Earth Observation for Quantifying Urban Growth and its Application to Sustainable City Development

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Contents

For Katy

Dla Jagody

Für meine Katharina und alle unsere Kinder

Foreword

Doing 'spatial' in R has always been about being broad, seeking to provide and integrate tools from geography, geoinformatics, geocomputation and spatial statistics for anyone interested in joining in: joining in asking interesting questions, contributing fruitful research questions, and writing and improving code. That is, doing 'spatial' in R has always included open source code, open data and reproducibility.

Doing 'spatial' in R has also sought to be open to interaction with many branches of applied spatial data analysis, and also to implement new advances in data representation and methods of analysis to expose them to cross-disciplinary scrutiny. As this book demonstrates, there are often alternative workflows from similar data to similar results, and we may learn from comparisons with how others create and understand their workflows. This includes learning from similar communities around Open Source GIS and complementary languages such as Python, Java and so on.

R's wide range of spatial capabilities would never have evolved without people willing to share what they were creating or adapting. This might include teaching materials, software, research practices (reproducible research, open data), and combinations of these. R users have also benefitted greatly from 'upstream' open source geo libraries such as GDAL, GEOS and PROJ.

This book is a clear example that, if you are curious and willing to join in, you can find things that need doing and that match your aptitudes. With advances in data representation and workflow alternatives, and ever increasing numbers of new users often without applied quantitative command-line exposure, a book of this kind has really been needed. Despite the effort involved, the authors have supported each other in pressing forward to publication.

So, this fresh book is ready to go; its authors have tried it out during many tutorials and workshops, so readers and instructors will be able to benefit from knowing that the contents have been and continue to be tried out on people like them. Engage with the authors and the wider R-spatial community, see value in having more choice in building your workflows and most important, enjoy applying what you learn here to things you care about.

Roger Bivand

Bergen, September 2018

Preface

Who this book is for

This book is for people who want to analyze, visualize and model geographic data with open source software. It is based on R, a statistical programming language that has powerful data processing, visualization and geospatial capabilities. The book covers a wide range of topics and will be of interest to a wide range of people from many different backgrounds, especially:

- People who have learned spatial analysis skills using a desktop Geographic Information System (GIS) such as QGIS, ArcMap, GRASS or SAGA, who want access to a powerful (geo)statistical and visualization programming language and the benefits of a command-line approach (**?**):

  > With the advent of 'modern' GIS software, most people want to point and click their way through life. That's good, but there is a tremendous amount of flexibility and power waiting for you with the command line.

- Graduate students and researchers from fields specializing in geographic data including Geography, Remote Sensing, Planning, GIS and Geographic Data Science
- Academics and post-graduate students working on projects in fields including Geology, Regional Science, Biology and Ecology, Agricultural Sciences (precision farming), Archaeology, Epidemiology, Transport Modeling, and broadly defined Data Science which require the power and flexibility of R for their research
- Applied researchers and analysts in public, private or third-sector organizations who need the reproducibility, speed and flexibility of a command-line language such as R in applications dealing with spatial data as diverse as Urban and Transport Planning, Logistics, Geo-marketing (store location analysis) and Emergency Planning

The book is designed for intermediate-to-advanced R users interested in geocomputation and R beginners who have prior experience with geographic data.

If you are new to both R and geographic data, do not be discouraged: we provide links to further materials and describe the nature of spatial data from a beginner's perspective in Chapter **??** and in links provided below.

How to read this book

The book is divided into three parts:

1. Part I: Foundations, aimed at getting you up-to-speed with geographic data in R.
2. Part II: Extensions, which covers advanced techniques.
3. Part III: Applications, to real-world problems.

The chapters get progressively harder in each so we recommend reading the book in order. A major barrier to geographical analysis in R is its steep learning curve. The chapters in Part I aim to address this by providing reproducible code on simple datasets that should ease the process of getting started.

An important aspect of the book from a teaching/learning perspective is the **exercises** at the end of each chapter. Completing these will develop your skills and equip you with the confidence needed to tackle a range of geospatial problems. Solutions to the exercises, and a number of extended examples, are provided on the book's supporting website, at geocompr.github.io.

Impatient readers are welcome to dive straight into the practical examples, starting in Chapter **??**. However, we recommend reading about the wider context of *Geocomputation with R* in Chapter **??** first. If you are new to R, we also recommend learning more about the language before attempting to run the code chunks provided in each chapter (unless you're reading the book for an understanding of the concepts). Fortunately for R beginners R has a supportive community that has developed a wealth of resources that can help. We particularly recommend three tutorials: R for Data Science (**?**) and Efficient R Programming (**?**), especially Chapter 2 (on installing and setting-up R/RStudio) and Chapter 10 (on learning to learn), and An introduction to R (**?**). A good interactive tutorial is DataCamp's Introduction to R.

Why R?

Although R has a steep learning curve, the command-line approach advocated in this book can quickly pay off. As you'll learn in subsequent chapters, R is an effective tool for tackling a wide range of geographic data challenges. We expect that, with practice, R will become the program of choice in your geospatial toolbox for many applications. Typing and executing commands at the command-line is, in many cases, faster than pointing-and-clicking around the graphical user interface (GUI) of a desktop GIS. For some applications such as Spatial Statistics and modeling R may be the *only* realistic way to get the work done.

As outlined in Section **??**, there are many reasons for using R for geocomputation: R is well-suited to the interactive use required in many geographic data analysis workflows compared with other languages. R excels in the rapidly growing fields of Data Science (which includes data carpentry, statistical learning techniques and data visualization) and Big Data (via efficient interfaces to databases and distributed computing systems). Furthermore R enables a reproducible workflow: sharing scripts underlying your analysis will allow others to build-on your work. To ensure reproducibility in this book we have made its source code available at github.com/Robinlovelace/geocompr. There you will find script files in the `code/` folder that generate figures: when code generating a figure is not provided in the main text of the book, the name of the script file that generated it is provided in the caption (see for example the caption for Figure **??**).

Other languages such as Python, Java and C++ can be used for geocomputation and there are excellent resources for learning geocomputation *without R*, as discussed in Section **??**. None of these provide the unique combination of package ecosystem, statistical capabilities, visualization options, powerful IDEs offered by the R community. Furthermore, by teaching how to use one language (R) in depth, this book will equip you with the concepts and confidence needed to do geocomputation in other languages.

Real-world impact

Geocomputation with R will equip you with knowledge and skills to tackle a wide range of issues, including those with scientific, societal and environmental implications, manifested in geographic data. As described in Section **??**, geocomputation is not only about using computers to process geographic data: it is also about real-world impact. If you are interested in the wider context and motivations behind this book, read on; these are covered in Chapter **??**.

Acknowledgements

Many thanks to everyone who contributed directly and indirectly via the code hosting and collaboration site GitHub, including the following people who contributed direct via pull requests Special thanks to Marco Sciaini, who not only created the front cover image, but also published the code that generated it (see `frontcover.R` in the book's GitHub repo). Dozens more people contributed online, by raising and commenting on issues, and by providing feedback via social media. The `#geocompr` hashtag will live on!

We would like to thank John Kimmel from CRC Press, who has worked with us over two years to take our ideas from an early book plan into production via four rounds of peer review. The reviewers deserve special mention here: their detailed feedback and expertise substantially improved the book's structure and content.

We thank Patrick Schratz and Alexander Brenning from the University of Jena for fruitful discussions on and input into Chapters **??** and **??**. We thank Emmanuel Blondel from the Food and Agriculture Organization of the United Nations for expert input into the section on web services; Michael Sumner for critical input into many areas of the book, especially the discussion of algorithms in Chapter 10; Tim Appelhans and David Cooley for key contributions to the visualization chapter (Chapter 8); and Katy Gregg, who proofread every chapter and greatly improved the readability of the book.

Countless others could be mentioned who contributed in myriad ways. The final thank you is for all the software developers who make geocomputation with R possible. Edzer Pebesma (who created the **sf** package), Robert Hijmans (who created **raster**) and Roger Bivand (who laid the foundations for much R-spatial software) have made high performance geographic computing possible in R.

Acknowledgements

Personal

I wish to sincerely thank both my supervisors Dr Biggs and Dr Roberts alongside my advisor Dr Boruff for their advice, contributions and enthusiasm throughout this thesis. Specifically, Dr Biggs continuously challenged how developed methodologies were applicable in applied planning terms, complemented by Dr Roberts who would challenge more technical aspects of the research and Dr Boruff who would often question the applicability to the bigger, global picture. Combined they have been a simply fantastic supervisory team that have undoubtedly developed my overall research skills. Beyond the methodological and technical aspects of the project the team have consistently encouraged me, provided numerous further opportunities and promoted both my work and I. I am extremely grateful the time all three academics have invested in me and for how much I have learnt from them over the last four years. I also thank those not officially involved with this thesis but have nonetheless contributed in ways they were probably unaware of. This is especially true of all those I have cycled with, taking my mind away from research, subsequently feeling refreshed and often having methodological breakthroughs. Similarly (soon to be Drs) Luke Brown and Micheline Campbell for their friendship, advice and support through the rollercoaster of emotions during the project. I thank Amelia Vincent for her unrelenting encouragement and empathy over the last four years. Finally I wish to thank my parents, Valerie and Angus MacLachlan, for their continued encouragement and investment throughout my entire education.

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Declaration of Authorship

I, Andrew Charles MacLachlan

declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Earth Observation for Quantifying Urban Growth and its Application to Sustainable City Development

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Urban growth dynamics in Perth, Western Australia: using applied remote sensing for sustainable future planning. Land, 6(1), p.9. [open access].

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Classified Earth observation data between 1990 and 2015 for the Perth Metropolitan Region, Western Australia using the Import Vector Machine algorithm, PANGAEA, https://doi.org/10.1594/PANGAEA.871017 data. [open access].

MacLachlan, A., Roberts, G., Biggs, E. and Boruff, B., 2017. Subpixel land-cover classification for improved urban area estimates using Landsat. International Journal of Remote Sensing, 38(20), pp.5763-5792. [open access].

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Urbanisation-Induced Land Cover Temperature Dynamics for Sustainable Future Urban Heat Island Mitigation. Urban Science, 1(4), p.38. [open access].

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2018. Earth Observation for Sustainable City Planning. [submitted to Global Environmental Change].

Smith, A., MacLachlan, A., Haworth, B., Biggs, E. and Maginn, P., 2018. Demonstrating the global potential of a high-resolution spatiotemporal population modelling framework. International Journal of Geographical Information Science [under review].

In all jointly published work presented in this thesis Andrew MacLachlan was responsible for sourcing data, liaising with planning authorities, devising methodological approaches, all analysis and producing and revising manuscript drafts. Dr Biggs and Dr Roberts contributed ideas, comments and data in a supervisory capacity based on their own expertise throughout the research. Dr Boruff supported the research in similar manner through an advisory role at the University of Western Australia. Author attribution statements for each individual paper are presented below, providing specific details into Andrew MacLachlan's responsibilities and the supervisory and advisory support supplied by Dr Biggs, Dr Roberts and Dr Boruff. All authors declare no completing interests.

Author attribution statements

Chapter 4, paper 1a

Chapter 4 corresponds to the publication:

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Urban growth dynamics in Perth, Western Australia: using applied remote sensing for sustainable future planning. Land, 6(1), p.1-14.

Andrew MacLachlan liaised with and obtained data from the Western Australian Department of Planning, analysed all data and produced manuscript drafts. The co-authors assisted in guiding the overall research objectives, provided methodological advice and revised manuscript text in a supervisor capacity. In particular Dr Biggs contributed valuable figure and policy recommendations whilst Dr Roberts ensured valid data normalisation suggesting analysis found in the supplementary material, section 4.7.

Chapter 4, paper 1b

The data produced using the methodology described in Paper 1a (main body of chapter 4) corresponds to the publication:

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Classified Earth observation data between 1990 and 2015 for the Perth Metropolitan Region, Western Australia using the Import Vector Machine algorithm, PANGAEA, https://doi.org/10.1594/PANGAEA.871017. Andrew MacLachlan produced and formatted the data for publication, with methodological advice from co-authors in a supervisory capacity.

Chapter 5, paper 2

Chapter 5 corresponds to the publication:

MacLachlan, A., Roberts, G., Biggs, E. and Boruff, B., 2017. Subpixel land-cover classification for improved urban area estimates using Landsat. International Journal of Remote Sensing, 38(20), pp.5763-5792.

Andrew MacLachlan was responsible for designing the methodology, processing all data and producing manuscript drafts. Co-authors agreed upon and guided the research questions, provided access to high resolution aerial data, gave methodological and practical advice and reviewed manuscript drafts in a supervisory capacity. More specifically, Dr Boruff provided high resolution data, with Dr Roberts advising Andrew MacLachlan on the best Object Based Image classification procedures.

Chapter 6, paper 3

Chapter 6 corresponds to the publication:

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2017. Urbanisation-Induced Land Cover Temperature Dynamics for Sustainable Future Urban Heat Island Mitigation. Urban Science, 1(4), pp.1-21.

Andrew MacLachlan designed the methodological procedure, processed and analysed all data and produced manuscript drafts. The co-authors assisted in guiding research objectives and provided valuable advice and manuscript comments in a supervisory capacity. Dr Biggs critically commented on policy applications and data output, especially Figure 6 8 that was selected for the Journal Issue front cover. Dr Roberts provided practical methodological advice and assisted in selecting appropriate data for figures and tables presented throughout the paper.

Chapter 7, paper 4

Chapter 7 corresponds to the pending publication:

MacLachlan, A., Biggs, E., Roberts, G. and Boruff, B., 2018. Earth Observation for Sustainable City Planning [submitted to Global Environmental Change].

Andrew MacLachlan identified and processed all data required used within the modelling methodology, produced figures, liaised with the City of Fremantle and drafted all versions of the manuscript. Co-authors guided the overall objectives ensuring linkage to previous work whilst also providing critical feedback in a supervisory capacity. Dr Biggs ensured policy relevance and critically commented on produced figures. Dr Roberts contributed ideas throughout and reviewed the final draft manuscript alongside Dr Boruff.

Signed: [signature removed from digital version] Date: 14/09/2018 Andrew MacLachlan

As a supervisor for this postgraduate student I certify that the authorship attribution statements above are true and accurate.

Signed: [signature removed from digital version] Date: 14/09/2018 Dr Biggs

As a supervisor for this postgraduate student I certify that the authorship attribution statements above are true and accurate.

Signed: [signature removed from digital version] Date: 14/09/2018 Dr Roberts

Chapter 1

Introduction

1.1 An expanding urban area

Urban areas only cover 0.5% of Earth's terrestrial surface and yet are one of the fastest growing land use types on a per area basis (Gashu and Egziabher, 2018; Powell et al., 2007; Sexton et al., 2013). Population growth is fuelling urbanisation with 55% of the planet's 7.6 billion people residing in urban areas in 2018, and which is expected to accommodate up to 68% of the global population by 2050 as a result of an estimated additional 2.5 billion people (Powell and Roberts, 2010; Sexton et al., 2013; Sharifi and Lehmann, 2014; United Nations, 2018). Land use and land cover change represent the main driving force in global environmental change, especially anthropogenic modifications from vegetated to impervious surface material, through which water does not infiltrate (Sundarakumar et al., 2012; Tan et al., 2009; Verburg et al., 2015). In order to accommodate the expected increase in population, urban area is predicted to triple by 2030 based on current trends, increasing total global coverage to 0.9% of Earth's terrestrial surface (2000 baseline of 652,825 km2) (Seto et al., 2012).

Urban growth, defined as the sum of the increase in developed land between two or more time periods, was traditionally thought of as an intrinsic process and metric of economic success (Sundarakumar et al., 2012). However, the benefits have now been carefully evaluated in conjunction with any adverse social, economic and environmental impacts. For example, continued outward expansion exponentially decreases resource efficiency due to vast infrastructural requirements, additional commuting time and household transportation expenditure (Batty et al., 2003; Downs, 2005). The alteration of natural land to impervious surfaces frequently induces the Urban Heat Island (UHI) effect whereby man-made urban areas obtain comparatively higher atmospheric and surface temperature than rural areas; the UHI effect is considered one of the major environmental problems posed to humans in the 21st century (Rizwan et al., 2008). In conjunction with expanding global urban areas and population growth the extent and magnitude of the UHI will continue to grow (Zhang et al., 2013). Furthermore, urbanisation can lead to income-based neighbourhood segregation which exacerbates social and ethnic divisions (Batty et al., 2003), and coupled with the UHI effect can result in sociodemographic-driven healthcare implications during heatwaves (Gronlund et al., 2015; Yu et al., 2010). Whilst urban expansion can generate benefits, accurate and timely information on the characteristics and associated impacts of urban expansion are critical for assessing current and future needs regarding urban growth and developing policy priorities for inclusive and sustainable [socioeconomic and environmental] development, as reflected in recent global initiatives e.g. the United Nations (UN) New Urban Agenda (UN-Habitat III, 2017), City Resilience Framework (CRF) (ARUP and The Rockefeller Foundation, 2015) and 2030 Sustainable Development Goals (SDGs) (Osborn et al., 2015). **The overall aim of this research is to demonstrate the application of EO data in quantifying urban growth and its impact on the UHI in order to illustrate its potential for informing both global and metropolitan sustainable city development goals.**

1.2 Defining urban area

The term 'urban area' is surrounded by conceptual vagueness, with definitions varying based on discipline origin e.g. academia, census bureaus and metropolitan development agencies (Bennett, 2001). Weeks (2010) defined 'urban' as a characteristic of place whereby a spatially concentrated population are organised around non-agricultural activities. This definition is composed of (i) population size, (ii) land area, (iii) population density, and (iv) economic and social organisation. However, due to increased population movement towards traditional urban centres and subsequent outward expansion, the urban-rural divide is becoming difficult to differentiate (United Nations, Department of Economic and Social Affairs, 2014; United Nations, 2016; Weeks, 2010). In an effort to mitigate the increasing pressure from rural-urban migration on city expansion and metropolitan services developing countries have initiated schemes to attract urban infrastructure to previously considered rural areas (Weeks, 2010). For example, the Vietnamese government initiated side-line productions with the slogan "leaving the land without leaving the village" (Rigg, 1998; Weeks, 2010). Similarly, China's Special Economic Zones (SEZs), offering corporations economic incentives, attempted to resolve socio-economic problems associated with the centrally administrated system whilst also importing a foreign knowledge base (Kam Ng and Tang, 2004). In 1980 the city of Shenzhen was designated as China's first SEZ, originally considered a tiny rural town located at the northern edge of Hong Kong with a population of only 0.3 million. By 2000 SEZ status resulted in a 23 fold population increase to an estimated 7 million (Kam Ng and Tang, 2004; Zhou et al., 2016). Nevertheless it is difficult to exactly determine at what point in time Schenzen's status changed from rural to urban due to the multitude of possible factors that could be considered (e.g. population, land area or economic organisation). Statistical bureaus define urban in various ways to ensure data availability for specific applications. For example, the Australian Bureau of Statistics (ABS) currently provide five definitions of urban area based upon differing Statistical Areas (SA) levels of collection. Due to the complexity of the ABS urban definitions they are summarised in Figure 1 1 (ABS, 2017). One important consideration within this framework is that the Greater Capital City Statistical Areas (GCCSAs) have only been in force since the 2011 census, replacing the statistical divisions that previously covered the greater metropolitan area, often referred to as the metropolitan region of each capital city constrained by Local Government Areas (LGA); consequently no previous census data is available for the complete GCCSAs (ABS, 2017).

Figure 1 1. Varying urban definitions associated with different datasets produced by the Australian Bureau of Statistics (ABS). Adapted from ABS (2017).

Similarly the United States of America (USA) Census Bureau provides further urban definition variation (Figure 1 2). The USA Census Bureau base urban categorisation on census blocks, tracts, cities and counties. Census blocks are the smallest geographic census area, established from visible features such as roads, property boundaries and rivers. Census tracts are representative of neighbourhoods as defined by the Census Bureau, generally obtaining between 2,500 and 8,000 people, with boundaries also defined on visible features. Cities and associated spatial boundaries are defined in legislation by the city government whilst Counties are based upon geographic, political and administrative subdivision of a State (U.S. Census Bureau, 2018).

Figure 1 2. Varying urban definitions associated with different datasets produced by the United States of America (USA) Census Bureau. Adapted from U.S. Census Bureau (2018).

In contrast the United Kingdom (UK) Office for National Statistics (ONS) rather more simplistically define urban as settlements with a population of 10,000 or more residents. Settlements are established from a grid of hectare cells (100m x 100m) over England and Wales, with residential properties inferred from Royal Mail's (UK's postal service) postcode address file assigned to cells. Residential density for a set of increasing radii surrounding each cell is calculated and compared to defined standards assigning each cell to a settlement type (e.g. village, town, urban fringe). Census Output Areas (OA), the smallest level of census data are combined with the classified cell output and defined urban if both classed as a settlement and obtaining a population of 10,000 or more (Bibby and Brindley, 2013).

These contrasting urban definitions and associated data are based upon local governments and organisations being able to best identify features that differentiate urban and rural (Brockerhoff, 2000). Nevertheless individual country specific approaches hinder cross country comparison and accurate global estimates due to the multitude of differing factors that are considered in determining urban extent.

Urban development strategies that outline future development and sustainability targets are frequently provided by metropolitan development agencies such as the Spatial Development Strategy For London (Mayor of London, 2016a), Perth's Directions 2031 (Western Australian Planning Commission, 2010a) and Johannesburg's Spatial Development Framework 2040 (City of Johannesburg Metropolitan Municipality, 2016). These documents often fail to definitively define the term urban, generating inconsistencies throughout national agencies. In the case of Perth, Western Australia (WA), initial urban estimates only covered the Perth Metropolitan Region (PMR) based upon cadastral land parcel valuations, with later estimates considering spatial modelling, multiple urban categories and the larger spatial extent of the Perth GCSSA (Western Australian Planning Commission, 2010a). Consequently, whilst the spatial extent of the defined metropolitan region or GCCSA will align with the ABS extents, urban estimations are derived from differing metrics.
The main overall limitation of the aforementioned classifications pertains to the assumption of a dichotomous urban and rural divide. However, due to the wide variations in urban designation, the UN Population Division (1950) originally proposed an urban-rural continuum (Weeks, 2010). Nevertheless, of the 228 countries for which the UN compiles data, around half define urban extent based on administrative boundaries, 51 use population size or density, 39 implement financial metrics, 22 have no definition and 8 define all (e.g. Singapore) or none (e.g. Polynesian countries) as urban (Brockerhoff, 2000). A lack of consistent national and international urban definitions precludes scientifically valid comparisons (Brockerhoff, 2000).

The advent of remote sensing provides an alternative approach for mapping urban areas. Sensors on board satellites provide consistent and reliable collection of data that when combined with approaches for classification can determine urban extent over time based upon unique and specific land cover characteristics. For this research urban is defined as a determinant of urban land cover as calculated from the spectral reflectance properties of temporally consistent user defined areas (termed Regions Of Interest (ROIs)) from satellite Earth Observation (EO) sensors: Landsat 5 Thematic Mapper (TM), and Landsat 8 Operational Land Imager (OLI). The reflected radiation monitored in each spectral band was combined in producing unique surface reflectance spectral signature for the ROIs subsequently matched to other similar pixels through classification methodologies. Due to the heterogeneity of urban areas and spectral confusion of classification methodologies associated with spectrally similar land cover classes (e.g. bare earth and urban) urban land cover was classified as either high or low urban albedo (Chen et al., 2014). The former represents surfaces with higher solar reflectivity (e.g. concrete) usually found in city centres whilst the latter denotes lower solar reflectivity (e.g. asphalt) commonly used in residential developments (Yang et al., 2015).

In this sense urban area depicts land cover representing the biophysical attributes of Earth's surface as opposed to land use that defines the human purpose or intent applied to the biophysical attributes (Lambin et al., 2001). Whilst this definition excludes population, economic and social organisation factors, it provides the longest temporal record of land cover derived from a replicable and temporally consistent methodology appropriate in determining further environmental relationships such as the association with temperature; important for planning (sustainable) development. Within this research development refers to an expansion of urban area based upon a change in land cover whilst sustainable is defined as actions causing minimal (or no) damage to the environment and humans enabling long-term continuation aligning with the UN's combined sustainable development definition of development "that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987, p.41).

1.3 Types of urban expansion

1.3.1 Urban growth

Within scientific literature urban growth is often conceptualised using a form of geographic data resulting in three main categories considering the relationship to existing urban areas, namely infill, expansion and outlying, with outlying obtaining three further sub categories of isolated, linear branch and clustered branch (Wilson et al., 2003; Yuan et al., 2005) (Figure 1 3). Infill growth is defined by the (re)development of a small land tract surrounded by urban land cover. Often characterised by the conversion of a non-developed area (e.g. 30 m2) to an urban surface with at least 40% of the surrounding area that is also defined as developed, usually occurring in areas of existing infrastructure (Bhatta, 2010; Wilson et al., 2003). Expansion growth constitutes conversion of non-developed area to developed, whilst being surrounded by no more than 40% existing developed area (Bhatta, 2010; Wilson et al., 2003). The overall limiting factor of these characterisations pertains to the assumption of conversion from non-developed land (known as a greenfield site), when other urban land cover could be converted from dormant use (e.g. wasteland or abandoned facilities, known as a brownfield site) to a form infill development. However, this type of conversion is difficult to determine without land use information accompanying geographic data. Outlying growth occurs beyond the existing developed area, in the isolated form it is characterised by one or several developed areas surrounded by minimal developed land. The linear branch form refers to a new linear development (e.g. roads) that are surrounded by non-developed areas. Finally the clustered branch form identifies large compact developments that are neither isolated nor linear in nature (Wilson et al., 2003).

Figure 1 3. Forms of urban growth as defined by scientific literature. Adapted from Bhatta (2010).

In contrast to academic literature, previously presented metropolitan level policy documents in section 1.2 stipulate infill targets and aspirations but often omit urban growth definitions providing no further subcategories (e.g. Perth and London) or vague definitions (e.g. Johannesburg) that are difficult to quantitatively assess. For example, the Johannesburg Metropolitan Municipality specified a linear future development scenario defined based on concentration of population and jobs along extensive transit corridors, but lack a measureable metric that would provide adequate monitoring. Whilst the Western Australian Planning Commission (WAPC) aim to achieve 47% of future development as infill by 2050, monitoring considered zoned and not necessarily developed industrial, commercial and residential land use defined as infill or greenfield based upon residential density above or below an unspecified threshold using census data (Western Australian Planning Commission, 2016a). In Australia, census data is collected every 5 years, restricting temporal monitoring of development and assuming that changes in density across a range of land use types that may not yet be developed is an accurate representation of infill development (Western Australian Planning Commission, 2016a). The vagueness associated with current policy definitions initiates difficulties for local governments in meeting specified targets and in the provision of policy-focused methodologies to accurately monitor urban development.

1.3.2 Urban sprawl

The expansion of low density suburbs into previously rural areas creates exurbs, urban or suburban areas and raises the notion of urban sprawl (Sun et al., 2013; Yuan et al., 2005). Currently there is no universally accepted definition of urban sprawl, with multiple studies using urban growth, urban sprawl, peri-urbanisation and exurban development interchangeably without providing definitive definitions (Schneider, 2012; Schneider and Mertes, 2014; Suarez-Rubio et al., 2012; Xian et al., 2012). Whilst Yuan et al. (2005) highlighted the requirement of an undeveloped land buffer between established area and new development, Castrence et al. (2014) simply stated urbanisation is a loss of open space and agricultural land that leads to urban sprawl. In terms of previously considered metropolitan policy documentation only Johannesburg provided a definitive sprawl definition revolving around dispersed over focused developed forms, whereas Perth's implied low density, greenfield detached housing dwellings located on the urban fringe and London's suggested development beyond the greenbelt. Consequently in a similar theme to urban growth, policy orientated urban sprawl ambiguity produces difficulties for both local governments and researchers in monitoring and identifying solutions when the very concepts aren't defined by metropolitan agencies.
Defining urban sprawl as a concept has highlighted ambiguity and conceptual vagueness (Bennett, 2001; Bhatta, 2010; Bhatta et al., 2010). Galster et al.

(2001) undertook an extensive evaluation of sprawl within the literature that revealed sprawl can be alternatively or simultaneously referred to as patterns of land use, processes of land development, causes of land use behaviours and consequences of land use behaviours (Bhatta, 2010; Bhatta et al., 2010; Galster et al., 2001). Furthermore, to add to the complexity, sprawl is also referred to as a noun and a verb. As a noun it signifies a condition representing an urban area at a particular time, whereas when used as a verb it defines a stage or process of development (Bhatta, 2010; Galster et al., 2001). Whilst a definitive definition of sprawl is contested, a general academic consensus exists that urban sprawl is characterised by unplanned and uneven pattern of growth resulting in inefficient resource utilisation (Bhatta, 2010; Bhatta et al., 2010; Sun et al., 2013), which is the definition followed in this research.

1.3.3 Urban growth and sprawl in Earth observation

It is important to establish that every type of urban growth should not be considered sprawl (Bhatta, 2010). Whilst the notion of sprawl attracts a negative connotation in terms of environmental and societal impacts, types of urban growth such as infill development are considered resolutions to urban sprawl. Consequently, sprawl should not be used interchangeably with urban growth and must be considered as its own separate entity. However, within EO studies this is often unfeasible due to similarities of materials and geometries that compose both urban sprawl and urban growth being indiscernible using medium resolution EO imagery. Therefore the majority of studies focus on monitoring urban growth as a holistic concept (which could encompass sprawl) as being the change in developed land between two or more time periods (e.g. Luo et al., 2014; Schneider and Mertes, 2014; Sexton et al., 2013; Song et al., 2016).

1.4 The urban heat island effect

1.4.1 Introduction

One of the main environmental impacts of urbanisation is the UHI effect, whereby urban areas obtain comparatively higher atmospheric and surface temperatures than surrounding rural areas (Cai et al., 2016; Howard, 1988; Hu and Brunsell, 2015; Voogt and Oke, 2003; Xie and Zhou, 2015). The modification of land cover properties as a result of urbanisation has been identified as the most extreme cumulative effect of land cover change, permanently influencing atmospheric energy exchange and altering local and regional climate change (Cai et al., 2016; Howard, 1988; Hu et al., 2015; Voogt and Oke, 2003; Xie and Zhou, 2015). Thus, UHIs are considered one of the major problems posed to humans in the 21st century, with the importance of understanding heat risk highlighted by extreme temperatures overtaking flooding and rising to the third highest cause of global disaster mortality (11.3%) between 2006 and 2015, behind only earthquakes (51.2%) and storms (24.9%) (Centre for Research on the Epidemiology of Disaster and the United Nations Office for Disaster Risk Reduction, 2016).

1.4.2 Urban heat island theory

The UHI phenomena is created through a shift in energy balance toward sensible heat over latent heat. The former represents heat exchanged by a body that changes temperature (e.g. conduction, convection or advection) whilst the latter is defined as energy released or absorbed by a body (e.g. evapotranspiration) (Sexton et al., 2013; Wong et al., 2013). The creation of UHIs is the result of two major factors: an increased spatial coverage of dark surfaces and the absence or removal of vegetation (Frumkin, 2002; Voogt, 2004). Dark urban surfaces obtain a low albedo (albedo being the fraction of shortwave radiation reflected from an object, in comparison to natural surfaces). Consequently, impervious surfaces (such as asphalt and concrete) absorb and retain a large proportion of the shortwave radiation during the daytime, reemitting this energy as long wave energy (or sensible heat) during the day (based on surface properties) and particularly at night (Zhao et al., 2016). However, due to the three dimensional structural arrangement of modern cities, a low Sky View Factor (SVF), defined as the ratio of radiation received (or emitted) by a planar surface to the radiation emitted (or received) by the entire hemispheric environment, frequently precludes efficient heat dispersion (Abutaleb et al., 2015; Frumkin, 2002; Kalnay and Cai, 2003; Lindberg and Grimmond, 2010; Sharifi and Lehmann, 2014; Voogt, 2004; Watson and Johnson, 1987; Zhao et al., 2016). The absence or removal of vegetation reduces solar radiation blocking to urban surfaces which inhibits heat emittance, diminishing evapotranspiration that cools the atmosphere through ambient heat dissipation (Frumkin, 2002). Further factors including air speed, cloud cover, cyclic solar radiation, building material type and anthropogenic energy sources can exacerbate this phenomena in a temporary (e.g. weather patterns) or more permanent (e.g. built environment) manner (Rizwan et al., 2008; Sheng et al., 2015).

Contributing UHI factors are commonly described through the energy balance equation whereby net radiation, defined as the balance between incoming and outgoing energy at the top of the atmosphere equates to the sum of sensible heat (energy heating the air), latent heat (energy used for evaporation) and surface conductive heat (energy heating the ground) fluxes. When applying the energy balance equation to UHI concepts sensible heat is representative of building thermal properties, latent heat is a function of vegetation coverage and surface conductive heat is dependent on surface albedo. Recent iterations have also included anthropogenic heat sources, representative of systems that emit heat such as air-conditioning and automobiles combined with net radiation equating to the sum of surface, latent and conductive heat fluxes (Arnfield, 2003).

1.4.3 Urban heat island categories

This section describes UHI categories and temporal forms, enabling appropriate terminology inclusion when discussing monitoring approaches leading to identification of current research and policy issues in relation to global and metropolitan sustainable city development goals, the latter part of the overall thesis aim.

1.4.4 Heat island layers

The UHI concept can be decomposed into three subcategories: the Boundary Layer Heat Island (BLHI), the Canopy Layer Heat Island (CLHI) and the Surface Heat Island (SHI) (Figure 1 4). BLHI and CLHI refer to warming of the urban atmosphere, with SHI indicating urban surface heat (Fabrizi et al., 2010; Voogt, 2004). The UCL and SHI are both located within the Urban Boundary Layer (UCL), extending up to around 1 km or more above the surface during daytime and shrinking to around hundreds of meters or less at night. The UCL is the layer of air closet to city surfaces and extending upwards to average tree or building height, whilst the SHI depicts the temperature Earth's surface as seen from above (Schwarz et al., 2012).

Figure 1 4. The main Urban Heat Island (UHI) components of the urban atmosphere. Adapted from Voogt (2004) and the USA Environmental Protection Agency (2008).

1.4.5 Heat island temporal form

Two different temporal forms of UHI exist: daytime and nighttime. Daytime UHI is largely driven by solar radiation and the thermal properties of urban surface materials, compared to nighttime UHI which is predominately controlled by the release of solar energy trapped during the day and additional anthropogenic energy sources (Zhao et al., 2016). Consequently, the temporal alteration of heat source generates two unique urban heat island profiles, daytime and nighttime. No clear consensus exists within the literature when identifying whether surface UHIs of the day (Cheval and Dumitrescu, 2014; Sun et al., 2015; Tran et al., 2006; USA Environment Protection Agency, 2008; Weng et al., 2004) or night (Fabrizi et al., 2010; Kenward et al., 2014; Sheng et al., 2015; Zhou et al., 2015) are more intense, with differences being based upon geographic location.

1.5 Urban heat island impacts

Elevated temperatures resulting from UHIs have been associated with detrimental health consequences (Goggins et al., 2012; Michelozzi et al., 2009; Tan et al., 2010), increased energy requirements (Santamouris et al., 2015), heightened emissions and economic expenditure (AECOM Australia, 2012; Frumkin, 2002; USA Environment Protection Agency, 2008). The following sections outline the effects of the UHI in terms of social, environmental and economic impacts.

1.5.1 Social impacts

The direct effect of heat on populations was first explored by Buechley et al. (1972), who established an exponential increase in the mortality rate relative to maximum temperature (Tan et al., 2010). Typically skin receives 5-10% of inactive cardiac output, during heat stress this can rise to between 50 and 70%. Consequently in order to maintain healthy blood pressure cardiac yield must be increased generating additional tension on the heart (Wong et al., 2013). Heat-related illnesses ensue if heat gain cannot be dissipated through physiological or thermoregulatory processes (Loughnan et al., 2013). Thus health issues can range from mild to life-threatening and commonly pertain to the cardiovascular and respiratory systems, including heat syncope or fainting, heat edema or swelling, heat tetany or hyperventilation (Basu and Samet, 2002; Frumkin, 2002; Loughnan et al., 2013). Excess heart strain can further exacerbate underlying conditions (e.g. ischemic heart disease and respiratory illnesses) or the health of vulnerable groups (e.g. elderly, high population density residents or high rise living residents) (Buchin et al., 2015; Tomlinson et al., 2011). The impact of the UHI effect on health is frequently presented in relation to respiratory hospital admissions and changes in mortality (Lowe, 2016; Michelozzi et al., 2009). For example, population adjusted excess mortality rates during the 1998 Shanghai heatwave were estimated at 27.3 per 100,000 within the urban area compared to only 7 per 100,000 in the exurban districts (Tan et al., 2010). In Hong Kong a 1 °C rise in temperature above 29 °C was associated with a 4.1% increase in mortality in areas with a high UHI intensity, compared to only a 0.7% in areas with a low UHI intensity (Goggins et al., 2012). Whilst in six “Mediterranean” (Barcelona, Ljubljana, Milan, Rome, Turin, and Valencia) and six “North-Continental” (Budapest, Dublin, London, Paris, Stockholm, and Zurich) cities a 2.1% and 1.2% increase in respiratory admissions was respectively observed across all age groups, increasing to 4.5% and 3.1% in the 75 plus age category (Michelozzi et al., 2009).

1.5.2 Environmental impacts

In terms of energy usage, for each degree of ambient temperature rise the increase in peak electricity load has been estimated between 0.45 and 4.6%, corresponding to around 21 W per degree rise per person (Santamouris et al., 2015). This is particularly problematic in countries where the majority of energy originates from fossil fuel combustion (e.g. Australia and USA). The increased energy requirement can elevate air pollutants such as sulphur dioxide (SO2), nitrogen oxides (SOx), particulate matter (PM), carbon monoxide (CO) and mercury

(Hg) all of which are considered harmful to human health (Frumkin, 2002; USA Environment Protection Agency, 2008). For example, using data across 25 USA communities, a rise of 10 g/m3 in two day average PM2.5 (particles with a diameter of less than 2.5 m) mass concentration was associated with a 0.74% increase in non-accidental deaths (Franklin et al., 2008).

1.5.3 Economic impacts

The collective impacts of the UHI were quantitatively estimated in the first ever economic assessment undertaken by the City of Melbourne (2012), with the annual UHI cost estimated at AUD 300 million. This was composed of costs associated with factors and services including health, transport, energy, anti-social behaviour, tree maintenance and animal care and mortality (AECOM Australia, 2012). Of these categories increased health costs dominated (AUD 282 million) overall expenditure, due to the dangers associated with extreme temperatures on human life and subsequent predicted mortality rise. The established impacts associated with the UHI highlight the importance of effective mitigation measures. However, recent research has estimated the impact of the UHI could increase the percentage of Gross Domestic Product (GDP) lost by 0.71% (in 2050) and 1.04% (in 2100) for the low Green House Gas (GHG) scenario and 0.80% (in 2050) and 1.79% (in 2100) under the very high GHG scenario due to exclusion from Global Climate Change (GCC) scenarios (Estrada et al., 2017). As a result the UHI effect has been included in updated international polices such as the Sendai Framework for Disaster Risk Reduction (UNISDR, 2015), SDGs (Osborn et al., 2015) and CRF (ARUP and The Rockefeller Foundation, 2015), yet these policies currently lack any methodological approach for UHI monitoring. Consequently, it is of vital importance to develop effective data-driven mitigation measures and planning policies to ensure the future sustainability of our cities.

Chapter 2

Monitoring urban growth and the urban heat island effect using Earth observation

2.1 Introduction

Chapter 1 outlined the concepts and issues of poorly planned urban development and the Urban Heat Island (UHI) effect. Chapter 2 builds upon this base knowledge through discussing current monitoring approaches and associated limitations that are addressed within this thesis.

2.2 Monitoring land cover change

Land cover data can be collected using traditional field surveys, however, for expansive urban metropolitan areas these are often unfeasible due to the required funding, person hours, strategic planning and annual replication for complete temporal and spatial coverage. As a result, data derived from field surveys is often incomplete, spatially aggregated, and temporally and geographically limited. Comparatively, satellite remote sensing enables efficient extraction of geographic land cover changes with considerable cost reductions in a timely and synoptic manner (Powell et al., 2007; Yuan et al., 2005). This is achieved through classification of unique surface reflectance signatures per pixel, being the fraction of incoming solar radiation reflected by the Earth's surface over a defined area (e.g. 30 m2) into predefined land cover classes.

Classifying an Earth Observation (EO) image in determining land cover change can be summarised by three main steps: preprocessing, classification and output evaluation. The majority of recent research advancements focus on classification, with comparatively fewer and more established methods for preprocessing and output evaluation. Three main image analysis approaches exist for extracting land cover estimates from EO data: classification algorithms, spectral indices and data-fusion approaches. Classification algorithms assign one or more user-defined land cover classes to a pixel in the digital image. For example, GlobeLand30 provided global land cover estimates divided into 10 classes, namely water bodies, wetland, artificial surfaces, cultivated land, snow/ice, forest, shrubland, grassland, bare earth and tundra from Landsat data with an overall accuracy exceeding 80% (Chen et al., 2015). However, the difficulties of extracting built-up areas is a known issue within the remote sensing community, resultant from spectral similarities between natural surface materials such as bare soil and man-made materials such as impervious surfaces leading to spectral confusion during classification (Herold et al., 2002; Lu et al., 2011; Varshney and Rajesh, 2014). New per-pixel spectral indices, such as the Normalized Difference Built-up Index (NDBI) (Zha et al., 2003), provide an alternative approach in determining the presence of a sole land cover class (e.g. urban), with a user-determined threshold establishing the value at which a pixel is assigned to the land cover type (Angiuli and Trianni, 2013; Xu, 2008; Zha et al., 2003). However, Schneider (2012) suggested analysis must move beyond mere consideration of spectral information to the temporal, spatial or polarimetric domain in order to resolve misclassification, particularly in an urban environment. In this sense, additional variables are obtained or computed and appended to original imagery for classification algorithm accuracy improvement. In the following sections an overview of preprocessing and output evaluation is provided, with a comprehensive literature review of current classification methodologies.

2.2.1 Image preprocessing

Image preprocessing entails correction for noise unattributed to surface reflectance, such as radiometric (atmospheric), geometric (image projection) and topographic (physical features) errors (Hansen and Loveland, 2012). Satellite data results in images experiencing differing radiometric conditions defined as the sensitivity of the sensor to incoming reflectance, due to variations in atmospheric conditions, solar illumination, sensor calibration, view angle and soil and vegetation changes (Du et al., 2002; Yang and Lo, 2000). Similarly, geometric misalignment and slope orientation in relation to incoming solar radiation can result in inconsistences when undertaking scene classification and thematic evaluation (Richter et al., 2009). The majority of studies exploring land use and land cover change have implemented medium spatial resolution (30 m) Landsat imagery, obtaining the longest, free temporal image repository of consistent medium spatial resolution data, with a temporal resolution of 16 days (Bagan and Yamagata, 2012a; Kressler and Steinnocher, 2001; Lu et al., 2011; Sexton et al., 2013; Sundarakumar et al., 2012; Tan et al., 2009). Landsat data are distributed as a surface reflectance product achieved through the Landsat Ecosystem Disturbance Adaptive Processing System (LEDPAS) and the Landsat 8 Surface Reflectance algorithm (L8SR) otherwise known as the Landsat 8 Surface Reflectance Code (LaSRC) for correction of atmospheric conditions (Hansen and Loveland, 2012; USGS, 2015). The former corrects for atmospheric effects using the Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer model, whilst the latter implements an internally developed algorithm (Hansen and Loveland, 2012; USGS, 2015). Additional processing to Level 1 Terrain-corrected data (L1T) corrects for both geometric and topographic errors using ground control points and a Digital Elevation Model (DEM) from the Global Land Survey (GLS) 2000 data set (Hansen and Loveland 2012). However, owing to the requirement of several parameters (i.e. Aerosol Optical Thickness (AOT), ozone and air temperature) for surface reflectance derivation assumptions or models of values are often implemented (Ju et al., 2012). Consequently, for removal of remaining post-atmospheric correction noise such as the brightening effect of cloud or darkening of cloud shadow, Sexton et al. (2013) put forward the notion of image standardisation based on pre-defined band specific values and subsequent normalisation for reduced inter-annual surface reflectance values. When classifying EO imagery over multiple years this approach permits the use of a single classification model as opposed to individual classification for each time point considered.

2.2.2 Image classification

Holistic image classification is achieved through a supervised or unsupervised methodology. In a supervised classification the user selects sample pixels termed Regions of Interest (ROI) that are representative of predefined land cover classes. ROIs are then input to a classification algorithm that identifies pixels with similar reflectance values to each provided land cover class for entire image classification. During an unsupervised classification an algorithm automatically separates image pixels into clusters obtaining similar spectral characteristics, with only a user defined number of classes. Owing to the majority of recent literature focusing on supervised classifiers due to the complexity and size of datasets this review shall be limited to supervised methodologies (Schneider, 2012).

2.2.3 Recent classification methodologies

Classifier selection is dependent on the nature of input data and desired output, defined as parametric or nonparametric. Parametric algorithms make assumptions regarding ROIs selected for training, such as a Gaussian distribution, whereas nonparametric algorithms do not make this assumption (Donnay and Unwin, 2001; Jensen, 2005). Popular traditional nonparametric classification algorithms include density slicing, parallepiped, minimum distance to mean, and nearest-neighbour, with Maximum Likelihood (ML) the most widely utilised parametric classifier (Jensen, 2005).

2.2.3.1 Maximum likelihood

The ML classification is based on Bayes' Theorem of decision making. It assigns each pixel to the most probable user-defined land cover class, rather than the minimum distance, through considering both the variances and covariances of class signatures (Atkinson and Lewis, 2000; Jensen, 2005). The ML algorithm permits specification of prior classification probability information (i.e. expected frequency of classes per scene). However, in reality, information of this sort is rarely available, with the majority of ML applications assuming equal class probability per scene and assigning land cover classification to pixels based upon the highest probability. The advantage of the ML classifier pertains to assignment based on probability often used in determining land cover (Fuller et al., 1994).

2.2.3.2 Spectral mixture analysis

More recently, parametric Spectral Mixture Analysis (SMA) and subsequently machine learning or 'expert systems' have been implemented to solve classification problems (Jensen, 2005; Okujeni et al., 2014). SMA considers the selection of spectrally unique endmembers, with image data being assigned the most appropriate match (Powell et al., 2007). It is based on the assumption that reflectance measured at each pixel is represented by the linear sum of endmembers weighted by the associated endmember fraction. In standard SMA a set number of representative endmembers, commonly between two and five, are extracted, with the entire image being modelled on their spectral characteristics (Powell et al., 2007). Endmember extraction normally revolves around identification of spectral extremes (e.g. Adams, 1995). However, selection of a limited number of extreme endmembers results in an inability to adequately represent the high spectral heterogeneity of the urban landscape (Powell et al., 2007). Consequently endmembers may not fully represent image spectral variability or a pixel may be modelled by endmembers that do not represent materials within its field of view. Both factors result in a reduction of classification accuracy (Powell et al., 2007). Due to being an original approach that could consider multiple endmembers whilst improving accuracy of ML and minimum distance approaches SMA has been used in establishing Vegetation-Impervious surface-Soil (V-I-S) fractions (Phinn et al., 2002) and analysing impervious surface distributions (Wu and Murray, 2003).

2.2.3.3 Multiple endmember spectral mixture analysis

Multiple Endmember Spectral Mixture Analysis (MESMA) extends this methodology through permitting the number and type of endmembers to alter on a per pixel basis attempting to represent the inherent spectral variability within land cover types over the entire image as a linear combination of constituent components (Okujeni et al., 2015, 2013; Powell et al., 2007; Weng and Pu, 2013). Mixture models are iteratively calculated for each pixel, comparing all possible endmember formulations, deriving the fit between measured and modelled signals. The model obtaining the lowest Root Mean Square Error (RMSE) is designated to the pixel (Okujeni et al., 2013). For each land cover class the MESMA library should obtain sufficient spectra to competently represent spectral variability. However, as the overall number of endmembers increases computational efficiency exponentially decreases. Thus, the endmember library should remain adequately small to maximise computational efficiency, whilst obtaining land cover spectral diversity within selected spectra (Powell et al., 2007). Due to the advantages of multiple endmember selection MESMA has been implemented in classifying land cover (Franke et al., 2009) and mapping forest fire burn severity levels (Quintano et al., 2013).

2.2.3.4 Machine learning algorithms

In contrast, Machine Learning Algorithms (MLAs) use an automated inductive approach for identification of patterns in data (Cracknell and Reading, 2014). The majority of research focusing on MLAs surrounds the predication of land cover from multi-spectral or hyperspectral surface reflectance measurements (Angiuli and Trianni, 2013; Braun et al., 2012; Rodriguez-Galiano et al., 2012; Schneider, 2012). MLA classification is derived by a discrimination function y=f(x), with inputs expressed as vectors d of the form (x_1,x_2,...,x_d), where y is a definitive set of c class labels (y_1,y_2,...,y_c). Using instances of x and y supervised machine learning trains the classification model, mapping image data to defined classes (Cracknell and Reading, 2014). Popular MLAs include Artificial Neural Networks (ANNs), Random Forests (RFs) and Support Vector Machines (SVMs).

2.2.3.5 Artificial neural network

Nonparametric ANNs are an interconnected group of nodes that use mathematical methods to process information in a self-adaptive system, attempting to ‘mimic’ a human brain (Bhatta, 2010; Hu and Weng, 2009). The Multi-Layer Perceptron (MLP) feed forward network is the most popular ANN; obtaining three layers - one input, one hidden and one output layer - each comprising of several nodes (artificial neurons). The input layer represents the original image, with each band representing one node. Classification is undertaken in the hidden layer, with results presented in the output layer. The learning ability originates from the learning algorithm, with the most popular being Back-Propagation (BP) otherwise known as delta rules (Hu and Weng, 2009). Learning is achieved through node weight assignment, with training samples input into the model. If the difference between the produced results and test sample is larger than the initial threshold, weights are altered for difference minimisation. The process is iterated until a pre-defined accuracy level is obtained or maximum iterations reached and a classified land cover output is produced (Candade and Dixon, 2004; Cracknell and Reading, 2014; Hu and Weng, 2009). ANNs have been widely used due to their robustness and ability to learn complex patterns, successfully implemented in ship detection (Tang et al., 2015), tree detection (Malek et al., 2014) and land use classification (Cheng and Han, 2016; Hu and Weng, 2009; Pacifici et al., 2009).

2.2.3.6 Random forest

RFs are a nonparametric ensemble learning method that implement a majority vote system to predict classes based on data partition from multiple Decision Trees (DT) (Breiman, 2001; Cracknell and Reading, 2014). Multiple trees are created, using a random subset of input features to reduce generalisation error, with the end user specifying the number of trees to be developed and number of features at each node. Each tree implements a bagging sample permitting growth based on differing training subsets, with a search across a random selection of input variables for derivation of a split per node (Cracknell and Reading, 2014; Gislason et al., 2006; Rodriguez-Galiano et al., 2012). Bagging facilitates training data creation through randomly resampling the original dataset, with each selected subset for tree growth containing a proportion of the training dataset. Samples not selected are input to the Out Of Bag subset (OOB). OOB samples not utilised for tree training can be classified by the tree for performance evaluation (Rodriguez-Galiano et al., 2012). DT design requires the determination of an attribute section and pruning method. The random forest classifier implements the Gini Index as the attribute selector method, measuring the impurity of an attribute compared to classes (Pal, 2005). DT can be constrained through a termination criterion threshold limiting growth size and therefore overfitting, termed pre-pruning. Additionally post-pruning techniques permit overall performance evaluation, due to being pruned with validation data. However, Breiman (1999) suggested that whilst the number of trees increases the generalisation error always converges without overfitting due to the Strong Law of Large Numbers, which states that the average results obtained from a large number of trials (or trees) should be near the expected value and will become closer with the more trials performed (Rodriguez-Galiano et al., 2012). Thus, for classification, each tree within the RF inputs a vote for the most popular class, with the output classification determined by the majority of tree votes (Gislason et al., 2006). RF are advantageous over other ensemble classification methodologies such as boosting and bagging through an improved methodological process and less intensive computational requirement being used in instances to classify: land cover (Gislason et al., 2006) and tree species (Immitzer et al., 2012).

2.2.3.7 Support vector machine

The nonparametric SVM classifier identifies an optimal maximum margin separating hyperplane, dividing the dataset into the predefined number of classes, with points on the margins termed support vectors (Braun et al., 2012; Foody and Mathur, 2006, 2004; Mountrakis et al., 2011; Qian et al., 2014; Vapnik and Chervonenkis, 1971). The underlying benefit of SVM is known as structural risk minimisation, whereby SVMs are able to minimise error on unseen data without prior assumptions made on the data probability distribution (Mountrakis et al., 2011). SVMs are linear binary classifiers assigning participant pixels into one of two possibilities. However, remote sensing derived land covers are often not linearly separable due to cluster overlap. Consequently implementation of soft margin and kernel methods aid inseparability through transforming data into high dimensional feature spaces (Euclidean or Hilbert) utilising non-linear functions to identify linear solutions (Braun et al., 2012; Mountrakis et al., 2011). In order to prevent over fitting SVM implements a two-dimensional grid search using stratified crossvalidation to search for the kernel (g) and regularisation parameter (C); (g) defines the width of the Gaussian kernel function whilst (C) controls training data and decision boundary maximisation plus margin errors (Zhu and Hastie, 2005). For derivation of more than two land cover classes additional methodological processes are required, common methods include one-against-all, one-against-one and directed acyclic graph SVM, whereby the binary nature of SVM is iterated in differing formants to derive the appropriate land cover classification (Chih-Wei et al., 2008; Mountrakis et al., 2011). SVMs are one of the most prominent and effective MLA due to structural risk minimisation applied to a variety of applications including land cover change detection (De Morsier et al., 2013), airport detection (Tao et al., 2011) and road extraction (Cheng and Han, 2016; Das et al., 2011).

2.2.4 Comparison of recent classification methodologies

Image classification accuracy is dependent on the selected classification methodology and the choice of internal parameters (Huang et al., 2002; Watanachaturaporn et al., 2008). Due to the parametric nature of the ML classifier it can often fail to represent land cover that might be multimodal, thus in certain circumstances ML has been outperformed by alternative classification algorithms (Melgani and Bruzzone, 2004; Mountrakis et al., 2011; Otukei and Blaschke, 2010; Watanachaturaporn et al., 2008). Similarly MESMA classification can be inefficient owing to additional computational demands associated with an increasing numbers of endmembers which often precludes selection and is consequently considered a more traditional method when compared to MLAs (Okujeni et al., 2015; Ram and Wang, 2013). In a comparison of ML, DT (e.g. RF), ANN and SVM classifiers, Watanachaturaporn et al. (2008) and Kotsiantis et al. (2006) found the SVM classifier to produce optimal accuracy. Similarly Huang et al. (2002) found SVMs obtain a higher accuracy than ML, DTs and ANNs indicating that the superior performance of SVM is attributed to the derivation of an optimal separating hyperplane (Foody and Mathur, 2006, 2004; Huang et al., 2002; Mountrakis et al., 2011). Whilst no single MLA can uniformly outperform all other MLAs across all data sets, in terms of overall accuracy the majority of literature preferences implementation of SVM due to its self-adaptability, efficient learning speed and limited training data requirements (Kotsiantis et al., 2006; Mountrakis et al., 2011).

2.2.5 Image spectral combinations

The reliable and accurate identification and extraction of built-up areas from medium resolution EO imagery (e.g. Landsat) is a known issue within the remote sensing community; originating from spectral heterogeneity of urban surfaces often resulting in spectral confusion during image classification (Herold et al., 2002; Lu et al., 2011; Varshney and Rajesh, 2014). Consequently new spectral indices, which in the most part do not require classification have been postulated as an alternative and more computational efficient approach.

Zha et al. (2003) proposed a built up index termed the Normalized Difference Built-up Index (NDBI) algorithm for identification of built up regions using the reflective bands: Red, Near-Infrared (NIR) and Mid-Infrared (MIR). NDBI makes the assumption that built up area has a high spectral reflectance in the MIR compared to the NIR. However, MIR vegetated spectral response can increase above NIR under drier conditions (Gao, 1996; Xu, 2008). Thus, Zha et al. (2003) implemented the Normalised Difference Vegetation Index (NDVI) to filter noise arising from vegetation. Nevertheless Xu (2008) stated that sole use of original spectral bands for construction of a built-up land index is inappropriate due to the composition of complex spectral features.

Consequently Xu (2008) followed the methodological framework of Ridd (1995), that the spatial composition of urban areas can be decomposed into Vegetation-Impervious surface-Soil creating the V-I-S model with the inclusion of water, grouping the urban area into: built up land, vegetation and open water (Ridd, 1995). Three indices of NDBI, the Soil Adjusted Vegetation Index (SAVI) and Modified Normalized Difference Water Index (MNDWI) represented the land cover categories respectively. MNDWI modifies the Normalized Difference Water Index (NDWI) through selection of the MIR band in place of the NIR band, remediating built up land noise for open water selection. SAVI was preferenced over NDVI due to greater sensitivity in detecting vegetation in low-plant covered regions such as urban areas, estimated to work with plant cover as low as

15% compared to NDVI at 30% (Xu, 2008). Aforementioned indices extracting unique features were then combined in the Index-based Built-up Index (IBI). However, the intrinsic issue of IBI pertains to selection of an appropriate user defined correction value for SAVI ranging from 0 for high plant densities to 1 for low plant densities. Furthermore complete land cover is assumed to be adequately modelled from built land, vegetation and water. Thus, analysis has resulted in urban area remaining mixed with bare earth, requiring additional polygon layers defining the urban region from an unspecified source to filter erroneous built up land for definitive extraction (Stathakis et al., 2012; Sun et al., 2015; Xu, 2008; Zha et al., 2003). Additionally, the nature of determining appropriate singular threshold values over heterogeneous urbans fails in global practicality and has the potential for the introduction of localised errors impacting reliability (Xu, 2008).

In contrast to the threshold approach presented by Xu (2008), Angiuli and Trianni (2013) proposed the Normalised Difference Spectral Vector (NDSV). Due to multiple indices presented throughout literature NDSV attempts a simultaneous merge for the production of intrinsically normalised globally consistent data whilst reducing ambiguities associated within individual indexes (Angiuli and Trianni, 2013; Patel et al., 2015). NDSV computes all possible indices through the combination of all bands. Thus, with 6 Landsat bands a total of 30 indexes are generated, but due to the symmetry of definition, 15 are negative representations of other indexes (Angiuli and Trianni, 2013; Patel et al., 2015). NDSV creates a normalised signature per pixel and is subsequently classified. Nevertheless, any index is founded upon assumptions, for example, NDVI is based on the rationale that green plants absorb solar radiation in the photosynthetically active radiation spectral region (400 – 700 nm) and reflect radiation in the NIR region. Therefore NDVI is usually highly correlated with Leaf Area Index (LAI) and has found to be sensitive to canopy background variations such as soil visible through the canopy (Jensen, 2009). Consequently NDVI can be unsatisfactory, especially when mapping senesced vegetation owing to reduced absorption in the visible bands and reflection in the NIR band (Jensen, 2005). This methodology also fails to directly extract urban extents owing to the requirement of a classification model.

2.2.6 Data fusion methodologies

Recent data fusion methodologies combine additional or computed data to existing spectral bands in order to improve classification accuracy (Rodriguez-Galiano et al., 2012). Popular approaches can be categorised into spatial, temporal and polarimetric domains extracting additional information from texture, temporal composites and radar respectively. The following sections outline and compare these procedures, determining current research trends and establishing the most appropriate methodological approach in quantifying the temporal urban growth section of the overall thesis aim.

2.2.6.1 Spatial domain

Texture analysis provides a representation of the visual characteristics of an image permitting incorporation of spatial information into image (e.g. Landsat) classification found to produce more accurate classifications of heterogeneous land covers such as urban (Møller-Jensen et al., 2005; Rodriguez-Galiano et al., 2012; Zhou and Troy, 2008). Co-occurrence texture measures such as mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation are computed using a moving rectangular window surrounding a central pixel. Nevertheless, an overarching issue pertains to window size; it must be large enough to capture variance, yet small enough to represent homogenous land cover (Møller-Jensen et al., 2005). Consequently, the window-based approach tends to smooth boundaries between discrete land cover types determined from medium-coarse resolution imagery, with the appropriate window size being difficult to discern and a rectangular window not necessarily representative of real land coverage (Møller-Jensen et al., 2005). Very high resolution (< 1 m) surface reflectance imagery, Light Detection and Ranging (LiDAR) and stereo imagery such as that procured during Perth's Urban Monitoring project and the State of Indiana's strategic plan can overcome these limitations, but are associated with high financial outlay and often infrequent repeat collections that currently preclude extensive temporal monitoring (e.g. 15 years) (Caccetta et al., 2012; The State of Indiana, 2017).

2.2.6.2 Temporal domain

Annual and multi-seasonal temporal image composites increase class spectral separability through stacking imagery from multiple dates into a single image (Bhatta, 2010; Castrence et al., 2014; Schneider, 2012; Sexton et al., 2013; Yuan et al., 2005; Zhu et al., 2012). This follows the logic that natural surfaces obtain a type of cyclical pattern resulting from changes in the proportion of land cover (e.g. mixtures of vegetation, soil and water) based on the time of year (Jensen, 2005). However, when natural surfaces are replaced with impervious structures the fluctuation will cease owing to the conversion to built-up land cover generally being unidirectional, identifiable from a multi-temporal signature in spectral space (Castrence et al., 2014). Regardless, the premise of this method is founded upon the assumption that limited or no change will have occurred within a complete temporal period of stacked imagery. Ideally, each variable used in classification should enable additional refinement for improved accuracy. Nevertheless, due to the number of bands within the multi-temporal image composite high variable correlation may be prevalent (Bhatta, 2010; Zhu et al., 2012). Redundancy can be overcome through principal component transformation, with components containing significant variance selected for classification (Bhatta, 2010). Whilst Zhu et al. (2012) acknowledged this issue through investigating the effect of increasing variables during classification they concluded that although some variables contribute relatively little, the trend is straightforward; more independent data results in higher classification accuracy.

2.2.6.3 Polarimetric domain

Synthetic Aperture Radar (SAR) data are playing an increasingly important role in remote sensing owing to all weather operational ability (Zhu et al., 2012). Although SAR images over urban areas provide low quality images due to problems associated with radar imaging in such an environment (i.e. multiple bouncing, layover and shadowing), SAR texture measures can provide valuable information in discerning urban areas (Dell'Acqua et al., 2003; Zhu et al., 2012). Isolated scattering of residential areas and crowded backscatters of inner city high density areas permit classification refinement, thus textural measures such as those descried within the spatial domain can aid identification of alternative urban forms (Zhu et al., 2012). However, the lack of freely available SAR data that temporally coincides with other satellite imagery (e.g. Landsat) frequently precludes extensive use.

2.2.7 Output evaluation

Accuracy assessment of classified data is key to ensure effective and appropriate data usage. Accuracy can be determined through visual inspection, non-site specific analysis, difference imaging, error budgeting and quantitative assessments (Congalton, 2001). Visual inspection is often the first step of assessment in ensuring the production of a valid output, but does not provide numerical quantification. Non-site specific analysis and difference imaging compare classified output between an alternative data source for a small spatial area and complete image respectively, providing a spatial component to map error. However, these methods fail in determining the accuracy of each individual land cover class, presented as difference in area estimates and difference images. Error budgeting estimates the total error of a project workflow based on analyst attributed values, combined in an error index (Congalton, 2001). Whilst this assists in determining and assessing data input, user and methodological error potential it fails in end user classification output accuracy estimation. A quantitative accuracy assessment is imperative in order to accurately report any modelled urban growth estimates, often omitted from values provided in metropolitan planning documents. An error matrix is the most common quantitative evaluation of classified remotely sensed data (Foody and Mathur, 2004; Friedl et al., 2010; Van de Voorde et al., 2011; Watanachaturaporn et al., 2008). An error matrix is a square array comparing the number of sample units correctly determined by the classifier in relation to a data source (e.g. original image or Google Earth) per land cover category. Outputs include (i) user's accuracy defined as the fraction of correctly classified pixels relative to all others classified as a particular land cover, (ii) producer's accuracy defined as the fraction of correctly classified pixels compared to ground truth data, and (iii) overall accuracy that represents the combined fraction of correctly classified pixels across all land cover types (Congalton, 2001). Quantitative accuracy metrics of this sort permit appropriate use of land cover products and parameterisation of further analysis that expands upon the classified output such as recent Urban Heat Island (UHI) studies that combine land cover data and satellite derived temperature.

2.2.8 Classification methodological conclusion

Mapping urban areas remains a complex challenge owing to the complex variation of materials and geometries that compose the urban environment and contribute to mixed spectral signatures (Schneider, 2012). Methodologies employed for extraction of urban areas from satellite imagery are diverse and often location dependent, with no current standardised best practice for urban monitoring. Throughout the literature spectral, spatial, temporal and polarimetric data have been used in differing formulations for urban area extraction.

Due to the limited past record of complete SAR data, required temporal analysis observed within academic and metropolitan studies (e.g. 15 years) is often unfeasible. Additionally, spectral analysis can be seasonally dependent, whilst spatial analysis can remove underlying trends through data smoothing and poor representation of real land cover due to a definitive rectangular moving window. Generation of unique multi-temporal spectral signatures increases the amount of independent data available for classification but the underlying assumption of minimal change between composited images is made. Due to these limitations, EO data is typically classified as standalone data (e.g. surface reflectance) by classification algorithms discussed in section 2.2.3. However, these methodologies have been found to significantly over or underestimate urban area by between 50-60% in complex landscapes such as the urban-rural frontier (Lu et al., 2011; Wu and Murray, 2003). Improving our ability to map urban area is currently an essential challenge due to the potential for classified land cover products to inform decision making such as determining future development strategies and informing further environmental analysis and policies (Bagan and Yamagata, 2014; Hepinstall-Cymerman et al., 2013; Miller and Small, 2003; Schneider et al., 2005).

2.3 Monitoring urban heat islands

Two forms of temperature affecting urban areas are frequently monitored in relation to an expanding urban area; air temperature and Land Surface Temperature (LST). The former often pertains to traditional meterological monitoring, whereas the latter is based on thermal measurements made from EO data. The following sections describe these two methodological approaches.

2.3.1 Traditional urban heat island methodologies

Air temperature represents Urban Canopy Layer (UCL) temperature; directly impacting human comfort and public health, monitored from static weather stations (Guo et al., 2014). For example, Shanghai's heatwave excess mortality rates (Tan et al., 2010), Hong Kong's UHI-mortality association (Goggins et al., 2012) and Melbourne's UHI economic assessment (AECOM Australia, 2012) used differenced temperature data from meteorological stations in rural and urban geographical locations to determine the UHI Intensity (UHII) (Tan et al., 2010). To account for the spatial variation in the UHI effect, the temperature measurements from weather stations are often spatially interpolated. The accuracy of the interpolated dataset can be dependent on the type of interpolation method, the number of points available and distance between them (Hattis et al., 2012). Consequently, whilst studies using point-based meteorological data provide a broad city scale view of the UHI, they are impractical for targeted mitigative planning actions (e.g. urban greening) due to the limited number of meteorological stations in many areas.

2.3.2 Remotely sensed land surface temperature

EO data overcomes the limitations of point based methods through providing near global coverage of LST on a per pixel basis using instruments that measure in thermal spectral wavebands. LST measurements are widely used to quantify the impact of land cover type on the Surface Heat Island (SHI), often related to air temperature in the same location, resulting in the term Surface Urban Heat Island (SUHI) (Schwarz et al., 2012; Voogt and Oke, 2003). In the context of characterising the UHI, LST is typically used, as opposed to air temperature due to the additional parameters required to compute air temperature such as surface properties, atmospheric conditions and solar angles that must be incorporated, assuming data availability during satellite overpass. Due to their advantages in monitoring temperature, satellite instruments including the Moderate Resolution Imaging Spectroradiometer (MODIS) (Wang et al., 2015), Landsat Thematic Mapper (TM) (Jimenez-Munoz et al., 2014; Rinner and Hussain, 2011; Sobrino et al., 2004), the geostationary Spinning Enhanced Visible and Infrared Imager (SEVIRI) (Blasi et al., 2016) and the Advanced Along-Track Scanning Radiometer (AATSR) (Fabrizi et al., 2010) have been used to monitor LST and the UHI effect. Nevertheless, current methodologies frequently fail in planning practicality due to the static temporal nature through consideration of limited (two or less) EO temperature images (Li et al., 2011; Tomlinson et al., 2011) alongside aggregation to broad land cover types or use of singular metrics such as the UHII (Cao et al., 2010; Imhoff et al., 2010; Zhou et al., 2016). For example Li et al. (2011) used temperature extracted from two Landsat images captured in March and July 2001 to infer the effects of landscape composition and configuration on the UHI in Shanghai. Whilst their results produced strong correlations between LST and landscape metrics, selection of single images obtained during spring (March) and summer (July) disregard the temporal component of LST (e.g. the complete annual temperature cycle) and fail to account for potential abnormalities in temperature on selected days (e.g. heatwaves) (Li et al., 2011).

Similarly, whilst Zhou et al. (2016) explored the spatio-temporal trends of the UHI throughout China using daily MODIS LST between 2003 and 2016, their analysis was restricted to comparison of the UHII using land cover data from only 2005 and 2010. The use of two classified land cover images restricted UHI analysis through the assumption of unchanged urban area between 2003-2007 (for the 2005 image) and 2008-2012 (for the 2010 image). Land cover changes within these timeframes had the potential to produce erroneous results alongside sole output of the UHII that precludes quantification of changes in land cover associated with temperature for targeted policy remediation (Zhou et al., 2016). Consequently, research must adapt to consider the needs and requirements of metropolitan development frameworks in order to assist in more sustainable future metropolitan development.

2.3.3 Localised temperature mitigation

In response to the UHI effect and updated international policies outlined in section 1.5 a variety of localised mitigation measures have ensued, categorised into voluntary and policy themes. The former represents demonstrative projects and incentives such as Sacramento's Tree Foundation providing free shade trees to Sacramento residents (USA Environmental Protection Agency, 2013). The latter incorporates the UHI into metropolitan frameworks such as Perth and Peel **?** (Western Australian Planning Commission, 2015a), The London Plan (Mayor of London, 2016a) and Johannesburg's Spatial Development Framework 2040 (City of Johannesburg Metropolitan Municipality, 2016). **However, these policies frequently fail in planning practicality through lacking any specific methodological requirement**. Consequently local governments have incorporated quantifiable policy requirements such as Seattle's Green Factor specifying minimum vegetation requirements, yet lacking placement guidelines that could result in sub-optimal locations (USA Environmental Protection Agency, 2013). Other local governments such as the City of Perth and Fremantle have initiated EO informed Urban Forest programmes to maintain and increase vegetation coverage (City of Fremantle, 2017; City of Perth, 2006). However, due to the lack of scientifically applied UHI mitigation studies and devolution of targets to local governments, varied, inconsistent and aggregated block scale LST methodologies provide the potential to misinform vegetation placement (City of Fremantle, 2017; City of Perth, 2006). The majority of academic literature implementing remotely sensed data analysing the UHI effect uses medium-low resolution satellite imagery (e.g. MODIS, 1 km and Landsat, 30 m), inappropriate for very small scale, localised UHI mitigation decisions. It is therefore imperative to provide policy-relatable methodologies in order to facilitate scientifically-valid decision making in ensuring the sustainability of our cities.

Chapter 3

Research aim and objectives

This short chapter outlines the overall research aim and objectives of this thesis. The aim of this research is to demonstrate the application of Earth Observation (EO) data in quantifying urban growth and its impact on the Urban Heat Island (UHI) in order to illustrate its potential for informing both global and metropolitan sustainable city development goals. In achieving this aim the research objectives are extracted from current themes and gaps, presented both in the main thesis introduction and in each paper style chapter. This is divided across the four paper style chapters each addressing their own objectives:

1. Provide a remotely sensed spatio-temporal assessment (paper 1a, chapter 4) and associated methodology (paper 1b, chapter 4) of change in urban area across the Perth Metropolitan Region (PMR) using a consistent methodology.

2. Develop an approach to remediate frequent over (or under) estimation of urban area classified from medium resolution satellite imagery through comparison to very high resolution aerial imagery — paper 2, chapter 5.

3. Investigate the spatio-temporal UHI characteristics at the sub-metropolitan level using a per pixel approach through (a) determining the complexities of the UHI effect and (b) deriving associations between land cover and temperature change at the intra-urban scale — paper 3, chapter 6.

4. Establish an operational methodology for evidence-based urban planning to optimise localised UHI mitigation through the use of EO data and open source spatial temperature models — paper 4, chapter 7.

3.1 Study site

This section provides an introduction and overview to the PMR in Western Australia (WA), the study site used throughout this thesis in achieving the objectives and overall aim. The City of Perth is the State Capital of WA and has undergone dramatic urban and population growth accredited to Australia's natural resources boom commencing around the start of the 21st century. Mining and petroleum exports dominate WA's export products attributing 95% of export earnings between 2010 and 2011, with sales rising from AUD 4.7 billion in 1996 to a peak of AUD 121.6 billion mid-2013 (Department of Mines and Petroleum, 2015). The majority of the urban growth has been identified as sprawling, outward and low-density by the Western Australian Planning Commission (WAPC) (Western Australian Planning Commission, 2015a). This is representative of the 'Australian dream' comprising of detached living within a green suburb on greenfield urban-fringe sites (Dhakal, 2014; Western Australian Planning Commission, 2015a). Consequently in comparison to other Australian state capitals Perth was Australia's fastest growing city (in terms of population) between 2007 and 2014 whilst only obtaining a maximum population density of only 3,662 people per square kilometre (Melbourne 10,827; Sydney 14,747) (ABS, 2015, 2011; Kennewell and Shaw, 2008). The pressures from this extensive low density and outward expansion has induced non-strategic and car centric development that has the potential to degrade social and environmental systems such as amenity servicing efficiency and habitat loss (Dhakal, 2014; Downs, 2005; Turner et al., 2010). The guide for the long term (2050) development of Perth specifies that future land rezoning must be the result of strategic urban planning as opposed to individual requests (Western Australian Planning Commission, 2015a). However, current urban monitoring within the PMR is based upon unrepresentative (e.g. land value information) and temporally varied data. Thus, owing to PMR's vast and rapid expansion alongside a globally diverse range of urban characteristics (e.g. compact central business district, older residential areas and new suburban developments) it provides a timely and relevant example to develop innovative solutions in determining temporally consistent urban area models whilst remediating frequently reported over (or under) urban estimation from medium resolution imagery.

In a similar theme under the sustainability key strategy within the long term development guide, recently devised metropolitan and local temperature mitigation plans use limited and/or aggregated data which could misguide remedial actions (Western Australian Planning Commission, 2012). Based on the lack of global investigation into the causes and consequences of the metropolitan and local UHI effect alongside Perth's large scale conversion of natural to impervious surfaces it provides a unique and globally important case study in resolving current limitations of expanding urban areas and their association to temperature. More specific information pertinent to each objective can be found within each paper style chapter, with further contextual study area information provided in chapter 4.

3.2 Thesis structure and methodological outline

This thesis is composed of nine chapters including two introduction chapters, this aim and objectives chapter, four chapters presented in the form of scientific journal articles aligning with the 'three-paper' format PhD submission, a discussion and final conclusion chapter. Each paper style chapter is taken from a published or submitted journal article, with minor editing to ensure consistency throughout the thesis. Whilst each paper explores unique research aims, Figure 3 1 outlines inter-linkages between the collective papers forming a coherent body of novel research contributions. Specifically temporal land cover data produced within the first paper is used within paper 2 and 3, with analysis from paper 3 informing paper 4 (Figure 3 2).

Figure 3 1. Outline of general thesis structure and paper linkages.

Figure 3 2. Data flow and linkage throughout papers presented in thesis.

Following this thesis introduction and literature review chapter 4 provides an applied example into using EO data for monitoring urban expansion in the city of Perth, WA. The implications of a rapidly expanding urban area are discussed and EO derived estimates are compared to those provided by the WAPC based upon temporally varied methodologies. This study provides the first EO temporal examination of land cover within Perth from normalised satellite imagery highlighting the applicability of EO data in accurate urban quantification for sustainable targeted planning practices and addressing the first thesis objective.

Building on the work in chapter 4, chapter 5 further analyses classified hard and sub-pixel 2007 land cover data in relation to classified high resolution (20 cm) aerial imagery. The hard classification refers to the dominant land cover within each Landsat pixel, whilst the sub-pixel classification represents the probability of a pixel containing a classification value. High resolution imagery was classified using Object Based Image Analysis (OBIA) and aggregated to Landsat pixels (30 m) producing the percentage of land cover and identification of the dominant land cover class per Landsat pixel area. Firstly, the two hard land cover datasets were compared, identifying overestimation from the Landsat classification. Addressing errors of this nature are essential owing to EO land cover data being used to influence policy decisions. Overestimation was remediated through the implementation of novel spatially explicit regression model approach between the high resolution percentage urban per Landsat pixel and the Landsat sub-pixel data that improved urban land cover estimations from medium resolution imagery, achieving the second thesis objective.

Chapter 6 uses 2003 and 2013 classified land cover data produced in chapter 4 alongside temperature data from the MODIS Terra sensor. The methodology overcomes current limitations of UHI studies such as use of temporally static land cover, assumption of urban homogeneity and disregard of a spatial component through global indices, inappropriate for policy incorporation. Land cover estimates were aggregated to MODIS resolution (1 km) producing the percentage of land cover per MODIS pixel for both 2003 and 2013. The dominant land cover change per MODIS pixel was identified and associated with the difference in temperature between 2003 and 2013. Consequently the presented novel analysis established ideal future land rezoning in relation to temperature change, accomplishing the third thesis objective.

Chapter 7 draws upon chapter 6 analysis in demonstrating an improved localised UHI mitigation approach. Current global, metropolitan and localised mitigation policies and strategies often fail in planning practicality through a lack of specificities or inappropriate data use. Chapter 7 demonstrates the power of EO data and spatial modelling in reducing localised temperature for a proposed redevelopment in the City of Fremantle, WA through optimum vegetation placement using a scientifically valid and policy integratable approach, advancing current policy and academic mitigation attempts, aligning with the final objective of this thesis.

Chapter 8 critically discusses the research significance, methodological transferability, global applicability, current critical challenges and future research potential.
Chapter 9 provides a summary of the key findings of the thesis in relation to the overall thesis aim.

Chapter 4

Urban growth dynamics in Perth, Western Australia: using applied remote sensing for sustainable future planning

4.1 Abstract

Earth observation data can provide valuable assessments for monitoring the spatial extent of (un)sustainable urban growth of the world's cities to better inform planning policy in reducing associated economic, social and environmental costs. Western Australia has witnessed rapid economic expansion since the turn of the century founded upon extensive natural resource extraction. Thus, Perth, the state capital of Western Australia, has encountered significant population and urban growth in response to the booming state economy. However, the recent economic slowdown resulted in the largest decrease in natural resource values that Western Australia has ever experienced. Here, we present multi-temporal urban expansion statistics from 1990 to 2015 for Perth, derived from Landsat imagery. Current urban estimates used for future development plans and progress monitoring of infill and density targets are based upon aggregated census data and metrics unrepresentative of actual land cover change, underestimating overall urban area. Earth observation provides a temporally consistent methodology, identifying areal urban area at higher spatial and temporal resolution than current estimates. Our results indicate that the spatial extent of

the Perth Metropolitan Region has increased 45% between 1990 and 2015, over 320 km2. We highlight the applicability of Earth observation data in accurately quantifying urban area for sustainable targeted planning practices.

4.2 Introduction

Over the last 15 years, Perth has experienced exponential economic growth with Gross State Product (GSP) increasing 218% (ABS, 2015). Originally labelled as the 'Cinderella State' due to its remote location and perceived neglect from the rest of Australia, Western Australia (WA) has experienced sustained discovery and extraction of natural resources since the beginning of the 21st century (Kennewell and Shaw, 2008). In response to a growing resource sector, the city of Perth has undergone extensive urban expansion at what Dhakal (2014) identified as an unsustainable rate. To this end, the Western Australian Planning Commission (WAPC) identified that Perth's urban footprint has increased from 631 km2 to 870 km2 in the 10 years between 2002 and 2012 (Western Australian Planning Commission, 2010a, 2015a). However, these figures should be considered with caution as data used in early estimates represent land parcel (Cadastral) valuations only (provided by the Western Australian Value General's Office), with later estimates (from 2009) based on multiple urban zoning classifications, and more recently (from 2010) spatial modelling taking into account land valuation and zoning (Western Australian Planning Commission, 2010b, 2009). The use of varied data and methods impacts confidence in the ability of the Commission's estimates to represent actual change in urban extent, especially when urban zoning information includes land identified for growth but not necessarily developed. Such inconsistencies could have potential to misinform future development decisions. Consequently, here we present a spatiotemporal assessment of change in areal urban growth based upon medium resolution remote sensing through a single classification model. This provides the first accurate depiction of urban expansion for one of the world's fastest growing cities—Perth, WA. We present our findings and discuss the implications of more accurately classified urban extents in facilitating scientifically evidence-based adaptive and targeted planning policies to help reduce environmental and socio-economic consequences of poorly planned development.

4.2.1 Earth observation for monitoring urban change

Mapping the spatial extent and temporal profile of urban growth from medium resolution satellite imagery facilitates a consistent, detailed characterisation of the actual urban footprint of a city (Angiuli and Trianni, 2013; Bagan and Yamagata, 2012b). Other conventional spatial datasets such as Cadastral data provide information on freehold and Crown land parcel boundaries including attributes such as ownership and value for a singular temporal period (Thompson, 2015). However, attributed data for a singular year provides an ineffective portrayal of actual parcel land cover and temporal change. Thus, the methods and results presented in this study provide foundational information for the development of planning regulations that ensure sustainable growth of our cities, particularly in the reduction of environmental risks from ever-increasing expansion along the wildland–urban interface (Turner et al., 2010). Specifically, Earth Observation (EO) data allows spatially detailed identification of locations where (un)sustainable urban growth is occurring which enables expansion limits to be imposed through targeted policies (Bettencourt and West, 2010). In this theme, Schneider et al. (2005) determined the spatial distribution of development zones from 1978 to 2002 in Chengdu, Sichuan province, China in response to the Go West policy of the 1990s, aimed at economically boosting the West of the country. Whilst the policy was successful in raising Gross Domestic Product (GDP) levels, urbanisation concurrently increased, generating issues of urban management, including service, infrastructure and resource deficiency. Their results indicated spatial clustering, specialisation of land use and peri urban development (not considered by the original policy) which were subsequently used to tailor policy in remediating issues, facilitating sustainable future urban development (Patino and Duque, 2013; Schneider et al., 2005). Similarly, Hepinstall-Cymerman et al. (2013) used classified Landsat data to monitor urban growth in regards to imposed growth boundaries in the Central Puget Sound, Washington, United States of America. Surprisingly, more new development occurred outside the growth boundaries than inside within their last time period, illustrating the ineffectiveness of the imposed policy leading to economic and ecological consequences, including a loss of avian diversity in native forest species (Hepinstall-Cymerman et al., 2013; Hepinstall et al., 2008). These studies highlight the potential effectiveness of EO data in consistently monitoring the spatiotemporal dynamics of urban development for applied policy outcomes and ensuring sustainable future planning decisions, for which such outputs are unachievable from traditional datasets.

4.2.2 The case of Perth

Perth's dramatic urban expansion can be attributed to Australia's minerals and energy boom commencing at the turn of the century. Queensland (QLD) and WA were at the forefront of the boom contributing the largest proportion of the nation's resources output, valued at 3.3% of GDP (ABS, 2015). In WA, mining and petroleum extraction dominate exports, peaking at 95% of the state's export earnings between 2010 and 2011 (Department of Mines and Petroleum, 2015). The increase in extraction was predominantly attributable to greater demand for raw materials from China, resulting in steady growth of the WA mineral and petroleum industry from AUD 4.7 billion in 1996 to a peak of AUD 121.6 billion mid-2013. However, in 2009, a 10.3% reduction in the overall value of mineral and petroleum resources resulted from falling commodity prices and the 2007–

2009 global financial crisis (Department of Mines and Petroleum, 2015). Again in 2012, a further 9% reduction in resource value was observed as uncertainty in global economic conditions increased (Department of Mines and Petroleum, 2015). The largest decline to date occurred between 2014 and 2015, with an additional 22% reduction in the value of mineral and petroleum resources as a result of surplus capacity, decreased demand, and decline in the value of the Australian dollar (Department of Mines and Petroleum, 2015). The temporal trend in resource value indicates a stagnation and decline since late 2013 (Figure 4 1).

Figure 4 1. Timeline of natural resource value (based on Department of Mines and Petroleum annual reports) fitted with a fourth order polynomial trend line and population (based on Australian Bureau of Statistics data) also indicating key milestones.

Perth is described as one of the most isolated cities in the world (pop. $>$ 1 million) and was Australia's fastest growing metropolis between 2007 and 2014; however, subsequent to a decline in natural resource value, a slowdown in population expansion soon followed (Figure 4 1) (Kennewell and Shaw, 2008). As a result, 2015 population statistics highlight the lowest population increase since records began with a 0.5% increase from the previous year (ABS, 2015; Kennewell and Shaw, 2008). In comparison to other Australian state capitals, based on the Australian Bureau of Statistics (ABS) 2011 population grid, Perth exhibits a relatively sparse spatial distribution of population with a maximum population density of only 3662 people per square kilometre (Melbourne 10,827; Sydney 14,747). Such low density population has generated high demand for dispersed housing, amenities and services, and has influenced changes to Perth's land use patterns in a non-strategic, "lot-by-lot fashion" based on a car-dependent lifestyle (Dhakal, 2014). Anthropogenic modifications of the landscape from vegetation cover to human-made impervious surfaces represent a critical driving force in both local and global environmental change (Kalnay and Cai, 2003; Vitousek et al., 1997). For example, abrupt, poorly planned and uncontrolled urban expansion can lead to environmental impacts which degrade ecological systems including habitat fragmentation and socio-economic issues that deteriorate efficiency of amenity provisioning, both of which can exacerbate localised climate change (Downs, 2005; Turner et al., 2010). Identifying impacts of Land Use and Land Cover (LULC) change on socio-ecological systems is vital for future sustainable urban development; as reflected in the "sustainable cities and communities" 2030 sustainable development goal and the effective land use planning criteria of the City Resilience Framework (CRF) (ARUP and The Rockefeller Foundation, 2015; Vitousek et al., 1997). It is essential for Perth to adapt current practices of outward suburban expansion to achieve more sustainable urban growth and become city-smart for accommodating the predicted additional half a million new residents by 2031, which will result in an overall population exceeding 2.2 million (Western Australian Planning Commission, 2010a).

4.3 Materials and methods

4.3.1 Data preprocessing

EO data have been extensively used to monitor the sustainability of urban areas (Li et al., 2015; Song et al., 2016). However, accurate identification and temporal monitoring of urban land is frequently precluded due to the coarse resolution (300 m–1 km) of a number of commonly used remotely sensed datasets including nighttime lights (1 km) and the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product (0.083°) (Potere et al., 2009; Song et al., 2016). Whilst 30 m resolution data (e.g. Landsat) are more suitable to detect nuances of urban development the majority of studies and classified products which have used these finer resolution products implement large temporal windows, negating the possibility of detailed temporal urban characterisation (e.g. GlobeLand30, Hu et al., 2015; Masek et al., 2000; Suarez-Rubio et al., 2012; Van de Voorde et al., 2011; Xian et al., 2012). This research provides the first comprehensive temporal evolution analysis quantifying land cover change and associated urban expansion for the Perth Metropolitan Region (PMR) using 30 m Landsat imagery, the longest temporal record of medium spatial resolution imagery, for seven sequential time snapshots between 1990 and 2015.

Cloud free imagery was acquired in or close to the month of July for 1990, 2000, 2003, 2005, 2007, 2013 and 2015. Analysis of imagery acquired from WA winter season coincided with peak green-up which provided the greatest contrast between spectrally similar surfaces (e.g. bare earth and urban) (Herold et al., 2002; Lu et al., 2011; Varshney and Rajesh, 2014). Imagery date selection was founded upon the strong positive relationship between Australian soil moisture (related to rainfall) and the Normalised Difference Vegetation Index (NDVI) (Chen et al., 2014), which exhibits an approximate one month lag between peak soil moisture and peak NDVI (Chen et al., 2014).

Productive photosynthesising plants use energy in the visible red (VIS) portion of the electromagnetic spectrum whilst reflecting in the near-infrared (NIR) region. NDVI ((NIR -VIS)/(NIR + VIS)) is a representative measure of growth allowing for the identification of green, healthy vegetation (Chen et al., 2014; Myneni et al., 1997; Piao et al., 2011), as illustrative of Southwest WA's winter months. A total of 14 images from Landsat 5 Thematic Mapper (TM) (eight images), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) (two images) and Landsat 8 Operational Land Imager (OLI) (four images) were acquired for the specified years. Seamless images were produced based on Voroni diagrams that locate the bisector between images; adjacent edges were identified as seamlines constraining effective mosaic polygons that specify inclusion pixels for the final mosaicked product, permitting less visible boundaries through blending overlapping pixels (Pan et al., 2009). Mosaicked images were subsequently clipped to the original PMR study area boundary.

The atmospherically corrected Landsat data used in this study were obtained from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) and the Landsat 8 Surface Reflectance (L8SR) algorithm (Hansen and Loveland, 2012; USGS, 2015). Some inherent residual noise remained, for example, due to the differences in modelled atmospheric correction parameters (Ju et al., 2012). To correct for this, surface reflectance values were standardised as:

p__(i,b)=p__(x,b)/ max __b (4.1)

where p__(i,b) is the standardised pixel value i, from band b based on the original surface reflectance x, standardised through division of a priori specific upper reflectance limit for each band (maxab): 0.1 (blue; 0.48 µm), 0.11 (green; 0.56 µm), 0.12 (red; 0.66 µm), 0.225 (near-infrared; 0.84 µm), 0.205 (shortwave-infrared; 1.65 µm), 0.150 (shortwave-infrared 2; 2.22 µm) (Sexton et al., 2013). Standardised values were then normalised per pixel j through cross band sum division:

p__(j,b)=p__(i,b)/(*i p*(i,b)) (4.2)

where *i p*(i,b) is the sum of each standardised pixel across all bands (Sexton et al., 2013). Normalised Landsat data obtained a statistically significant reduction of spectral variation per land cover class within (inter) and between (intra) each image (see Supplementary Figure 4 5).

4.3.2 Data classification

The normalised Landsat imagery was classified using the Import Vector Machine (IVM) which builds upon the popular Support Vector Machine (SVM) methodology (Roscher et al., 2012). In order to obtain the optimum classification, the IVM algorithm explores all possible subsets of training data for optimal selection (termed import vectors) which are derived through successively adding training data samples until a given convergence criterion is met (Roscher et al., 2012). Data samples are selected according to their contribution to the classification solution. However, a pure forward system is unable to remove import vectors that become obsolete after addition of other vectors. Therefore the implemented version of IVM utilised here is a hybrid forward/backward strategy that adds import vectors whilst concurrently testing if they can be removed in each step, thus leading to a sparse and more accurate solution (Roscher et al., 2012). Furthermore, the IVM selects data points from the entire distribution resulting in a smoother decision boundary which is based on the optimal separating hyperplane in multidimensional space compared to that of SVM algorithms (Braun et al., 2012). The benefits of the IVM algorithm have resulted in this approach being successfully applied in a number of studies (e.g. Braun et al., 2012, 2011; Roscher et al., 2010; Suess et al., 2014) due to its accuracy and performance advantages over alternative methodologies including SVM and the traditional Maximum Likelihood (ML) classifier (Braun et al., 2011; Roscher et al., 2010).

Model training samples were selected using the July 2005 Landsat 5 TM image coinciding with the month post maximum rainfall of all considered Landsat 5 TM and 7 ETM+ to facilitate optimum spectral seperability (Chen et al., 2014). Land cover was defined as high albedo urban (e.g. concrete), low albedo urban (e.g. asphalt) or other. Two urban classes were initially identified in order to reduce confusion between spectrally similarly classes (e.g. urban and bare earth) being merged post-classification to represent complete urban coverage (Hu and Weng, 2009). For each class, 250 pixels were randomly selected as training data, which is consistent with Foody and Mathur (2006) and Pal and Mather (2003) (see supplementary section 4.7.2). Training data parametrised the IVM algorithm, creating a classification model of spectral profiles that are compared to Landsat spectral profiles for classification. The classification model was then applied to all Landsat 5 TM and Landsat 7 ETM+ images obtaining similar spectral wavebands, considered to be equivalent (Flood, 2014). However, due to Landsat 8 OLI sampling different spectral regions, a new classification model was developed using the same training areas, as these were deemed to remain representative of the land cover, but with Landsat 8 OLI spectral wavebands (Flood, 2014; Roy et al., 2016). Validation was performed through an accuracy assessment based on an independent dataset (Google Earth high resolution imagery) consistent with Landsat acquisition months following previously published methods (e.g. Bagan and Yamagata, 2014; Cunningham et al., 2015; Dorais and Cardille, 2011; Song et al., 2016; Sun et al., 2015; Zhu and Woodcock, 2014). For each land use category, 50 pixels per class per year were visually identified and classified based on the majority land cover within the coincident Landsat pixel from Google Earth imagery for the available years 2000, 2003, 2005, 2007, 2013 and 2015 consistent with recommended land cover accuracy sample size of Congalton (2001).

4.4 Results

The spatial footprint of PMR development has increased 48.61% between 1990 and 2015, over 320 km2 (Figure 4 2 and Figure 4 3), with a 40.56% increase occurring since 2000. The classification accuracy assessment indicates an average overall accuracy of 81.06% and Kappa Coefficient of 0.73 being comparable to other studies (e.g. Bagan and Yamagata, 2014; Gislason et al., 2006; Luo et al., 2014; Sundarakumar et al., 2012) (see Supplementary Table 4 1 and Supplementary Table 4 2). Urban expansion mirrors population increase and as population growth has slowed, urban development has concurrently exhibited a levelling trend compared to expansion previously observed (Figure 4 3).

Figure 4 2. Urban expansion within the Perth Metropolitan Region (PMR) between 1990 and 2015. Vast urban growth has been observed in PMR with graduating colours exhibiting outward expansion (a); (b) and (c) exhibit static snapshots of urban extent from 2000 (b) and 2015 (c); whilst (d) depicts percentage of urban change per subnational administrative boundary (Local Government Area (LGA)).

Figure 4 3. Time line of urban expansion in kilometers squared derived from Earth observation data with associated classification error derived from validation data (points indicating classified image years). Alongside population data in millions per year since 1988 (based on Australian Bureau of Statistics data, 2015 data is projected) with key natural resource milestones indicated, and average annual urban and average annual population growth rate indicated between classified image years.

WAPC's urban estimates of the PMR from Directions 2031 (the strategic plan for the Perth and Peel region) were provided for comparison to those produced within this study (Western Australian Planning Commission, 2010a). WAPC's estimates note an expansion from 637 km2 to 813 km2 between 2001 and 2012. Our results indicate an expansion of 747.41 km2 to 1050.57 km2 from 2000 to 2013 illustrating an overall underestimation by WAPC figures (Figure 4 4). Within suburban areas surrounding the two major cities in the metropolitan region, Perth and Fremantle, WAPC's estimates underrepresent the amount of urban area derived from EO, being more pronounced in 2013 than 2000. The Local Government Area (LGA) of Stirling South Eastern (LGA outlines displayed in Supplementary Figure 4 6) represented the maximum overestimation in 2013 urban area with 34.47% (2000: 9.95%) additional urban area per km2 of LGA established on a difference of 2.89 km2, 41.91% (2000: 0.83 km2, 14.99%) between EO data and WAPC's estimates. Outer Northern and Southern LGA WAPC urban values were consistently underestimated, with the LGA of Belmont representing the maximum underestimation of percent per km2 of LGA in 2013 with 23.62% (2000: 12.60%) due to a difference of 9.37 km2, 40.39% (2000: 5.00 km2, 26.46%). Prior to 2009, WAPC's estimates were solely based upon land parcel valuations from the Western Australian Value General's Office, consequently valuation thresholds designating land to urban may have been inappropriately applied to outer suburban LGAs, where land might be developed but less valuable than central LGAs.

For urban estimates post 2005, two urban land zones, urban and urban deferred, are used within the Perth Metropolitan Region Scheme (MRS), the division of the State Planning Policy Framework applicable to the PMR, pursuant to the Planning and Development Act (2005) that inform recent WAPC land parcel based estimates (Western Australian Planning Commission, 2016b, 2010c). Urban land refers to locations where activities in line with urban development are permitted, but not necessarily constructed (e.g. housing and commercial use) whilst urban deferred represents land suitable for future development with remaining planning, servicing or environmental issues (Western Australian Planning Commission, 2016a, 2010c). For land to be assigned urban deferred, it must obtain characteristics of the urban zone including being able to provide essential services, a logical progression of development, and able to satisfy regional requirements (e.g. roads and open spaces). The 2012 WAPC estimates were derived from stock of land zoned urban or urban deferred, cadastral land plot and value information, conditional subdivision approvals, and ongoing regional rezoning and subdivisions (Western Australian Planning Commission, 2012). Similarly to 2000, valuation data may misrepresent suburban urban land cover resulting in overestimation. Inclusion of additional variables that are unrepresentative of actual land cover change (e.g. rezoning and conditional approvals) could exacerbate differences between WAPC and EO derived urban estimates (Figure 4 4 (b)), leading to the potential confounding of errors in WAPC estimates.

Figure 4 4. Percentage differences relative to local government area size, permitting a change metric standardised by Local Government Area (LGA) area between Earth Observation (EO) and the Western Australian Planning Commission's (WAPC) urban estimates for (a) 2000 (EO) and 2001 (WAPC) and (b) 2012 (WAPC) and 2013 (EO), whilst (c) depicts the percentage difference in the relative urban rate of change (km2 per LGA area) between 2000 and 2013 (EO) and 2001 and 2012 (WAPC). Positive values indicate underestimation by WAPC whilst negative values represent overestimation by WAPC.

4.5 Discussion

WA state government planning documentation states that the majority of new development within the PMR has occurred as low-density suburban growth, responding to consumer preferences and market forces (Western Australian Planning Commission, 2015a). Additionally, sustainable policy objectives suggest that new development should be managed and focused on current communities, making the most efficient use of existing urban areas (Western Australian Planning Commission, 2010a, 2015a). Planning policy research has highlighted issues of outward urban expansion as being costly in economic, environmental and social terms based on dispersed service requirements, habitat fragmentation and neighbourhood segregation (Downs, 2005). Thus, urban expansion in the PMR may result in further economic, social and environmental costs associated with servicing and maintaining low-density lifestyles, owing to the rapid outward urban growth estimates between 2000 and 2007 (Downs, 2005; Turner et al., 2010).

In contrast, the witnessed slowdown of urban growth, population and natural resource value since 2013 indicates the possibility that the 'boom' of previous years has reached a turning point. Stagnation of urban growth implies that issues associated with spatially distributed urban areas might be contained to the current urban extent. Nevertheless, it is conceivable that prosperous future economic circumstances could initiate growth at a rate previously observed, and that the economic slowdown might be a temporary hiatus responding to current economic conditions (Perry and Rowe, 2014). For example, in 2014–2015, WA continued to attract the largest proportion of state mineral exploration expenditure at 58%, with QLD (the second ranked stated) obtaining only 20% (Department of Mines and Petroleum, 2015). Furthermore, as of September 2015, WA had an estimated AUD 171 billion in mineral and petroleum projects under construction, with a further AUD 110 billion allocated for future expansion (Department of Mines and Petroleum, 2015). Comparatively, during the peak (mid-2013) in terms of total sales, WA only had an estimated AUD 160 billion worth of projects under construction and a further AUD 108 billion for future development (Department of Mines and Petroleum, 2015). Whilst 2014–2015 observed the greatest decline in total sales of resources, sustained investment and improved global economics could reinvigorate the industry and reinitiate urban expansion within the PMR.

Future development (urban and urban deferred) is guided by Directions 2031 amending the MRS and local planning schemes (Western Australian Planning Commission, 2015b, 2015c, 2015d, 2015e, 2010a). WAPC aims to achieve 47% of future development as infill and a 50% increase in average residential density by 2050 of 10 dwellings per urban zoned hectare and 15 per new urban zoned hectare (Western Australian Planning Commission, 2010a). In monitoring progress towards the infill target, zoned development land within the PMR is considered, including residential, industrial and commercial land uses (Western Australian Planning Commission, 2015a). Densities are defined as infill or greenfield if above or below an undocumented residential threshold from census data (Western Australian Planning Commission, 2016a). Initial results from Delivering Directions 2031, 2014 report indicate the requirement of a significant increase in infill development if the above targets are to be met (Western Australian Planning Commission, 2014). Similarly, average residential density monitoring has been achieved with land valuation data (from the Valuer General's Office) for major activity centres, being unrepresentative of actual density change and providing an incomplete metropolitan comparison (Western Australian Planning Commission, 2014). Inclusion of EO data would permit quantitative evidence of urban expansion, infill and density at a higher spatial and temporal frequency than current census based estimates. This would facilitate credible, evidence-based efficient targeted action founded upon improved representative urban area, insuring infill and density attainment. In this theme, Schneider et al. (2005) and Hepinstall-Cymerman et al. (2013) used spatial metrics (e.g. urban area mean patch size) based on classified Landsat data in either pre-defined census units (Hepinstall-Cymerman et al., 2013) or development corridors (Schneider et al., 2005) to monitor development type (infill or expansion) over time for adapting inappropriate static urban development policy. Using EO derived land cover data in this manner aids in understanding dynamics of the urban environment through monitoring, planning and mitigating land use changes that impact natural assets and increase vulnerability of city systems (Hepinstall-Cymerman et al., 2013; Miller and Small, 2003; Patino and Duque, 2013). Information of this sort aligns with criteria of the CRF in improving city resilience from effective land use planning, possible at lower expense and higher temporal frequencies than in situ measurements (ARUP and The Rockefeller

Foundation, 2015).

The universal methodology implemented within this research lends itself to credibly inform policy in a similar manner in other global cities through monitoring urban expansion in order to identify rapid, unsustainable development. For example, Jakarta, obtaining the world's second largest urban area with a population of 28 million, has yet to have any quantitative urban area delineation (Pravitasari et al., 2015; Seto et al., 2011). Identification of actual urban growth in developing cities is vital to city planners, environment managers and policy makers due to the difference between planned growth and actual growth (Patino and Duque, 2013). Such information could be of critical importance for regulating urban expansion due to extreme poverty and high level of risk to environmental hazards, such as that posed from flooding (Marfai et al., 2014; Suryahadi and Sumarto, 2003). EO data presents many opportunities for added value within urban planning policy, and additional analyses could be pursued into specific human-induced environmental issues, such as detecting thermal changes in the urban environment for planning issues associated with urban heat islands (e.g. cooling provisions) and their impact on human health (e.g. air quality).

4.6 Recommendations

Consistent and accurate LULC estimates are a vital aspect of sustainable urban development throughout the world, especially considering the predicted additional 2.5 billion city dwellers by 2050. LULC models that require agents that are representative of land use decisions can often fail in practicality due to the difficulty in quantifying driving forces of change and multi-level relationships. Models of this nature are also temporally independent, with each annual iteration implementing new data or data not representative of actual LULC change. EO data provides a replicable detailed representation of the complete urban extent requiring no additional data. The use and application of EO data reported within this paper highlights several improvements to WAPC policy for consistent urban area estimations with associated accuracy measures. Therefore it is recommended that planning authorities, such as WAPC, integrate EO data to achieve the following: (1) provide scientific urban estimates based on a temporally consistent model within future regional structure plans, metropolitan region and local planning schemes; (2) monitor infill development at a higher temporal frequency than census years for policy targeting to meet key goals; (3) monitor urban density through areal urban expansion compared to current metrics using land valuations; and (4) restrict development based on temporal urban analysis that degrades amenity efficiency and ecological systems whilst promoting development in locations to maximise efficiency and long-term sustainability. Additional EO datasets (e.g. finer resolution Sentinel 2 satellite imagery or aerial imagery) could be used to refine planning decisions based on areas of concern identified from Landsat. For example, finer spatial resolution datasets could facilitate enhanced feature extraction, optimising sustainable planning decisions through the identification of candidate infill sites. EO data of this nature provides an essential tool for timely planning policy that is adaptive to changes in urban landscape to mitigate socio-environmental issues associated with poorly planned urban areas for the future sustainability of our cities.

4.7 Supplementary material

This supplementary material section supports the main chapter and thesis through providing further detail into the summarised methods and results, pertaining to three concepts, namely the: standardisation and normalisation methodology, accuracy assessment and locations of Local Government Areas (LGAs). In the first instance a statistical comparison between the original un-corrected and corrected imagery is provided to highlight the reduction in inter and intra-year variance for land cover types demonstrating the validity of a single classification model for multiple years of imagery. Whilst key overall accuracy metrics are provided within the main chapter this supplement provides additional measures for each classified image for appropriate contextualisation if used by other researchers (accessible online). Similarly, Supplementary Figure 4 6 supports Figure 4 4 and text comparing estimates produced within the main chapter to that of the Western Australian Planning Commission (WAPC) through visually identifying the LGAs. A short discussion surrounding other considered approaches and a list of data used within the chapter are also provided to demonstrate the entirety of analytical process.

4.7.1 Standardisation and normalisation

The non-urban land cover class was composed of four classes defined based on existing literature (e.g. Feyisa et al., 2016; Hu and Weng, 2009; Schneider, 2012) and study area characteristics. These classes were forest, water, grassland and bare earth. Grassland and forest were also merged to create a single vegetation class. A complete set of land cover classes enabled examination of statistical differences generated from normalisation (Supplementary Figure 4 5). The Coefficient of Variation (CV) statistic was calculated to describe the amount of variability relative to the mean spectral reflectance of the post classification datasets (Brown, 1998). The CV was calculated for pre- and post-normalisation datasets for both intra-year class reflectance, which describes the variability within each class per year, and the inter-year reflectance, which describes the variability of each class across all imagery dates. Post-normalised Landsat data exhibited statistically significant lower inter- and intra-CV with $T = 0$, $Z = -2.154$, $p = 0.016$, $r = -0.359$ and $T = 0$, $Z = -2.418$, $p = 0.008$ $r = -0.373$, respectively.

The test statistic (T) was obtained from dataset differencing (pre- minus post-processed images), representing the lowest value of the sum of positive ranks (values increased) or negative ranks (values decreased). Hence, $T = 0$ dictates that post-processed data consistently obtained a lower value than pre-processed imagery, statistically significant at $p < 0.05$ (Field, 2009). Therefore, reduced intra and inter year variance facilitates more appropriate one model classification for Landsat 5 TM and Landsat 7 ETM+ and another for Landsat 8 OLI.

Supplementary Figure 4 5. Inter year classification reflectance variation categorised by classified output for each spectral band for: pre (a) and post (b) normalisation correction.

4.7.2 Accuracy assessment

For each land use category, 50 random pixels per class per year were visually identified and classified based on the majority land cover within the coincident Landsat pixel from Google Earth imagery for the available years: 2000, 2003, 2005, 2007, 2013 and 2015 (Congalton, 2001). Both user's accuracy (fraction of correctly classified pixels relative to all others classified as a particular land cover), producer's accuracy (fraction of correctly classified pixels compared to ground truth data) and associated Kappa coefficients were consistently high except for the producer accuracy of bare earth which has an average accuracy of 53.33% (Supplementary Table 4 1 and Supplementary Table 4 2). This is due to the known spectral similarities between bare earth and impervious surfaces, and water and shadow which resulted in spectral confusion during classification (Feyisa et al., 2016; Herold et al., 2002; Lu et al., 2011; Sawaya et al., 2003; Varshney and Rajesh, 2014).

Supplementary Table 4 1. Classification accuracy and associated Kappa Coefficient per year of classified Landsat. Year Accuracy (%) Kappa Coefficient 2000 82.33 0.75 2003 80.33 0.72 2005 82.00 0.74 2007 84.00 0.78 2013 79.00 0.70 2015 78.67 0.70 Average 81.06 0.73

Supplementary Table 4 2. Producer's and User's accuracy per year of classified Landsat imagery. Producer Accuracy Bare Earth Vegetation Urban Water 2000 56.00 96.00 90.00 66.00 2003 50.00 97.00 85.00 68.00 2005 52.00 98.00 86.00 72.00 2007 48.00 98.00 83.00 94.00 2013 52.00 99.00 81.00 62.00 2015 62.00 99.00 80.00 52.00 Average 53.33 97.83 84.17 69.00 User Accuracy Bare Earth Vegetation Urban Water 2000 84.85 76.80 84.11 94.29 2003 69.44 76.98 83.33 94.44 2005 81.25 78.40 81.13 97.30 2007 68.57 80.33 87.37 97.92 2013 68.42 73.88 83.51 100.00 2015 75.61 73.88 83.33 89.66 Average 74.69 76.71 83.80 95.60 Local government areas

Supplementary Figure 4 6. Local Government Areas (LGAs) located in Perth Metropolitan Region (a); with (b) exhibiting LGAs South and West of the Swan River and (c) LGAs North and East of the Swan River.

4.7.3 Other considered data and approaches

In classifying the Landsat data a multitude of alternative approaches were attempted before arriving at one detailed within the main chapter. These included the use of different pre-processing data methodologies, classifiers and data combinations. Originally raw uncorrected (digital number) Landsat data was corrected using the Atmospheric Radiometric Calibration of Satellite Imagery (ARCSI) tool that makes use of the Py6S radiative transfer model (Bunting, 2017). However, due to the lack of availability of a number of required model parameters Landsat surface reflectance data was preferenced for consistency and repeatability. Numerous other classifiers and data combinations were tested including Support Vector Machines (SVMs) (Mountrakis et al., 2011), Multiple Endmember Analysis (MESMA) (Powell and Roberts, 2008), spectral indices such as the Normalised Difference Spectral Vector (NDSV) (Angiuli and Trianni, 2013) and classification of multi-temporal Landsat surface reflectance composites (Castrence et al., 2014). Nevertheless these were all found to produce unfavourable results in comparison to the presented approach or were unable to compute sub-pixel estimates (required within further chapters). Further information and discussion on these approaches is provided within section 2.2.

In a similar theme alternative data sources were considered and tested for classification validation such as GlobeLand30 (Chen et al., 2015) and the European Space Agency's (ESA) Climate Change Initiative (CCI) annual global land cover (300 m) time series (1992-2015) (European Space Agency, 2017). However, these products are constrained by limited temporal frequency (e.g. GlobeLand30), inadequate resolution (e.g. CCI), their own internal errors (e.g. based upon an accuracy assessment) and selection of global reference data that could fail to represent the land cover heterogeneity within the Perth Metropolitan Region. Consequently this prior work and reasoning guided the analysis undertaken in chapter 4.

4.7.4 Chapter data list

This section provides an overview of the data presented and analysed within this chapter.

Supplementary Table 4 3. Summary of the data, sources and applications used within chapter 4. Data Source Application Annual population data Australian Bureau of Statistics Contextual information Annual natural resources value The Government of Western Australia, Department of Mines and Petroleum annual reports Contextual information Landsat surface reflectance data, path 112 and 113, row 82 Dates and paths 1990: 14/04 (path 112), 7/05 (path 113) 2000: 23/08 (path 112), 1/10 (path 113) 2005: 12/07 (path 112), 19/07 (path 113) 2007: 6/10 (path 112), 9/07 (path 113) 2013: 22/10 (path 112), 13/10 (path 113) 2015: 9/08 (path 112), 17/09 (path 113) Sensors Landsat 5 TM: 1990, 2003, 2005, 2007 Landsat 7 ETM+: 2000 Landsat 8 OLI: 2013, 2015 United States Geological Survey Earth Explorer system Land cover analysis High resolution data (read only) Google Earth Accuracy assessment Comparison urban estimates Western Australian Planning Commission Comparison to the Commission's estimates

Spatial boundary outlines Australian Bureau of Statistics Comparison to the Commission's estimates

Chapter 5

Subpixel land cover classification for improved urban area estimates using Landsat

5.1 Abstract

Urban areas are Earth's fastest growing land use that impact hydrological and ecological systems and the surface energy balance. The identification and extraction of accurate spatial information relating to urban areas is essential for future sustainable city planning owing to its importance within global environmental change and human-environment interactions. However, monitoring urban expansion using medium resolution (30-250 m) imagery remains challenging due to the variety of surface materials that contribute to measured reflectance resulting in spectrally mixed pixels. This research integrates high spatial resolution orthophotos and Landsat imagery to identify differences across a range of diverse urban subsets within the rapidly expanding Perth Metropolitan Region, Western Australia. Results indicate that calibrating Landsat derived sub-pixel land cover estimates with correction values (calculated from spatially explicit comparisons of sub-pixel Landsat values to classified high resolution data which accounts for over (under) estimations of Landsat) reduces moderate resolution urban area over (under) estimates by on average 55.08% for the Perth Metropolitan Region. This approach can be applied to other urban areas globally through use of frequently available and/or low cost high spatial resolution imagery (e.g. using Google Earth). This will improve urban growth estimations to help monitor and measure change whilst providing metrics to facilitate sustainable urban

development targets within cities around the world.

5.2 Introduction

Urban areas are estimated to cover only 0.5% of Earth's surface yet are one of the fastest growing land use per area basis (Bettencourt and West, 2010; Schneider et al., 2010, 2009). Population growth has resulted in increased urbanisation with 54% of the planet's seven billion people in 2014 residing in urban areas with an additional 2.5 billion urban dwellers projected by 2050, whilst concurrently increasing the proportion of world's urban population to 66% (Powell et al., 2007; Powell and Roberts, 2010; Sexton et al., 2013; Sharifi and Lehmann, 2014; Song et al., 2016; United Nations, Department of Economic and Social Affairs, 2014). Alteration of natural land cover to anthropogenic impervious surfaces has been identified as the most extreme cumulative effect of land cover change, generating numerous socio-economic consequences including: amenity provision efficiency, ecological degradation and the Urban Heat Island (UHI) effect (Cai et al., 2016; Howard, 1988; Hu and Brunsell, 2015; Xie and Zhou, 2015). Accurate information on urban land use and land cover is therefore imperative for monitoring expansion and planning policy targeting for future sustainable development of our cities (Bettencourt and West, 2010; Wu and Murray, 2003). Earth Observation (EO) enables consistent, detailed characterisation of the actual urban footprint of a city having been mapped and monitored using remotely sensed data at a range of spatial and temporal scales for associated implications (Akbari et al., 2003; Friedl et al., 2002; Imhoff et al., 1997; Schneider et al., 2010; Sexton et al., 2013). However, accurate and consistent monitoring of urban land cover is frequently precluded by coarse spatial (e.g. 1 km Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product) and temporal (e.g. 2000 and 2010 GlobeLand30 product) resolution of such datasets (Lu et al., 2014; Song et al., 2016).

Urban mapping remains challenging due to the heterogeneity of surface materials and surface structure which contributes to pixel surface reflectance that are often difficult to disentangle (Herold et al., 2002; Lu et al., 2011; Schneider, 2012; Varshney and Rajesh, 2014). When delineating urban land cover from remotely sensed data, spatial resolution is considered the most important factor which provides increased visibility of discrete surface features (e.g. buildings) and greater pixel homogeneity over medium to coarse spatial resolution satellite imagery (e.g. Landsat and MODIS) (Myint et al., 2011). Nevertheless, high spatial resolution data often lack temporal acquisition consistency (e.g. airborne orthophotos) or are expensive to purchase (e.g. commercial satellite imagery). Consequently, in order to best monitor urban land use and land cover change, datasets must have an adequate spatial and temporal resolution to discern change. In this regard, data from the Landsat series of satellites provides the longest time-series of consistent, medium spatial resolution imagery that has been extensively applied to urban area mapping (Powell et al., 2007; Schneider and Mertes, 2014; Song et al., 2016; Sundarakumar et al., 2012; Wilson et al., 2003; Yuan et al., 2005). Accurate quantification of anthropogenic landscape modification is of critical importance due to associated environmental, anthropogenic and climatic impacts (Kalnay and Cai, 2003). Urban estimates from Landsat data have been used within global biogeochemistry and climate models (Zhu and Woodcock, 2014), further scientific studies such as UHI investigations (Hu et al., 2015) and targeted urban development policies (Hepinstall-Cymerman et al., 2013; Schneider et al., 2005). Whilst comparative studies (e.g. Li et al., 2014) have shown marginal holistic image accuracy difference between algorithm selection on per-pixel Landsat classification assuming sufficient training data. Traditional per-pixel methods, such as the maximum likelihood classifier (discussed in supplementary section 5.9.1), have been found to significantly over or underestimate urban area from Landsat data (Lu et al., 2011; Wu and Murray, 2003). Addressing this error is important when accurate classifications are required for monitoring change in land use patterns whereby calculations of urban extent can influence decision-making (e.g. policy for sustainable urban development) (Bagan and Yamagata, 2014; Hepinstall-Cymerman et al., 2013; Miller and Small, 2003; Schneider et al., 2005). Due to the heterogeneity of urban areas, sub-pixel classification methodologies have been increasingly applied to medium spatial resolution data to more accurately represent the mixture of land covers within a pixel (Lu et al., 2011; Lu and Weng, 2006; Powell and Roberts, 2008; Wang et al., 2013; Weng and Pu, 2013). This has been achieved through variations of Spectral Mixture Analysis (SMA) where a set number of representative endmembers, frequently following the Vegetation, Impervious and Soil (V-I-S) framework, are used to model the entire image based on their spectral characteristics (Powell et al., 2007; Ridd, 1995). However, endmembers may not fully represent image spectral variability or a pixel may be modelled by endmembers that do not represent materials within its field of view resulting in an inability to adequately portray the high spectral heterogeneity of the urban landscape (Powell et al., 2007). Support Vector Machine (SVM) spectral unmixing attempts to resolve this issue through consideration of a large number of training pixels which provides preferential accuracy in comparison to SMA although high dimensional data and large training samples can hinder its performance (Wang et al., 2013).

Comparatively the novel sub and hard pixel Import Vector Machine (IVM) classifier permits simultaneous multi-class comparison whilst continuously testing training samples for validity providing a more accurate solution (Roscher et al., 2012). IVM has been found to consistently outperform decision trees, artificial neural networks and maximum likelihood algorithms (Huang et al., 2002; Kotsiantis et al., 2006; Watanachaturaporn et al., 2008), with preferential (Braun et al., 2012) and comparable results to SVM (Roscher et al., 2010). However, due to the heterogeneity of urban areas it is important to calibrate these subpixel approaches against high spatial resolution data that capture the diverse characteristics found within urban environments (Lu et al., 2011). Perth, Western Australia (WA) is characterised by extensive urban diversity, surpassing all other major Australian and United States cities in terms of suburban development (Kelly et al., 2011; U.S. Department of Commerce, 2013). It therefore provides a suitable case study for assessing the ability of Landsat to map urban development, which is a pre-requisite for appropriate policy incorporation. This paper describes an approach to map the urban extent of the Perth Metropolitan Region (PMR) using an IVM classifier applied to medium spatial resolution imagery. The impact of sub-pixel land cover heterogeneity is investigated by comparing the urban area estimates to those derived from very high spatial resolution (20 cm) imagery. An innovative, spatially explicit correction to account for over (or under) estimation of urban area is derived which improves the urban land cover estimates from medium resolution imagery.

5.3 Study area

The PMR (Figure 5 1 (a)), WA has experienced sustained urban development since the 21st century in response to a rapidly growing resource sector (Kennewell and Shaw, 2008). The majority of recent urban growth within the PMR has transpired as outward low-density development resulting in a maximum population density of 3,662 km2 which is 33.45% and 24.83% lower than Melbourne (10,827) and Sydney (14,747) respectively (ABS, 2015; Western Australian Planning Commission, 2015a). The notion of the 'Australian dream', depicted as detached living in a green suburb, is most pronounced in Perth (Western Australian Planning Commission, 2013a). As a result 79% of the current housing is detached, compared to 62% in Sydney, 72% in Melbourne and a national average of 74% (Kelly et al., 2011; Western Australian Planning Commission, 2013b). Globally, Australia surpasses other developed countries in terms of detached suburban living with England having 42% of housing as either detached or semi-detached (Department for Communities and Local Government, 2015). Similarly only 64.2% of United States of America (USA) housing stock is detached, with Perth eclipsing all of the major 25 USA metropolitan areas in terms of detached housing (U.S. Department of Commerce, 2013). Low population density and outward expansion witnessed in Perth has generated high demand for dispersed amenities and services in a non-strategic, "lot-by-lot fashion" (Dhakal, 2014). Suburbanisation of this nature has been identified as unsustainable due to impacts on ecological systems (e.g. habitat fragmentation) and socio-economic issues (e.g. amenity provisioning costs), with accurate urban area identification essential for sustainable future planning and maximum resource efficiency, particularly in Perth owing to its globally high suburbanisation and distributed population (Western Australian Planning Commission, 2013a).

Figure 5 1. Landsat 8 Operational Land Imager (OLI) true colour image mosaic of the Perth Metropolitan Region (9 August 2015 [path 112] and 17 September

2015 [path 113]). The locations of the high spatial resolution aerial image subsets are indicated by coloured overlays (a), with Western Australia identified in (b) and Perth city (c). Therefore, the PMR provides a globally diverse range of urban characteristics (e.g. compact urban central business district, older residential areas and new suburban developments) facilitating broad dataset comparison opportunities between Landsat and high spatial resolution urban area estimates. The high spatial resolution data identifies the complexity of these suburban and urban areas, which is obscured in medium and coarse spatial resolution datasets. This permits the extraction of individual features such as buildings, roads and vegetation that compose the urban environment and which are represented as a spectrally mixed pixel in Landsat imagery (illustrated in Figure 5 2) (Myint et al., 2011).

Figure 5 2. Comparison of true colour high spatial resolution data (a) (acquired from 14 March 2007) and Landsat surface reflectance (b) (acquired on 6 October 2007 [path 112]), highlighting the spatial detail captured by high-resolution imagery (c) and the same areas as observed by Landsat (d) for the subset East Beechboro used within this study. Definitive feature detection from high resolution data can assist in refining urban area estimates produced from moderate spatial resolution satellite imagery (Lu et al., 2011; Wu and Murray, 2003). More accurate satellite derived urban area estimates are imperative for ensuring appropriate data use for policy and environmental variable applications in order to mitigate the consequences of unsustainable urban development. This aligns with the criteria of effective land use planning within the City Resilience Framework (CRF) which is designed to improve city resilience (ARUP and The Rockefeller Foundation, 2015).

5.4 Data

5.4.1 Landsat data

Cloud free Landsat scenes were obtained for 2007 from Landsat 5 Thematic Mapper (TM), coinciding with high resolution orthophotos (described in section 5.4.2). Imagery were acquired within winter months (9 July 2007 for path 113 and 6 October 2007 for path 112) corresponding with peak vegetation green-up which limits issues concerning the spectral separation between senescent vegetation, bare earth and some impervious surfaces (Chen et al., 2014; Feyisa et al., 2016). Landsat imagery was processed to standard terrain correction (Level 1T), geometrically and topographically corrected using Ground Control Points (GCPs) and a Digital Elevation Model (DEM) from the Global Land Survey 2000 dataset (Hansen and Loveland, 2012). Landsat 5 TM surface reflectance values were derived from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDPAS) (Hansen and Loveland, 2012; Masek et al., 2006) which corrects for atmospheric effects using the Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer model (Vermote et al., 1997).

5.4.2 High spatial resolution airborne imagery

Radiometrically calibrated multispectral red (0.58-0.77 µm), green (0.48-0.63 µm), blue (0.41 µm -0.54 µm) and near-infrared (0.69-1.00 µm) orthophotos were acquired over 19 cloud free days commencing on 14 March 2007 as part of the Perth and Peel Urban Monitor Programme (Caccetta et al., 2012). Aerial imagery, obtained between 10:00 and 14:00 to reduce shadow effects, were captured using a Microsoft UltraCAM-D at a height of 1300m resulting in a spatial resolution of 20 cm. Forward and side frame overlap of 60% and 30% respectively permitted automatic Digital Surface Model (DSM) extraction using geometric control points provided by WA's land information authority (Landgate). Extraction of ground points exclusively representing terrain variations facilitated derivation of a Ground Elevation Model (GEM) which, when subtracted from the DSM, generated a Relative Elevation Model (REM), depicting elevation relative to ground points.
Spatial and temporal inconsistencies in reflectance can arise from atmospheric scattering and absorption; instrument noise and Bidirectional Reflection Distribution Function (BRDF) effects. The latter describes the systematic variation in reflectance across an image due to differences in view and illumination angles and which is dependent on the surface 3D structure (Collings et al., 2011). The orthophotos were provided as a surface reflectance product, corrected for multiplicative and additive errors over frames (e.g. instrument noise and atmospheric effects) and within frame viewing and illumination geometry (Caccetta et al., 2012; Collings et al., 2011). Image preprocessing consisted of two steps. Firstly, a combined BRDF and atmospheric correction procedure was applied to retrieve surface reflectance for each image acquisition. Linear BRDF model parameters from the Li Sparse reciprocal kernel (Wanner et al., 1995) were used to correct for BRDF effects. Atmospheric perturbations were corrected by assuming that the obtained digital number represented the relative reflectance affected by spatially dependent multiplicative and additive terms. These combined steps generated an internally consistent mosaicked dataset. 'True' surface reflectance was estimated through fitting global offset and gain values to replicate laboratory measured calibration targets based on the assumption that relative reflectance requires a linear transformation to true reflectance (Collings et al., 2011).

5.5 Methodology

5.5.1 Landsat preprocessing

The two Landsat scenes covering the study area were combined to form a seamless image mosaic following the methodology of Pan et al. (2009). Voroni diagrams were created on the bisector between images with adjacent edges defined as seamlines, identifying effective mosaic polygons that specify pixels from each image to include in the final mosaic, facilitating less visible boundaries through blending of overlapping pixels (Pan et al., 2009) (Figure 5 1 (a)). Due to remaining residual noise in the mosaicked imagery caused by factors such as the brightening effect of thin clouds and atmospheric correction differences, surface reflectance values were standardised following the approach identified by Sexton et al. (2013):

p_(i,b)=p_(x,b)/ max _b (5.1)

where p_(i,b) is the standardised pixel value i, from band b based on the original surface reflectance x, standardised through division by a waveband specific upper reflectance limit which are: 0.10 (blue; 0.48µm), 0.11 (green; 0.56µm), 0.12 (red; 0.66µm), 0.23 (near-infrared; 0.84µm), 0.21 (shortwave-infrared; 1.65µm), 0.15 (shortwave-infrared 2; 2.22µm). The standardised values (p_(i,b)) were then normalised against the summed band standardised values:

p_(j,b)=p_(i,b)/(*i p*(i,b)) (5.2)

where *i p*(i,b) is the sum of each standardised pixel across all bands (Sexton et al., 2013). This approach has been found to satisfactorily reduce variations generated from inherent residual noise across mosaicked imagery, for example due to differences in modelled atmospheric parameters within the LEDAPS algorithm (Luo et al., 2014; Sexton et al., 2013) (Figure 5 3 (a)). Statistical assessment of image radiometric normalisation provided in MacLachlan et al. (2017a) found that the post-processed Landsat data exhibited significantly lower inter and intra Coefficient of Variation (CV) when compared to the pre-processed data.

Figure 5 3. Summary of classification procedures for (a) Landsat and (b) high-resolution orthophoto data.

5.5.2 Landsat classification

The 2007 Landsat data was classified as a time series of data for seven sequential periods between 1990 and 2015 using an IVM classifier produced in MacLachlan et al. (2017a). The method uses a hybrid strategy which assesses whether new samples (termed import vectors) can be removed in each forward step in order to provide a smoother decision boundary which ideally leads to a more accurate solution (Roscher et al., 2012). Samples are selected based on how much their incorporation decreases the objective function to minimise the decision boundary to form the optimal separating hyperplane between overlapping clusters (e.g. land cover types) in spectral feature space (Mountrakis et al., 2011; Roscher et al., 2012; Zhu and Hastie, 2005). IVM generates two outputs, a soft (sub-pixel) dataset which defines the probability of a pixel containing a given classification value (e.g. land cover type) and a traditional 'hardened' classified dataset (Braun et al., 2012). Training samples were collected from the

12th and 19th July 2005 Landsat 5 TM image composite, coinciding with peak vegetation greenness which provides the greatest spectral separability between vegetated and non-vegetated surfaces (Chen et al., 2014; Feyisa et al., 2016). Six land cover types were defined based on existing literature (e.g. Feyisa et al., 2016; Hu and Weng, 2009; Schneider, 2012) and scene analysis which are high reflectance urban (e.g. concrete), low reflectance urban (e.g. asphalt), forest, water, grassland and bare earth. Two urban land cover classes are specified to reduce spectral confusion between spectrally similarly classes (e.g. urban and bare earth) (Hu and Weng, 2009). For each land cover type, 250 pixels were randomly identified from across the image for training the IVM classifier which follows the approach used by Foody and Mather (2006) and Pal and Mather (2003). The IVM algorithm is parameterised using the training data that generates a classification model consisting of spectral profiles for each land cover type, which are then matched to the Landsat mosaic during classification.

The resulting per-pixel (hardened) classification indicates that the total urban extent of the PMR has increased 45.32% (sub-pixel estimate of 32.96%) between 1990 (hardened estimate 706.88 km2, sub-pixel estimate 736.93 km2) and 2015 (hardened estimate 1027.22 km2, sub-pixel estimate 979.84 km2) (MacLachlan et al., 2017a). This can be broken down into low reflectance urban cover expanding from a hardened value of 592.83 km2 (sub-pixel estimate 668.46 km2) to 839.00 km2 (sub-pixel estimate 850.87 km2) and high reflectance urban cover increasing from a hardened value of 114.05 km2 (sub-pixel estimate 135.32 km2) to 188.20 km2 (sub-pixel estimate 214.06 km2) across the same temporal period.

5.5.3 Google Earth Landsat accuracy assessment

Google Earth imagery consistent with the Landsat acquisition date was used to assess the accuracy of the hardened Landsat classification following previously published methods (e.g. Bagan and Yamagata, 2014; Cunningham et al., 2015; Dorais and Cardille, 2011; Song et al., 2016; Sun et al., 2015; Zhu and Woodcock, 2014). Using the Google Earth imagery, 300 random locations (50 per land cover class) within the PMR which were visually identified and compared to the classified land cover data, consistent with recommended land cover accuracy sample size of Congalton (2001) (Song et al., 2016). The 2007 Landsat classification obtained an accuracy of 84.00% and a Kappa Coefficient of 0.78. Urban land cover estimates had a producer's accuracy of 83.00% and user's accuracy of 87.37%. MacLachlan et al. (2017a) provide a full breakdown of urban temporal change and associated accuracy for all imagery in the Landsat time series (1990-2015), with the Landsat classification data available from the pangaea open access publisher (DOI: 10.1594/PANGAEA.871017) (MacLachlan et al., 2017b).

5.5.4 Aerial image classification

Urban areas are complex, heterogeneous environments which are challenging to classify even when using high spatial resolution multi-spectral imagery (Lu et al., 2011; Varshney and Rajesh, 2014). Within urban areas, traditional moderate and coarse spatial resolution pixel based classification methods present multiple challenges due to the land surface spatial heterogeneity and the spectral similarity between urban and non-urban materials (Myint et al., 2011). To characterise the influence of spatial resolution on the ability to map urban areas, high spatial resolution multispectral ortho-imagery (20 cm) were classified into the four broad land cover types. To reduce data processing requirements, four 3 km2 subsets were chosen that are representative of the land cover composition and spatial heterogeneity found within Perth (Figure 5 1 (a)). These subsets are an out of town development area (East Beechboro), the Central Business District (CBD), an older suburban area (Palmrya, Melville) and a largely vegetated region (Keysbrook). Using the high spatial resolution multispectral imagery and a relative elevation model, an Object Based Image Analysis (OBIA) method was applied to classify each subset into vegetation, urban, bare earth and water (Figure 5 3 (b)). OBIA methods are often applied to high spatial resolution imagery as they include spatial, textural and spectral information to classify the scene (Myint et al., 2011). Incorporating surface elevation measurements into urban classifications has been found to improve building (urban) extraction accuracy (Aguilar et al., 2012; Poznanska et al., 2013). Surface elevation estimates and Normalised Difference Vegetation Index (NDVI) data provided additional urban classification parameters, with refinement (e.g. additions and alterations) made based on object spatial, spectral and textural properties. Unlike the Landsat imagery, the airborne imagery were collected during the late dry season when the grass was senescent which resulted in textural and spectral similarity between bare earth and roads. To mitigate the impact of potential misclassification between these features, Landgate road and, where appropriate, rail vector datasets were used for identification of coincident image objects for urban assignment.

Table 5 1. The percentage of different land-cover types within the classified high spatial resolution subsets (Figure 5 1). Subset Vegetation (%) Urban (%) Bare earth (%) Water (%) East Beechboro 81.00 16.56 2.37 0.07 CBD 33.33 65.66 0.91 0.10 Palmrya 57.29 42.21 0.42 0.08 Keysbrook 97.36 0.90 1.56 0.18

5.5.5 Dataset comparison and Landsat refinement

In order to compare the orthophoto and Landsat land cover classifications, the two urban (high and low reflectance) and two vegetation (woodland and grassland) Landsat land cover classes were merged so that both land cover classifications contained four identical classes. To facilitate comparison between the high spatial resolution orthophoto-derived classification and the Landsat classification, the orthophoto land cover data is aggregated to Landsat spatial resolution to provide a 'soft' and a 'hard' land cover dataset. To create the soft 30 m2 orthophoto-derived classification, each resampled 30 m2 pixel area contains the proportion of each land cover type within it (Lu et al., 2011) (Figure 5 3 (b)). This dataset was subsequently 'hardened' by assigning the pixel land cover type according to the dominant land cover found within the 30 m2 area. The comparison methodology is to firstly compare the per-pixel (i.e. hardened) Landsat land cover classification with the aggregated (30 m2) orthoimage classification. Misclassified Landsat pixels are assessed further to establish the conditions that lead to erroneous classification using the sub-pixel proportion information (i.e. soft classification datasets). The latter are also used to identify a spatially explicit correction model to improve urban area estimates from moderate spatial resolution imagery.

5.6 Results

5.6.1 Orthophoto and Landsat land cover comparison

A comparison is conducted between the orthophoto land cover classification, aggregated to 30 m2 spatial resolution using the majority land cover, and the IVM 'hardened' Landsat classification. At its native spatial resolution (20 cm; Figure 5 4 ((a-d)(i))), the orthophoto land cover classification (Figure 5 4 ((a-d)(ii))) captures the land cover spatial heterogeneity found within each region and highlights the difference in the spatial structure between these regions.

Figure 5 4. (i) High spatial resolution true colour orthophotos, (ii) land-cover maps, and (iii) the agreement between the orthophoto classification resampled to 30 m2 and the Landsat classification for: (a) an out of town development area (East Beechboro), (b) old inner city urban area (central business district), (c) older suburban area (Palmrya, Melville), and (d) predominantly vegetated site (Keysbrook). In (iii), areas depicted as 'true' indicate those 30 m2 pixels where the orthophoto land-cover type, based on the dominant land cover in the 30 m2 area, and Landsat land-cover type are in agreement. A comparison is carried out between the orthophoto land cover classification, aggregated to 30 m2 spatial resolution, and the 'hardened' Landsat classification. Figure 5 4 (iii) illustrates the spatial agreement between these datasets and highlights those pixels where the same land cover type (true) has been assigned to a pixel in both classifications. The areas which are more homogeneous at Landsat's spatial resolution, such as the CBD (urban, Figure 5 4 (b)) and Keysbrook (vegetation, Figure 5 4 (d)), have greater level of agreement (73.14% and 95.68% respectively). In contrast, the more heterogeneous subsets (East Beechboro and Palmrya, Figure 5 4 (a and c)), have much lower levels of agreement (56.09% and 32.03% respectively). The differences in agreement result from the sub-pixel heterogeneity at 30 m2 spatial resolution. Table 5 2 shows the percentage of

Landsat pixels which contain >50% of a given land-cover for each subset region.

Table 5 2. The percentage of pixels which contain >50% of a given land-cover type in each region. Subset Vegetation (%) Urban (%) Bare earth (%) Water (%) East Beechboro 87.57 9.84 1.89 0.06 CBD 26.14 72.81 0.74 0.05 Palmrya 66.71 32.33 0.21 0.07 Keysbrook 98.90 0.05 0.88 0.11

To investigate the influence of sub-pixel heterogeneity on the ability of Landsat to identify the pixel land cover type, the classification accuracy is determined as a function of the percentage of urban area within each Landsat pixel for all four subsets (Figure 5 5). The urban percentage cover within each Landsat pixel is derived from the orthophoto land cover classification which has been aggregated to 30 m2 and which provides the proportion of each land cover within each pixel. The accuracy of the hardened Landsat classification was determined through comparison against the 'hardened' (e.g. aggregated to 30 m2) orthophoto land cover classification where the per-pixel land cover type was determined based on the land cover type with the greatest sub-pixel proportion. Figure 5 5 indicates that the hardened Landsat classification results in a relatively high accuracy, with an average of 85.40% (excluding Keysbrook), for pixels containing >50% urban land cover (according to the high spatial resolution land cover classification). In the subsets of East Beechboro, the CBD and Palmrya, the overall Landsat classification accuracy drastically declines to 1.99-6.21% when urban land cover within a 30 m2 pixel area decreases to 40-50%. The classification accuracy then increases with decreasing sub-pixel urban cover which is particularly evident with Landsat pixels containing 0-10% urban cover. Keysbrook, on the other hand, is a largely vegetated region and exhibits lower accuracy with increasing urban land cover.

Figure 5 5. Landsat classification accuracy as a function of the percentage urban cover within Landsat image pixels (as derived from the high spatial resolution land-cover data set) for each of the four subsets. In the Keysbrook subset, no Landsat pixels contained >60% urban land cover.

In order to understand the counter-intuitive behaviour of such as rapid decrease in classification accuracy in pixels which contain between 40-50% urban area (Figure 5 5), an analysis of the percentage of pixels classified as a given land cover type is presented. To do so, all pixels containing different ranges in urban percentage cover (e.g. 0-10%, 20-30% etc) were identified using the high spatial resolution land cover dataset. The total percentage of each land cover type was calculated for all pixels that contained urban percentage cover within each range urban percentage cover (e.g. 0-10%, 20-30% etc) using hardened IVM Landsat land cover dataset and the aggregated high spatial resolution land cover dataset (i.e. defined by the dominant land cover type within a 30 m2 pixel area).

Figure 5 6 illustrates the percentage of pixels identified as a given land cover type as indicated by the hardened Landsat land cover dataset and the hardened high spatial resolution orthophoto land cover dataset for pixels which contain differing percentage urban cover (e.g. 0-10%) derived using the original high spatial resolution orthophoto land cover classification for the East Beechboro subset. This area was selected as it is an intermediate area in terms of land cover heterogeneity (Figure 5 2 and Figure 5 4 (a)). The results indicate that the hardened Landsat classification consistently overestimates urban land cover when compared to the 'hardened' high spatial resolution classification which has been aggregated to 30 m2 based on the dominate land cover within the Landsat pixel area for pixels with 10-50% urban defined by high resolution data. Table 5 3 and Figure 5 7 illustrates the sub-pixel (30 m2) percentage urban land cover for East Beechboro with the original reflectance imagery for this area shown in Figure 5 2. The hardened high spatial resolution land cover dataset (left bar in each plot (Figure 5 6)) indicates that pixels containing <50% urban land cover are largely dominated by vegetation. In contrast, Landsat largely identifies these pixels as being either urban or vegetated to differing extents and more correctly identifies pixels with 0-10% urban land cover as being predominantly vegetated. For example, pixels containing 40-50% urban area are correctly identified as being vegetated (98.45% of pixels within this range) by the hardened high spatial resolution land cover dataset since these pixels contain on average 54.72% vegetation, 44.83% urban and 0.45% bare earth. In contrast, the hardened Landsat land cover dataset identifies 5.65% of pixels containing 40-50% urban cover as being vegetation, 74.28% being urban and 20.07% being bare earth. As the percentage of urban land cover decreases, the overall accuracy of the hardened Landsat classification increases due to the increase in Landsat vegetation cover which increases from 5.65% (40-50% urban cover) to 75.41% (0-10% urban cover). The results are similar for the other regional subsets. The rapid decrease in accuracy between 40-50% and 50-60% (Figure 5 5) appears extreme as the subset regions are dominated by vegetation and urban land cover (Table 5 1) which results in the aggregated 30 m2 pixels being assigned to vegetation when the percentage urban cover is <50% (Figure 5 6 (a-e)) or urban when the percentage urban cover is >50% (Figure 5 6 (f-j)).

Figure 5 6. Land-cover type disaggregation for urban land cover (according to the orthophoto imagery) Landsat pixels in East Beechboro. The left axis indicates the total percentage cover of a given land-cover type using all of the pixels within a given range of urban percentage cover range for: (a) 0–10%, (b) 10–20%, (c) 20–30%, (d) 30–40%, (e) 40–50%, (f) 50–60%, (g) 60–70%, (h) 70–80%, (i) 80–90%, and (j) 90–100%. For each percentage urban land-cover graph, the left bar illustrates the overall percentage of pixels from the hardened high spatial resolution classification identified as a given land types whilst the right bar indicates the percentage of hardened Landsat pixels mapped as a given land-cover type. Table 5 3. Urban area estimates (km2) from high spatial resolution orthophoto land cover data for each subset and those from the corresponding hard and soft IVM Landsat classification. The overestimation of urban area by the hardened Landsat land cover classification is evident. Percent difference to high resolution (%) 111.69 21.62 81.42 266.26 Percentage cover of subset area (%) 35.06 79.85 76.55 3.30 Landsat urban area sub-pixel (km2) 3.12 6.78 4.90 0.39 Percent difference to high resolution (%) 118.66 30.54 103.60 252.22 Percentage cover of subset area (%) 36.21 85.71 85.94 3.17 Landsat urban area (km2) 3.22 7.28 5.50 0.28 Percentage cover of subset area (%) 16.56 65.66 42.21 0.90 High resolution urban area (km2) 1.47 5.58 2.70 0.08 Subset East Beechboro CBD Palmrya Keysbrook

Figure 5 7. Comparison of percentage urban area aggregated to 30 m2 from high-resolution data (a) and IVM 'soft' Landsat classification (b) highlighting the (overestimation) between the high (c) and moderate (d) spatial resolution estimates for the East Beechboro subset. The classified high spatial resolution data are shown in (e) with the moderate spatial resolution grid (30 m2) overlaid for context (e).

The results in Figure 5 6 suggest that the spectral data used to train the IVM classification (discussed in section 5.5.2) contained spectrally 'mixed' pixels resulting in land cover type misclassification. To investigate this, the spectral reflectance from Landsat pixels containing 20-30% urban cover for the Palmrya subset, which had the lowest overall agreement and which were identified as being mostly vegetated by the hardened high spatial resolution land cover dataset, are extracted and compared to the spectral reflectance profiles used to train the IVM classification algorithm. Figure 5 8 indicates that there are strong similarities between the average spectral reflectance profile used to train the IVM classification algorithm and the average spectral profile of the misclassified pixels. This suggests that the IVM classification algorithm is accurately representing the Landsat pixel spectral reflectance properties but that the training data used to develop the classification model contained a high proportion of mixed pixels.

Figure 5 8. Average spectral reflectance profile for misclassified pixels (red) from the Palmrya subset for pixels containing 20–30% urban cover compared to the average spectral reflectance profile of pixels used to train the IVM classification algorithm (blue). For (a) forest, (b) low urban reflectance, (c) high urban reflectance, and (d) bare earth. The error bars show the standard deviation.

Pure (i.e. homogeneous) pixels are conventionally selected to train classification models (e.g. Weng and Pu, 2013) but these are inherently difficult to identify in urban areas owing to the multitude of land covers within a Landsat pixel area. Using the high spatial resolution classification, the percentage of pure pixels, defined here as those containing between 90-100% of a single land cover type, were identified (Table 5 4). It is evident that some regions contain a high percentage of pure pixels for a given land cover type, such as vegetation in Keysbrook (92.05%), but that other land cover types within a region typically have much lower percentages of pure pixels. Pure urban pixels are particularly limited in all subset regions. Whilst the CBD subset obtains a high percentage of pure urban pixels (28.77%) these are predominately urban areas with high spectral reflectance (e.g. concrete), differing from subsets with urban areas which have urban areas with both high and low spectral reflectance (e.g. East Beechboro; Figure 5 2).

Table 5 4. Percentage of 'pure' pixels (defined here as comprising 90-100% of given landcover within a Landsat pixel area) from the high spatial resolution imagery. Subset Vegetation (%) Urban (%) Bare earth (%) Water (%) East Beechboro 53.93 0.15 0.34 0.03 CBD 8.98 28.77 0.35 0.00 Palmrya 5.80 2.13 0.00 0.01 Keysbrook 92.05 0.00 0.00 0.00

5.6.2 Comparison between Landsat and high spatial resolution impervious surface estimates

Landsat data have been widely applied to map impervious surface area in order to assess its effects on: urban growth dynamics (Masek et al., 2000), the UHI effect (Hu et al., 2015) and surface run-off (Weng, 2001). Figure 5 6 indicates that the 'hardened' Landsat IVM classification overestimates urban land cover, particularly for pixels containing <50% urban area. The IVM classifier also provides a 'soft' land cover dataset that quantifies the sub-pixel land cover proportions.

Here we investigate the utility of the sub-pixel Landsat urban land cover estimates by comparing them to those derived from the high spatial resolution land cover dataset (20 cm) which is used to provide the actual land cover proportion within each 30 m2 pixel area. Urban area estimates from each of the four subsets (Figure 5 1 (a)) were spatially averaged over different size spatial windows (30 $\times$ 30 m, 90 $\times$ 90 m, 150 $\times$ 150 m and 210 $\times$ 210 m) in order to account for any errors resulting from pixel heterogeneity, spatial misregistration, residual atmospheric and BRDF effects and phenological differences (Ghimire et al., 2010; Ju et al., 2012; Liang et al., 2001; Lu et al., 2011; Maiersperger et al., 2013) that may increase the uncertainty in estimating land cover proportions (Lu et al., 2011; Sexton et al., 2013). Comparison of impervious surface proportions at 30 m2, for example the CBD subset (Figure 5 9), reiterates the overestimation of urban area at 30 m2 spatial resolution, with a clustering of values toward the upper percentage boundaries associated with lower urban area estimates from the high spatial resolution classification. When neighbourhood averaging is applied, the agreement in urban area typically improves with increasing window size although the subset specific bias remains consistent (Table 5 5). It is also evident that urban area is still overestimated with decreasing urban sub-pixel proportion even when utilising the sub-pixel IVM Landsat classification results.

Figure 5 9. Relationship between the sub-pixel urban area percentage cover estimated from the IVM sub-pixel Landsat classification and the high spatial resolution orthophoto classification in the Central Business District (CBD) subset for (a) 30 $\times$ 30 m window, (b) 90 $\times$ 90 m window, (c) 150 $\times$ 150 m window, and (d) 210 $\times$ 210 m window.

Table 5 5. Comparison between high (20 cm2) and moderate (30 m2) spatial resolution sub-pixel impervious surface estimates considering differing kernel sizes over four subsets (Figure 5 1) within the PMR.

Subset Kernel size (m) R2 Scatter Bias Root Mean Square Error (RMSE) East Beechboro 30 30 0.41* 26.65 18.68 32.54

90 90	0.68*	16.95	18.66	25.21
150 150	0.75*	14.11	18.71	23.44
210 210	0.80*	12.52	18.74	22.54

CBD 30 30 0.26* 28.41 14.38 31.84 90 90 0.53* 16.65 14.37 22.00 150 150 0.61* 13.18 14.38 19.51 210 210 0.66* 11.30 14.36 18.28 Palmrya 30 30 0.04* 26.65 34.54 43.62 90 90 0.16* 13.56 34.61 37.17 150 150 0.19* 10.15 34.64 36.10 210 210 0.17* 8.45 34.67 35.69 Keysbrook 30 30 0.24* 11.85 2.51 12.11 90 90 0.52* 7.47 2.51 7.88 150 150 0.60* 5.89 2.50 6.40 210 210 0.63* 4.98 2.50 5.57

5.6.3 Refining Landsat estimations using high spatial resolution data

Sub-pixel land cover heterogeneity influences Landsat urban area overestimation which must be considered in order to reduce the bias and improve Landsat derived urban area estimation (Herold et al., 2002; Lu et al., 2011; Schneider, 2012; Varshney and Rajesh, 2014). The complexity and diversity of urban areas identified here from high spatial resolution data, with biases ranging from -2.50% to -34.67%, highlights the inappropriateness of applying a single model to adjust the moderate spatial resolution urban area estimates in a metropolitan region (e.g. Lu et al., 2011). The Landsat sub-pixel urban areas estimates from all four subsets were stratified based on the Landsat sub-pixel derived urban area and calibrated against the percentage of urban area from the high spatial resolution classification within each moderate spatial resolution pixel area. Both datasets were averaged at the neighbourhood level using a 210 × 210m window as this provided the best overall relationship (Table 5 5). Stratification of Landsat sub-pixel urban estimates into divisions of 10%, consistent with previous results, were selected to develop (using 50% of the data) and test (remaining 50% of the data) regression models to improve the dataset agreement (Lu et al., 2011). The applied spatially explicit models reduced the bias and Root Mean Square Error (RMSE) between the predicted (moderate spatial resolution) and observed (high spatial resolution) estimates (Table 5 6). It is evident from Table 5 6 that the adjustment made to the Landsat urban area estimates reduced the overestimation difference of urban area by between 34.38% and 80.67%, with the largest improvement found within Keysbrook. Whilst the corrected Landsat urban area estimates still overestimates the urban area compared to the high spatial resolution dataset the corrected moderate spatial resolution urban area reduces moderate resolution urban area over (under) estimation by on average 55.08% in comparison to the high spatial resolution dataset reducing the average overestimation from 11.86 km2 per subset to just 0.09 km2 (Table 5 6). In the case of this study area, this approach is appropriate for producing more accurate urban area statistics. Due to the frequently reported over and under estimation of land cover estimates by moderate spatial resolution data this approach can refine urban estimates for planning development policies that may inform decision makers (Hepinstall-Cymerman et al., 2013; Schneider et al., 2005; Zhu and Woodcock, 2014). However, the derived correction values are not globally applicable since the spatial structure and makeup of urban and suburban areas varies regionally, nationally and globally. Nevertheless the methodology implemented here could be replicated to produce localised correction values from other sources of high resolution imagery (e.g. digitisation of Google Earth imagery) to calibrate urban area estimates from moderate spatial resolution data.

Table 5 6. Comparison between calibrated moderate (30 m2) and high (20 cm2) resolution sub-pixel impervious surface estimates with a kernel size of 210m. * = statistically significant relationship ($p<0.05$). Corrected percent difference to high resolution (%) 8.83 -11.93 15.71 35.29 Corrected Landsat urban (km2) 2.72 10.88 8.10 0.19 Uncorrected percent difference to high resolution (%) 72.47 22.45 57.32 115.96 Uncorrected Landsat urban (km2) 5.32 15.36 12.48 0.50 High resolution urban (km2) 2.49 12.26 6.92 0.13 Root Mean Square Error (RMSE) 6.76 14.61 12.53 1.38 Bias 1.54 -7.12 7.43 0.37 R2 0.84* 0.52* 0.12* 0.62* Subset East Beechboro CBD Palmrya Keysbrook

5.7 Discussion

Refined urban estimates are vital in ensuring suitable sustainable and strategic planning decisions are implemented (Bettencourt and West, 2010; Wu and Murray, 2003). The hybrid spatial resolution approach applied here to estimate urban area was necessary due to the difficulty in accurately estimating urban area using a traditional per-pixel classification methods. This was due to a combination of the sensors moderate (30 m2) spatial resolution, land surface heterogeneity and the selection of 'mixed' pixels for use in training the classification algorithm. The overall classification accuracy, determined using Google Earth imagery, was on average 84.00%, which is similar to that found in other studies, albeit for different urban areas (e.g. Bagan and Yamagata, 2014; Gislason et al., 2006; Luo et al., 2014; Sundarakumar et al., 2012). Closer examination of the moderate spatial resolution classification results using a higher resolution dataset indicates that when urban land cover within a 30 m2 area decreases to 40-50% (based on high spatial resolution classification) the Landsat classification accuracy decreased from 85.40% to between 1.99 and 6.21%. This resulted from the Landsat classification overestimating urban area in comparison to high spatial resolution data (Figure 5 5) which more correctly identified these pixels as containing a greater per-pixel proportion of vegetation. Pixels containing 40-50% urban cover, contained on average 54.50% vegetation cover excluding Keysbrook. The dominance of vegetation and urban land covers in the regional subset, when ascribed to a 30 m2 pixel area based on the majority land cover, results in a rapid change in classification accuracy. Strong spectral similarities between training data and misclassified pixels (Figure 5 8) suggests that the spectral reflectance observations used to train the classification algorithm contained spectrally mixed pixels. The average percentage urban area within a moderate spatial resolution pixel area derived from the high resolution data was 16.56%, 65.66%, 42.21% and 0.90% for East Beechboro, CBD, Palmyra and Keysbrook respectively. The percentage of 'pure' pixels, defined as those containing over 90% urban land cover, was 28.77% for the CBD but <2.50% for the suburban regional subsets. This highlights the difficulty in selecting pure pixels at moderate spatial resolution and in accurately disentangling mixed spectral reflectance's without the aid of high spatial resolution data. Overestimation of urban extent was most prominent in Keysbrook, where vegetation dominates the subset (97.36%, Table 5 1). In this instance, Landsat derived urban area corresponded to 0.28 km2 compared to 0.08 km2 from high spatial resolution classification; a difference of only 0.20 km2 but which equates to 251.74%. In terms of total area difference, the East Beechboro and the CBD Landsat subsets were found to contain 1.75 km2 and 1.70 km2 more urbanised area, whilst Palmyra data overestimated urban area by 2.79 km2 compared to the high spatial resolution equivalent due to its suburban nature and associated pixel heterogeneity (Figure 5 4).

Spatially averaging the Landsat and orthophoto land cover classifications, to account for potential errors in the datasets (Ghimire et al., 2010), improved their relationship although Landsat still overestimated urban area with differing bias per subset. Over (under) estimation of urban land from Landsat estimations could result in an under (over) prediction on further environmental variables (e.g. UHI) or policy applications. Multiple studies have used classified per-pixel moderate spatial resolution data to influence policy changes through monitoring urban growth (e.g. Hepinstall-Cymerman et al., 2013; Schneider et al., 2005). However, per-pixel methodologies fail to address the issue of mixed pixels, which, as shown here, can result in overestimation of urban area (average: 126.25%, equivalent to 57.58 km2 within the PMR) (Lu et al., 2011). Sub-pixel methods attempt to remedy this issue, but have been found to inaccurately separate impervious land cover from other land cover types resulting in poor representation of impervious surface area (Lu et al., 2011). Consequently over estimation of urban area may have resulted in sub-optimal policies that fail to maximise resource and amenity efficiency (Downs, 2005; Turner et al., 2010).

Calibrating Landsat urban estimates using high spatial resolution data reduces the bias, RMSE and improves urban area estimation. However, the range of bias values across subsets of differing urban land cover characteristic highlights the inappropriateness of a single regression model due to pixel heterogeneity influencing overestimation (Lu et al., 2011). Spatially explicit models, as presented here, permit varying moderate spatial resolution refinement by considering the influence of surface heterogeneity. Whilst the limited availability of low cost high spatial resolution data can preclude analysis of this type, subset digitisation of Google Earth or Unmanned Aerial Vehicle (UAV) imagery may provide a suitable alternative for calibrating Landsat data for improved urban area estimates. Enhanced estimates of urban area would facilitate planning policies which avoid potential environmental and socio-economic consequences of urban development than can result from policies based on over (or under) predicted urban area (ARUP and The Rockefeller Foundation, 2015). For example, classified Landsat data was used to identify spatial clustering, peri urban development and specialisation of land use in Chengdu, Sichuan province not considered by China's original 1990 Go West policy, aimed at economically boosting the West of the country. Results were used to reform policy and remediate issues of urban management including: service, infrastructure and resource deficiencies (Schneider et al., 2005). However, traditional Landsat classification may over (or under) estimate urban area and result in ineffective planning, environmental and policy decisions (Miller and Small, 2003; Pravitasari et al., 2015). Therefore classified sub-pixel data alongside high spatial resolution imagery (e.g. UAV, Google Earth, high spatial resolution aerial or satellite imagery) as presented here can refine urban estimates facilitating improved decision making whilst maximising often limited financial resources. This is especially important in developing countries in regards to directing urban development and resources based on factors including: poverty, environmental hazards (e.g. flooding) and current amenity centres (Marfai et al., 2014; Suryahadi and Sumarto, 2003).

5.8 Conclusion

Landsat imagery from 2007 was used to map the urban extent within the PMR using an IVM classifier which provides both a per-pixel and a sub-pixel classified datasets. The 2007 Landsat classification overall average accuracy was 84.00% with associated Kappa coefficient of 0.78. Comparison between the Landsat per-pixel urban area and urban area estimates obtained from a high spatial resolution (20 cm) orthophoto-derived classification indicates that the moderate spatial resolution classification overestimates urban extent by 126.25 % on average, which is equivalent to 57.58 km2 in the study area. Similarly, when the high spatial resolution urban area estimates are compared to those derived using a sub-pixel Landsat classification, the latter still overestimates urban extent by 120.25%.

Accurately quantifying urban expansion within the PMR due to the large population growth over the last decade is important in order to make the efficient use of current resources and to avoid additional amenity, environmental and health expenditure that can impact sprawling cities. Landsat data provides the longest time series of medium spatial resolution imagery to map and monitor urban area. However, the reported over and underestimation inhibits accurate quantification of urbanised land cover which increases uncertainty within global climate models, environmental studies and targeted urban planning policy. Neighbourhood averaging, to account for potential errors in the datasets, improved the agreement between the two datasets but Landsat sub-pixel overestimation still remained. The broad differences in bias between the difference subsets indicates that a single regression model is inappropriate to heterogeneous urban land cover estimates. Therefore, the moderate spatial resolution urban area estimates were corrected using spatially explicit regression models which, on average, across the four subsets reduced the bias and RMSE by 17.02 km2 and 6.65 km2 respectively, whilst reducing moderate resolution urban area over (under) estimation by 55.08% Current and future EO satellites that provide complimentary data with enhanced spatial, spectral and temporal resolution, such as Sentinel-2, may further reduce over or under estimation of urban area experienced by moderate spatial resolution sensors such as Landsat. Similarly, high spatial resolution satellite sensors, such as Worldview-3, are able to remediate discrepancies by capturing the fine spatial detail of urban environments but their cost and small swath limit their widespread application. This might change with companies, such as Planet, which are launching large numbers of small micro-satellites that provide high spatial resolution data more frequently. Accurate urban land cover and land use mapping is essential in understanding the impact of urban expansion on, for example, social-ecological systems and human-health and will improve future sustainable planning of our cities.

5.9 Supplementary material

This supplementary material sections supports the main chapter and thesis through providing a review surrounding classifier selection, pertinent to the selection of the Import Vector Machine (IVM) classifier implemented in generating the classified Landsat image used within the chapter. A short discussion surrounding other considered approaches and a list of data used within the chapter are also provided to demonstrate the entirety of analytical process.

5.9.1 Classification methodologies

Currently two main image analysis techniques exist for urban mapping: spectral indices and classification algorithms. Spectral indices such as the Normalised Difference Built-up Index (NDBI) have been used to delineate urban areas from non-urban (Zha et al., 2003). NDBI identifies built up regions using a ratio of the shortwave-infrared (SWIR) and near infrared (NIR) wavebands and assumes that built up areas have higher SWIR reflectance (Xu, 2008). In comparison to ground truth observations, NDBI-derived classification from Landsat Thematic Mapper (TM) over Nanjing, China was found to result in an overall accuracy of 92.6% (Zha et al., 2003). However, due to the heterogeneous nature of urban environments, the identification of built up areas by thresholding a spectral index is not always reliable (Xu, 2008).

The Impervious Build-up Index (IBI) attempts to mitigate for this by using a combination of a number of thematic indices namely: NDBI, the Soil Adjusted

Vegetation Index (SAVI) and the Modified Normalised Difference Water Index (MNDWI) (Xu, 2008). The index amplifies the identification of built up land through the inclusion of ancillary information on the presence of bare surfaces (SAVI) and water bodies (MNDWI) resulting in positive values for pixels identified as being urban (Xu, 2008). Nevertheless, urban areas often remain an inseperable mix of impervious and bare earth surfaces which require additional post-processing to delineate (Stathakis et al., 2012; Sun et al., 2015; Zha et al., 2003).

In the second instance, classification algorithms are defined as parametric (e.g. Maximum Likelihood (ML)) or nonparametric (e.g. Decision Trees (DT)), depending on whether training samples can be represented by a Gaussian probability density function (Donnay and Unwin, 2001; Jensen, 2005). Maximum Likelihood accounts for the variance-covariance within class distributions and has been implemented for monitoring land cover change and to derive sub-pixel proportions (Atkinson et al., 1997; Shalaby and Tateishi, 2007). However, due to the parametric assumption of multivariate normal data, the ML classifier can often fail to represent land cover that might be multimodal (Melgani and Bruzzone, 2004; Mountrakis et al., 2011; Otukei and Blaschke, 2010). An example of this issue is illustrated in semi-arid locations, such as grasslands, which are sensitive to precipitation timing and volume that can result in differing multimodal spectral-temporal profiles (Friedl et al., 2002). A decision tree methodology was utilised to generate the United States of America National Land Cover Database 2001 (NLCD 2001) resulting in a nonparametric approach able to handle continuous and nominal data, interpretable classification rules and swift application (Homer et al., 2004). Nevertheless, DTs can be negatively affected by pruning methods, for example Pessimistic Error Pruning (PEP) introduces a continuity correction value, within error estimation on no theoretical basis, resulting in under or over pruning (Esposito et al., 1997; Otukei and Blaschke, 2010; Pal and Mather, 2003).

More recently, Machine Learning Algorithms (MLA) or 'expert systems' (e.g. Support Vector Machine (SVM)) have been implemented for image classification (Jensen, 2005; Okujeni et al., 2014) using an automated inductive approach for identification of patterns in data (Cracknell and Reading, 2014). SVM is a nonparametric binary statistical learning methodology that separates a dataset into example classes (training data) based on a decision boundary, or hyperplane, with an aim to minimise misclassification. The optimal maximum margin separating hyperplane divides the data into a predefined number of classes, with points on the margins termed 'support vectors' (Foody and Mathur, 2006, 2004). The underlying benefit of SVM pertains to structural risk minimisation, whereby SVMs are able to minimise error on unseen data without prior assumptions on the distribution (Mountrakis et al., 2011; Vapnik and Chervonenkis, 1971). SVMs are linear binary classifiers which, when deriving more than two classes, require implementation of an additional process, either a one-against-all or one-against-one analysis. One-against-all solves for the multiple optimisation problem, which separates one class from the remaining classes. Comparatively one-against-one combines multiple classifiers and performs pair-wise comparisons using a 'voting' process to assign a pixel to a land cover class, based on the class assigned the most votes (Chih-Wei et al., 2008; Mountrakis et al., 2011; Pal and Mather, 2005). Within SVMs implementation of soft margin and kernel methods aid separability through the introduction of additional variables that ignore hyperplane outliers and transform data into high dimensional feature spaces (Euclidean or Hilbert) utilising non-linear functions to identify linear solutions respectively (Braun et al., 2012; Cortes and Vapnik, 1995; Melgani and Bruzzone, 2004; Mountrakis et al., 2011).

SVMs have been extensively used for classification purposes, due to their ability to ignore inherent image errors and to avoid overfitting (Foody and Mathur, 2006; Mountrakis et al., 2011). SVMs have obtained broad applicability for land cover classification using data from a multitude of sensors such as HyMAP (Camps-Valls et al., 2004), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Zhu and Blumberg, 2002) and Landsat (Knorn et al., 2009) producing classification results with accuracies between 85% and 95%.

5.9.2 Other considered data and approaches

In proposing the research within this chapter multiple other datasets were considered in replace of Landsat. These included: GlobeLand30 (classified Landsat data for 2000 and 2010) (Chen et al., 2015), the European Space Agency's (ESA) Climate Change Initiative (CCI) annual global land cover (300 m) time series (1992-2015) (European Space Agency, 2017) and yearly MODIS land cover products (500 m or 0.05°) (Friedl et al., 2002). Nevertheless these products are constrained by: resolution, temporal frequency, collection dates to closely match the high resolution imagery and global accuracy assessments that might fail to represent the Perth Metropolitan Region. Additionally, using data produced within chapter 4 enabled greater flow throughout the thesis. Similarly, other datasets under consideration in replace of the high resolution orthophotos included that from Google Earth (through digitisation) and digital elevation data from Geoscience Australia (5 metre resolution) (Geoscience Australia, 2015). However, the potential for analyst error alongside lower resolution elevation data could have potentially exacerbated errors within the classification process. Consequently, object based image analysis of the high resolution orthophotos was selected as it provided a repeatable approach with minimal subjectivity (Myint et al., 2011).

5.9.3 Chapter data list

This section provides an overview of the data presented and analysed within this chapter.

Supplementary Table 5 7. Summary of the data, sources and applications used within chapter 5. Data Source Application Classified Landsat land cover data (including sub pixel estimates) from 2007 Raw data information (2 images) Landsat 5 TM, 6/10 (path 112), 9/07 (path 113), row 82 Chapter 4 or (MacLachlan et al., 2017b) Comparison to high resolution urban estimates High resolution (20cm) orthophotos comprised of four spectral bands, digital surface and elevation models Sensor Microsoft UltraCAM-D Collection dates 19 could free days from 14/03/2007 Australian Commonwealth Scientific and Industrial Research Organisation Perth and Peel Urban Monitoring Programme To compare classified high resolution data to that of Landsat in order to remediate Landsat's overestimation Railway and road vector data Landgate Classification of the high resolution imagery

Bibliography