3.7). Cultural services can also be integrated via Pacione's acknowledgement that UEQ also has social interpretations involving concepts of neighbourhood liveability. By applying ecosystem services within UEQ, this also acknowledges that the benefits produced by ecosystem services sit within a wider social and environmental context. Development of the research in Chapters 6 – 7 could analyse how the clusters and hotspots could be converted into an aggregated measurement of environmental quality, in parallel to Smith *et al.,* (2013), who suggest a set of well-being domains that can be linked to ecosystem services for a US index.

There is a general assumption that green, natural environments are all positive and healthy, while grey, urban landscapes are negative and ugly (Ord *et al.,* 2013). This is largely upheld in this thesis with more urban character types presenting lower ecosystem service generation levels (Section 6.3.3). However, much architectural and urban research has focused on the aesthetic beauty of modern building (Degen *et al.,* 2008). For example, Ozguner and Kendal (2006) found that natural landscapes within urban areas were perceived by some to be unkempt, valueless and even frightening. Projects in city centres are striving to create beautiful, open and accessible public spaces. This is particularly considered in modern city centres and shopping malls (Degen *et al.,* 2008). These may include areas of vegetation or water features, commonly, this is not feasible and so architectural solutions have been found. Bravo (2012) suggests that historical cities provide a unique character to which local residents can relate and belong to. In terms of recreation, the built environment also provides access to activities not accessible in green spaces. These include recreational services including jogging for fitness, but also include more alternative activities such as skate parks or parkour (freerunning) (Kidder, 2012, Lin *et al.,* 2013).

Lele (2013) suggest that the ecosystem services framework should be used to analyse issues rather than provide answers for policies. It should be used to give decision makers a better understanding of ecological situations so that they can go forward to ask other more relevant questions than merely the dollar value of a service provided. As an alternative, Blaschke (2006) promotes a paradigm of sustainable landscapes by focussing on how human activities can be related to landscape patch composition and patterns. This more directly links with the spatial elements of urban planning and that natural capital generation can be directly linked to a holistic physical domain. In adopting a landscape-based platform for ecosystem service analysis, this thesis fits alongside the sustainable landscape concept by providing information on the landscape components required to generate valuable multifunctional urban greenspaces. This could be useful information for comparing against landscape patterns required for landscape sustainability, thus linking the potential for generating benefits with the capacity for the processes to continue.

Although, Blaschke (2006) highlight issues integrating societal values that need to be resolved. Valles-Plannells *et al.,* (2014) continues to suggest that landscapes incorporate a further level of integration above ecosystems by already incorporating human activities within them. This has spurred authors such as Termorshuizen and Opdam (2009) and Frank et al., (2012) to adopt the phrase 'landscape services'.

9.5. Conclusions

This thesis has created and evaluated an innovative approach for creating a landscape mosaic using remotely-sensed spectral indices and land cover measurements. The research builds on recognised relationships between properties of the landscape mosaic and the flow of ecosystem services. Methods have been developed to simulate these relationships based on a demand for improved spatial analysis of the generation and accessibility of ecosystem services (Haines-Young and Potschin, 2008). The methods applied have been designed to operate alongside other UKNEA TABLE tools (UKNEAFO, 2014), which therefore aligns methods with a national framework of assessment.

The discussions in this chapter have revealed a number of limitations throughout the research and highlighted avenues for future research that may address or review these limitations. The landscape mosaic accuracy compares favourably to a map created using traditional supervised classification methods. In particular, the bare earth land cover is more readily classified, which may lend itself to further studies relating to the use of vacant land in urban areas (Heckert, 2013). The landscape models produced in Chapter 5 have provided a useful platform for ecosystem service research, but also hold significant potential for other branches of ecological and urban research. For example, a focus on spaces that contain a lack of ecosystem services could be related to analysis of flood risk and urban heat islands. An intermediate research programme should first validate the methods used to create land cover and land use maps across an urban area. Repetition of research in similar post-industrial urban areas such as Leeds and Sheffield would provide a useful comparison. Additionally, the application of these methods in different type of urban centre would provide a measure of the flexibility and generalisation of the methods. For example, more carefully planned urban areas may be easier to map due to more easily defined urban regions.

Based on a review of the literature, five ecosystem services were considered: carbon storage, water flow mitigation, climate stress mitigation, aesthetics, and recreation. While these do represent services important to urban areas and urban residents, other ecosystem services could be integrated to enhance the measurements of landscape multifunctionality. For example, other regulatory services could include air quality regulation (Bolund and Hunhammar, 1999) and noise buffering (Daltrop *et al.* 2012), which are more challenging to measure across a city. In terms of cultural services, the place-based ecosystem services approach recommends emphasis of the unique character of place as context for the interaction of ecosystem services and people. Consequently, analysis of sites of historical importance and spiritual significance may be important (Haines-Young and Potschin, 2008). However this would require a different array of measurement methods to those implemented in this research. Alternatively, Tengberg *et al.* (2012) promote an integrated approach, where multiple benefits may be related to a range of different cultural services. Finally, the addition of provisioning services could incorporate a growing trend of urban agriculture, which includes community farming, rooftop and home gardens and urban orchards (Alig *et al.* 2004). These projects produce a range of consumable crops, but also promote a suite of ecosystem services such as pollination, natural pest control and climate regulation (Lin *et al.* 2015).

This research has introduced explicitly spatial approaches to the mapping and characterisation of ecosystem clusters. These approaches have revealed new patterns not previously realised by more traditional methods. Hotspot analysis has provided evidence that regulating services draw from similar natural resource locations, while cultural services have more diverse sources. Spatial hotspots that consider the attributes of neighbouring pixels were compared against aspatial hotspots based on value thresholding. Results suggest that the approaches are complementary and should be used in concert to provide a full picture of ecosystem service generation. In particular, spatial hotspots highlight the larger regions of aesthetic service generation, while the aspatial hotspots highlight the influence of individual street trees. Spatially derived clusters of ecosystem services are statistically stronger than those derived by more traditional methods. The spatial units applied are not restricted to arbitrary administrative boundaries and better reflect ecological patterns. However, the research limits each Output Area to a single land use type. In particular, this limits the characterisation of non-domestic land uses, which cover industrial parks and city centres, which have very different morphologies. Consequently, there is scope for further research into more sophisticated methods of characterisations. These could use fuzzy methods to introduce multiple land use membership based on probabilities or proportions of land cover patterns (Zhang and Foody, 2001).

This research has considered multifunctional relationships between ecosystem services in terms of characterising clusters. Evidence from Chapter 7 suggests that spatial methods produce stronger and more different ecosystem service clusters. Additional benefits from use of the spatial methods include the object-based approach to deriving spatial units, which are more appropriate for ecological measurements. While other studies by Raudsepp-Hearne *et al.,* (2010) and Ericksen *et al.,* (2012) suggest clear and direct relationships between landscape character types and ecosystem services, this research has found less well defined patterns that could be better explained using fuzzy methods based on probabilities.

The third dimension of feature heights is a key novel feature that has been integrated throughout the research. In particular, the measurement of ecosystem service accessibility using observer line-of-sight has provided new insights into how services may be consumed. The accessibility and visibility analysis has provided evidence for the importance of urban trees as mitigators of ‘grey’ views, and urban parks as multifunctional generators of multiple ecosystem services. Key results from Chapter 8 show that more of Salford is visible than physically accessible and the visible space is generally greener and hence more likely to produce ecosystem services. Further, views of Salford tend to be greener as observer height from the ground increases. This has proven to be particularly important for cultural service consumption and other ecosystem services where consumption does not require physical interaction with the service (Bagstad *et al.* 2013). Viewshed analysis has been originally introduced to ecosystem service research to provide new insights into cultural service consumption. This includes the location of the most visible urban greenspaces and the features that most strongly influence these patterns. In particular, this provides great potential for less tangible services such as aesthetics, where immediate physical interaction is not required.

Evaluation of spatial relationships between ecosystem services and the physical landscapes in this thesis provides a practical method for improved measurement and management of the natural environment in urban areas. This research considers accessibility as a proxy for ecosystem service consumption but does not consider any alternative measures of consumption. An interesting parallel research approach could focus on economic measures for verification (Boyd and Banzhaf, 2007). This would provide a standardised method of measurement that would align with established programmes such as TEEB (2009). For regulating services measured, it may be of more value to focus on measurements of demand and the location and severity of related hazards. For example, closer integration of the Urban Heat Island effect and the climate stress mitigation ecosystem service could provide a more intelligent interpretation of the value of the service.

Tradeoffs and synergies cannot be directly analysed from the results produced in this research. However, the research does demonstrate a useful first step in determining service levels at a landscape scale by highlighting potential areas for monitoring or improvement. These can then be isolated for further analyses of future development scenarios to determine more information on potential tradeoffs and synergies. To evaluate how services are actually generated alongside each other, the nature of the service and the way in which it consumes resources must be considered. To gain actual information on tradeoffs and synergies, data needs to be collected on the actual levels of generation provided. This is a challenging prospect across a landscape and may only be possible at a local scale.

A key challenge for the future of ecosystem services is how to move forward to integrate differing streams of science to produce a comprehensive measurement of cultural ecosystem services. Research is continuing under natural and social sciences and applying quantitative and qualitative research methods, but there are still distinct gaps that need to be bridged in order to communicate the different outputs between different types of scientist and between academic scientists and political decision makers. Programmes such as the UKNEA are developing a common framework of measurements, assessments and tools to integrate ecosystem services, but, similar to all multi-disciplinary research, a method of linking different scientific and practical languages is required to fully realise the potential for the ecosystem services framework.

10. References

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Appendix A

Aesthetics ecosystem service descriptor values (from Radford and James, 2013)

		Aesthetic values			
		3	2	1	0
1.1 Private	1.1.1	There are no broken or boarded up windows visible.	Percentage of properties with broken/boarded up windows is <10% but ≥0.01%.	Percentage of properties with broken/boarded up windows is ≥10 but <40%.	Percentage of properties with broken/boarded up windows is ≥40%.
	1.1.2	There is no evidence of vandalism.	There is some evidence of vandalism to property but this is scarce or dismissible.	There is evidence of vandalism is parts of the site but not others.	Vandalism to private properties is a problem, i.e. there are numerous buildings with broken windows, litter in front gardens, graffiti on properties etc.
	1.1.3		There are no burnt out properties present.	Burnt out properties are present but are under reconstruction/ renovation.	There are burnt out properties present.
	1.1.4	Majority of properties and gardens are neat and tidy with vegetation, maintained to a high level.	Majority of properties and gardens are neat and well maintained but some properties lack proper maintenance, e.g. some gardens may be overgrown/litter, toys etc strewn over front gardens.	The majority of properties are Poorly maintained (e.g. untidy and overgrown gardens, house in disrepair or unpleasant external view such as curtains falling down etc). However, quite a few properties are still highly maintained	Majority of gardens are poorly kept (vegetation unkept or overgrown or sealed surfaces in poor state of repair. May be untidy, i.e. toys/rubbish/household items present in garden) and the external view of the house in poor state of repair or untidy (e.g. curtains falling down, windows broken etc).
	1.1.5	Percentage of private properties with trees in front gardens is ≥60%.	Percentage of private properties with trees in front gardens is <60% but ≥30%.	Percentage of private properties with trees in front gardens is <30% but ≥10%.	Percentage of private properties with trees in front gardens is <10%.
	1.1.6	The site is open, consisting largely of fields/green space. May contain some manmade features such as a few houses or a road.	The site is mostly open. Houses, if present, are spaced apart and may be penetrated with areas of green space.	The site is built up but with some, or one, large area of green space.	The site is mostly built up with very little green space.

	1.1.7	The majority of defensible territories are large, with large gardens to the front and rear of properties.	Most defensible territories are large or medium, with some smaller properties present.	Most defensible territories are small but contain some large/medium.	Defensible territories are very small, e.g. the site consists mainly of terraced housing with only small courtyards to the rear of the properties.
1.2. Public	1.2.1	During the survey of the site no stray dogs were seen roaming.	During the survey of the site no more than 1 dog was seen roaming.	During the survey of the site more than one but no more than 4 dogs were seen roaming.	During the survey of the site 4 or more dogs were seen roaming.
	1.2.2	Dog fouling bins and signs present. Very little – no dog fouling spotted within the site (e.g. only one sighting).	Very little/no dog fouling present within the site. Lack of dog fouling bins and/or signs.	Dog fouling a problem despite the presence of bins.	Dog fouling a problem. No bins or signs.
	1.2.3	No more than 2 sightings of litter or vandalism were noted.	More than two events of littering or vandalism but no more than 7 were noted.	There were between 8 – 12 events of littering and vandalism noted.	Litter and vandalism is significant. More than 12 events were noted.
	1.2.4		Furniture is present, well located and in good condition (i.e. no vandalism, graffiti, etc.)	Furniture is present but is scarce or vandalised, in a poor condition or poorly located.	There is no furniture present.
	1.2.5	There are two or more types of water feature present (e.g. fountain, pond, stream, river, lake etc.). The water appears clean, where appropriate, the features are well maintained.	Only one type of water feature is present. This feature is well maintained/clean.	There is more than one type of water feature present but they contain dirty water, are in a state of disrepair or, where appropriate, lack adequate maintenance.	There are no water features present or only one water feature which is in a state of disrepair or clearly polluted.

	1.2.6	Three or more varieties of public green space typologies are present (e.g. playing fields, parks, communal gardens). These are well kept. Alternatively, less green spaces are present but these are large in size, providing a variety of functions, e.g. walking trails, woodlands etc.	One or two types of green spaces are present. These are well kept and offer a variety of recreational functions (e.g. playground, kickaround area, seating).	One or two types of green space present. These may be limited in size and facilities.	No green space present.
	1.2.7	Street trees/trees are present in public areas. These are abundant and mostly mature or a mixture of young and mature trees.	Street trees/trees are present in public areas but are mostly young.	Few trees/street trees are present.	No street tree/trees are present in public areas.
	1.2.8	A wide variety of vegetation is present (e.g. flower beds, grass verges, street trees, hanging flower baskets) and are maintained to a high standard.	A wide variety of vegetation is present (e.g. flower beds, grass verges, street trees, hanging flower baskets). Most are maintained to a high standard.	Vegetation is lacking or poorly maintained.	No vegetation present in public areas.
1.3 Both	1.3.1		There are no abandoned cars.	There is only one abandoned car.	There is more than one abandoned car.
	1.3.2	All cars are legally parked.	Only 1 car is illegally parked.	Two or three cars are illegally parked.	More than three cars are illegally parked.
	1.3.3	The outlook is predominantly residential or green.	The outlook is predominately residential with occasional commercial properties.	The outlook is a mixture of commercial, residential and industrial properties.	The outlook is predominately industrial or commercial and lacking in green or open space.
	1.3.4	The site is dominated by vegetation such as fields, trees, flowers. Only few or no manmade structures.	The outlook is largely green with manmade features permeated with trees, green space, grass verges etc.	The predominant outlook is not green but contains some or areas which are largely vegetated.	The predominant outlook is not green and is dominated by manmade features/brown fields etc.