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Cities and Global Sustainability: Insights from emission and ecological efficiency

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" If you can dream—and not make dreams your master; If you can think—and not make thoughts your aim; If you can meet with Triumph and Disaster And treat those two impostors just the same; [..] If you can fill the unforgiving minute With sixty seconds' worth of distance run, Yours is the Earth and everything that's in it, And—which is more—you'll be a Man, my son!"

- Rudyard Kipling, 1895

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Abstract

In the wake of 21st century, humanity witnessed a phenomenal raise of urban agglomerations as powerhouses for innovation and socioeconomic growth. Driving much of national (and in few instances even global) economy, such a gargantuan raise of cities is also accompanied by subsequent increase in energy, resource consumption and waste generation. Much of anthropogenic transformation of Earth's environment in terms of environmental pollution at local level to planetary scale in the form of climate change is currently taking place in cities. Projected to be crucibles for entire humanity by the end of this century, the ultimate fate of humanity predominantly lies in the hands of technological innovation, urbanites' attitudes towards energy/resource consumption and development pathways undertaken by current and future cities. Considering the unparalleled energy, resource consumption and emissions currently attributed to global cities, this thesis addresses these issues from an efficiency point of view. More specifically, this thesis addresses the influence of population size, density, economic geography and technology in improving urban greenhouse gas (GHG) emission efficiency and identifies the factors leading to improved eco-efficiency in cities. In order to investigate the influence of these factors in improving emission and resource efficiency in cities, a multitude of freely available datasets were coupled with some novel methodologies and analytical approaches in this thesis.

Merging the well-established Kaya Identity to the recently developed urban scaling laws, an Urban Kaya Relation is developed to identify whether large cities are more emission efficient and the intrinsic factors leading to such (in)efficiency. Applying Urban Kaya Relation to a global dataset of 61 cities in 12 countries, this thesis identified that large cities in developed regions of the world will bring emission efficiency gains because of the better technologies implemented in these cities to produce and utilize energy consumption while the opposite is the case for cities in developing regions. Large cities in developing countries are less efficient mainly because of their affluence and lack of efficient technologies. Apart from the influence of population size on emission efficiency, this thesis identified the crucial role played by population density in improving building and on-road transport sector related emission efficiency in cities. This is achieved by applying the City Clustering Algorithm (CCA) on two different gridded land use

datasets and a standard emission inventory to attribute these sectoral emissions to all inhabited settlements in the USA. Results show that doubling the population density would entail a reduction in the total CO_2 emissions in buildings and on-road sectors typically by at least 42 %. Irrespective of their population size and density, cities are often blamed for their intensive resource consumption that threatens not only local but also global sustainability. This thesis merged the concept of urban metabolism with benchmarking and identified cities which are eco-efficient. These cities enable better socioeconomic conditions while being less burden to the environment. Three environmental burden indicators (annual average NO_2 concentration, per capita waste generation and water consumption) and two socioeconomic indicators (GDP per capita and employment ratio) for 88 most populous European cities are considered in this study. Using two different non-parametric ranking methods namely regression residual ranking and Data Envelopment Analysis (DEA), eco-efficient cities and their determining factors are identified. This in-depth analysis revealed that mature cities with well-established economic structures such as Munich, Stockholm and Oslo are eco-efficient. Further, correlations between objective eco-efficiency ranking with each of the indicator rankings and the ranking of urbanites' subjective perception about quality of life are analyzed. This analysis revealed that urbanites' perception about quality of life is not merely confined to the socioeconomic well-being but rather to their combination with lower environmental burden.

In summary, the findings of this dissertation has three general conclusions for improving emission and ecological efficiency in cities. Firstly, large cities in emerging nations face a huge challenge with respect to improving their emission efficiency. The task in front of these cities is threefold: (1) deploying efficient technologies for the generation of electricity and improvement of public transportation to unlock their leap frogging potential, (2) addressing the issue of energy poverty and (3) ensuring that these cities do not develop similar energy consumption patterns with infrastructure lock-in behavior similar to those of cities in developed regions. Secondly, the on-going urban sprawl as a global phenomenon will decrease the emission efficiency within the building and transportation sector. Therefore, local policy makers should identify adequate fiscal and land use policies to curb urban sprawl. Lastly, since mature cities with well-established economic structures are more eco-efficient and urbanites' perception reflects its combination with decreasing environmental burden; there is a need to adopt and implement strategies which enable socioeconomic growth in cities whilst decreasing their environment burden.

Zusamenfassung

Im Laufe des 21. Jahrhunderts verzeichnete die Menschheit eine gewaltige Zunahme urbaner Agglomerationen als Motor für Innovation und sozioökonomisches Wachstum. Angetrieben durch die nationale (und in wenigen Fällen auch globale) Wirtschaft, dieser gigantische Aufstieg der Städte ist allerdings auch mit einer Zunahme von Energie- und Ressourcenverbrauch sowie erhöhter Abfallerzeugung verbunden. Ein Großteil der anthropogenen Transformation der Umwelt in Form von Klimaveränderungen von der lokalen Ebene bis in die planetarische Dimension findet derzeit in Städten statt. Angenommen dass bis zum Ende des Jahrhunderts die gesamte Menschheit in einer Art Schmelztiegel miteinander verbunden sein wird, dann hängt ihr Schicksal von der Umsetzung innovativer und überlegender Entwicklungspfade heutiger und zukünftiger Städte ab. Angesichts des unvergleichlichen Energie- und Ressourcenverbrauchs sowie der Emissionen, die derzeit in Städten verursacht werden, befasst sich diese Arbeit mit genau diesen Fragen aus der Perspektive der Effizienz. Genauer gesagt, diese Arbeit befasst sich mit dem Einfluss der städtischen Größe, Dichte, Wirtschaftsgeographie und Technologie zur Verbesserung der Emissionseffizienz der städtischen Treibhausgase, mit dem Ziel die Faktoren, die zu einer Verbesserung der Ökoeffizienz in Städten führt, zu identifizieren. Um den Einfluss dieser Faktoren auf die Verbesserung der Emissions- und Ressourceneffizienz in Städten zu untersuchen, wurden in dieser Arbeit eine Vielzahl von frei verfügbaren Datensätzen mit neuartigen Methoden und analytischen Ansätzen gekoppelt.

Durch die Verschmelzung der bereits etablierten Kaya-Identität‘ mit den kürzlich entwickelten urbanen Skalierungsgesetzen wird eine 'urbane Kaya-Relation' entwickelt, um herauszufinden, ob Großstädte emissionsärmer also effizienter sind und welche Faktoren zu dieser (In-)Effizienz führen. Dafür wurde die 'urbanen Kaya-Relation' auf einen globalen Datensatz für 61 Städte in 12 Ländern angewendet. Die vorliegende Arbeit kommt zu dem Ergebnis, dass den Großstädten in den entwickelten Regionen der Welt Effizienzgewinne aufgrund des Einsatzes besserer Technologien für die Produktion und Nutzung von Energie gelingt, während für die Städte in Entwicklungsländern das Gegenteil gilt. Großstädte in Entwicklungsländern sind weniger effizient,

vor allem wegen ihres Wohlstands und des Mangels an effizienten Technologien. Abgesehen vom Einfluss der Bevölkerungsgröße auf die Emissionseffizienz, zeigt diese Arbeit auch die entscheidende Rolle der Bevölkerungsdichte bei der Effizienzsteigerung im Bau- und Transportsektor. Dies wird durch die Anwendung des City Clustering Algorithmus (CCA) auf zwei verschiedene raster-basierte Landnutzungsdatensätze und ein Standard-Emissionskataster erreicht, um die sektoralen Emissionen allen bewohnten Siedlungen in den USA zuzuordnen. Die Ergebnisse zeigen, dass eine Verdoppelung der Bevölkerungsdichte eine Verringerung der CO2-Gesamtemissionen in Gebäuden und Straßenverkehrssektoren um typischerweise mindestens 42 % bedeuten würde. Unabhängig von der Bevölkerungsgröße und -dichte werden Städte häufig für ihren intensiven Ressourcenverbrauch verantwortlich gemacht, der nicht nur die lokale, sondern auch die globale Nachhaltigkeit bedroht. Diese Arbeit verbindet das Konzept des urbanen Metabolismus mit Benchmarking und identifiziert Städten, die ökoeffizient sind. Diese Städte bieten bessere sozioökonomische Bedingungen und belasten die Umwelt weniger. In dieser Studie werden drei Indikatoren für die Umweltbelastung (jährliche durchschnittliche NO2-Konzentration, Abfallaufkommen pro Kopf und Wasserverbrauch) und zwei sozioökonomische Indikatoren (BIP pro Kopf und Beschäftigungsquote) für die 88 bevölkerungsreichsten europäischen Städte berücksichtigt. Mithilfe von zwei verschiedenen Rankingmethoden, einerseits dem regression residual ranking' und der Data Envelopment Analysis' (DEA), werden ökoeffiziente Städte und ihre Bestimmungsfaktoren identifiziert. Die gründliche Analyse ergab, dass die gewachsenen Städte mit etablierten städtischen Wirtschaften wie München, Stockholm und Oslo ökoeffizient sind. Weiterhin wurden Zusammenhänge zwischen objektiven Ökoeffizienz Einstufungen (ranking) mit den Einstufungen hinsichtlich einzelner Indikatoren sowie der subjektiven Wahrnehmung der Stadtbewohner über ihre Lebensqualität analysiert. Diese Analyse ergab, dass sich die Wahrnehmung der Lebensqualität von Stadtbewohnern nicht nur auf das sozioökonomische Wohlergehen beschränkt, sondern auch auf die Kombination mit einer geringeren Umweltbelastung.

Zusammenfassend lässt sich sagen, dass die Ergebnisse dieser Dissertation drei generelle Schlussfolgerungen zur Verbesserung der Emissions- und Ökoeffizienz in Städten enthalten. Erstens stehen Großstädte in Schwellenländern wie China, Indien und Brasilien vor einer großen Herausforderung, ihre Emissionseffizienz zu verbessern. Vor diesen Städten stehen drei Aufgaben: (1) Einsatz effizienter Technologien zur Stromerzeugung und Verbesserung des öffentlichen Verkehrs, (2) Bekämpfung der Energiearmut und (3) Sicherstellung, dass diese Städte keine Energiekonsummuster entwickeln, die dem infrastrukturellen Lock-in-Verhalten' der Städte in entwickelten Regionen ähneln. Zweitens wird die fortschreitende Zersiedelung der Städte als globales Phänomen die Emissionseffizienz im Bau- und Verkehrssektor verringern. Daher sollten die lokalen politischen Entscheidungsträger angemessene fiskal- und landnutzungspolitische Maßnahmen zur Eindämmung der Zersiedelung der Städte festlegen. Schließlich müssen Strategien verabschiedet und umgesetzt werden, die das sozioökonomische Wachstum in den Städten ermöglicht und gleichzeitig die Umweltbelastung verringert, wie es in den gewachsenen Städten bereits heute vorzufinden ist.

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Abbreviations

CCA	City Clustering Algorithm
CDP	Carbon Discosure Project
CO_2	Carbon Dioxide
DEA	Data Envelopment Analysis
EPA	United States Environment Protection Agency
EIU	The Ecoonomic Intelligence Unit
EU	European Union
GDP	Gross Domestic Product
GHG	Greenhouse Gases
GLC	Global Land Cover
GRUMP	Global Rural-Urban Mapping Project
ICLEI	International Council for Local Environmental Initiatives
IEA	International Energy Agency
IIASA	International Institute for Applied System Analysis
IPCC	Intergovernmental Panel on Climate Change
NCD	NMIM County Database
NMIM	National Mobile Inventory Model
NO_2	Nitrogen Dioxide
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
OrthLS	Orthogonal Least Squares
VMT	Vehicle Miles Travelled

UN United Nations

UNFCCC United Nations Framework Convention on Climate Change

Dedicated to my beloved parents…

Chapter 1

Introduction

Cities and human civilization are intimately bound together, a bond which is an essential key to understand human history (Bairoch 1988). The advancements in agriculture during the neolithic revolution paved way for the advent of cities which later played a major role in one of the major turning points in the history of humanity i.e. the Industrial Revolution (Davis 1955; Geddes 1915). Attracting specified people together to the same place at the same time, cities globally emerged as crucibles of creativity and innovation (Batty 2012; Grubler et al. 2013). Humanity reached a new milestone in the year 2007 as urban areas became home to more than 50 % of the world population and evolved into "Homo Urbanus" (Crane 2005). Currently, a city of the size of Vancouver ($\sim$ 600,000 people) is being constructed by humanity at the rate of twice a week (McDonald 2008). Projected to host entire humanity by the end of this century (Batty 2011), the ultimate fate of humanity predominantly lies in the hands of technological innovation, urbanites' lifestyle and development pathways of current and future cities.

The on-going urbanization is profoundly related to economic structure and development, changes in social organization, landuse, and patterns of human behaviour and therefore influences natural systems and socioeconomic regimes simultaneously (Bettencourt et al. 2007). Triggered by the quest for socioeconomic growth, despite being a relatively nascent global phenomenon, rapid urbanization over the past few decades has led to some serious problems concerning global sustainability such as climate change and its impacts on food, energy, water, public health and global economy (Seto and Satterthwaite 2010; Bettencourt and West 2010). Much of the mankind's transformation of the earth's environment in terms of environmental pollution from local levels to planetary scale by emitting greenhouse gasses (GHG's) is currently taking place in cities (Hoornweg et al. 2016). Harboring more than 50 % of the global population, contemporary cities generate 80 % of the GDP while consuming ∼75 % of the energy supply, releasing approximately three quarters of global CO_2 emissions (UN 2014; Seto et al. 2014) and the bulk of the environmental pollution. This unparalleled scale of resource consumption and the subsequent environmental pollution (and GHG emissions) in cities is currently posing significant challenges to local and global sustainability. At the same time, cities are also vulnerable hotspots to the adverse impacts of climate change. Threats of climate change include flooding and damage to critical infrastructure, increasing intensity of urban heat island effect, cascading impacts on the food, energy and water nexus all of which are vital for proper functioning of the city (Neumann et al. 2015; Leck et al. 2015; Li and Bou-Zeid 2013).

However, a growing body of literature showed that larger agglomerations are efficient as they offer distinct economies of scale. Bettencourt et al. (2007) showed how a city of 10 million population is typically 15 % more efficient in terms of its material and energy use compared to two cities each with 5 million population. Satterthwaite (2008) argued that the percentage of global GHG emissions attributed to cities would be misleading as these emissions originate from the consumption patterns of the individuals and not directly from cities. Dodman (2009) depicted that per capita GHG emissions in cities is less than the average for the countries in which they are located and discussed how denser cities and large population concentrations offer a number of advantages for environmental management. Similarly, a study by Kennedy et al. (2015) on the energy and material flows in 27 megacities for a decade (2001-2011) revealed the efficiency of these large agglomerations. The findings of this study showed that the rate of GDP growth in these cities is double to that of the rate of growth in usage of electricity and fuel for ground transportation.

Since contemporary cities are acknowledged to play a pivotal role in global sustainability and climate change mitigation (Rosenzweig et al. 2010; Creutzig et al. 2015; Kennedy et al. 2014), this thesis addresses issues concerning urban GHG emissions and resource consumption from an efficiency point of view. More specifically, this thesis identifies structural, socioeconomical and technological factors contributing to emission efficiency and factors contributing to improved resource efficiency in cities. The emission efficiency component of this thesis is based on the recently developed "Urban Scaling" approach (Bettencourt et al. 2007) where the slope of the linear regression determines whether larger cities are more efficient compared to smaller cities and vice-versa. Further details about this approach are given in Chapter 1.2. The urban resource efficiency component of this thesis is addressed based on the idea of "Extended metabolism model of human settlements" developed by Newman (1999).

Section 1.1 is a brief introduction to urban metabolism, energy consumption and subsequent GHG emissions based on the state-of-the-art literature. The following sections (1.2, 1.3, 1.4) elaborate on the existing research gaps in factors leading to emission and resource efficiency. The research questions and methodology of this thesis are presented in section 1.5.

1.1 Urban Metabolism, Energy Consumption and GHG emissions

The contemporary science of cities has bid adieu to the previous notion of conceiving cities as organized top-down complex entities constantly seeking for equilibrium (Batty 2012). The state-of-the-art literature draws three analogies between cities and the biosphere with increasing degree of complexity. At a primitive level, cities are sought as 'organisms' resulting from numeorus bottom up evolutionary processes (Berry 2005). Transforming raw materials, fuel and water into built environment, human biomass and waste; cities are also percieved as dynamic and complex ecosystems (Decker et al. 2000). However, unlike natural ecosystems, the growth patterns of cities and their sustenence can be altered by external (technical) processes. Therefore, cities are also percieved as "eco-technical super-organisms" (Girardet 2008).

Urban metabolism studies give the much required systems approach to studying and applying sustainability practices in cities (Pincetl et al. 2012). These studies involve large scale quantification of energy and resource flows in cities (Kennedy et al. 2011). From a metabolism standpoint, sustainable development in cities can be broadly defined as the reduction of resource consumption and undesirable by-products (i.e. waste generation and environmental pollution) while improving the desirable outcomes that enable livability (Kennedy et al. 2007; Newman 1999). Further, urban metabolism studies for a large set of cities will enable peer-to-peer learning in the reduction of environmental impacts and enhancing sustainability (Zhang et al. 2015).

Useful energy being the principle driver of physical and socioeconomical systems, is one of the crucial resource flow in urban environments from an urban metabolism point of view (Doherty et al. 2009). Currently, predominated by fossil fuels, this form of useful energy is the main source for urban GHG emissions and human induced climate change (International Energy Agency 2008). Quantifying the share of global urban energy consumption and subsequent emissions is extremely challenging owing to the difficulty in defining and delineating urban areas from their rural counterparts and the differences in accounting approaches (i.e. consumption versus production) and is currently limited to either top-down or bottom-up approaches (Seto et al.

2014). The International Energy Agency (2008) (IEA) estimated that urban primary energy use at the global level to be 67 % while a study by the International Institute for Applied System Analysis (IIASA) estimated that the share of urban final energy use to range from 56 % and 78 % with a central estimate at 76 % (Grubler et al. 2013; International Energy Agency 2008). In terms of GHG emissions, the global urban energy related CO_2 emissions is estimated to range from 53 % and 87 % with a central estimate also at 76 % (Seto et al. 2014).

While climatic and socio-demographic factors, coupled with affluence are the main factors influencing energy consumption, their combination with economic geography, technology, infrastructure and urban form (population size and density) are the overarching factors that influence urban GHG emissions (Marcotullio et al. 2013; Kennedy et al. 2009; Seto et al. 2014). Apart from these intrinsic factors, the total emissions in a given region can be further decomposed using the Kaya Identity (Kaya 1990). The Kaya Identity is similar to the IPAT equation (further details in section 1.2). It defines emissions as a product of population, affluence (GDP per capita), energy intensity (i.e. energy per unit of GDP) and carbon intensity of energy (i.e. emissions per unit of energy) and enables further decomposition of key factors influencing emissions in a given region (Raupach et al. 2007). Although mostly limted to analyzing emission drivers at a national level, the application of Kaya Identity at city scale provides better insights into the demographical, economic geographical and technological aspects determining emissions at city scale.

The Urban Energy Assessment (Grubler et al. 2013) concluded that the per capita urban energy consumption and the GHG emissions in developed regions of the world are less than the national average while the opposite is the case with cities in developing regions. Similarly, a study by Rybski et al. (2017) concluded that given the state of emissions in global cities, further urbanization will bring emission efficiency gains in developed regions while the opposite is the case for cities in developing regions. A recent global study by Zhang et al. (2017) depicted an inverted U-shaped relationship between the percentage of urbanization and CO_2 emissions with a turning point around 73.80 %. The urban emissions from countries such as China, India and Brazil will be unprecendeted by the time they reach this turning point. Therefore, efficient technologies and effective landuse policies while improving urban infrastructure in developing regions offer an opportunity to leapfrog by adopting such low carbon development pathways. Such a development pathway will avoid the lock-in behavior currently exhibited in the developed regions predominated by urban population (Unruh and Carrillo-Hermosilla 2006). Recent literature showed a significant potential urbanization wedge for reducing energy usage in the developing regions while considering a development pathway which includes a compact urban form and policies that encourage public transportation (Creutzig et al. 2015).

Since the state-of-the-art literature clearly identifies urban population size, density, affluence, economic geography and technology as crucial factors determining urban GHG emissions, it is necessary to have an in-depth understanding about the influence of these factors on urban GHG emissions. Further, from an urban metabolism point of view, on-going urbanization trend will exacerbate the urban resource consumption patterns. Therefore it is crucial to identify factors contributing to improved resource efficiency in cities.

1.2 Influence of Urban Population, Affluence and Technology on GHG Emisisons

"What is the influence of human population on the Earth's environment?" This is an epochal question since Thomas Malthus and Charles Darwin (Chertow 2000). Population growth leads to an increase in consumption of resources which inturn is a function of affluence and technology used to produce what is consumed (Rosa and Dietz 2012). Holdren and Ehrlich (1974) devised a simple equation to quantify the cumulative effect of population, affluence and technology on Earth's environment which is often refered to as IPAT equation. Here, the environmental impact (I) is described as the product of three variables: population (P), affluence (A) and technology (T). The Kaya Identity (introduced in Chapter 1.1) is a form of IPAT equation used to explain GHG emission growth trends via decomposition analysis.

Recent literature showed that all the three variables within the IPAT equation have a profound impact on the subsequent emissions. For instance, using panel data (1975-1996) for 93 countries, Shi (2003) found out that a 1 % increase in population within a country will lead to a more 1 % increase in emissions. Analysis by Martínez-Zarzoso and Maruotti (2011) on the impact of urbanization on CO_2 emissions found the significant influence of urbanization rate coupled with urban population size and affluence on subsequent emissions in developing countries. Decomposing the emission drivers in countries applying the Kaya Identity, Raupach et al. (2007) highlighted the need to decarbonize by adopting better technologies in both developing and developed nations. Given the rapid urbanization rate, urban population, urbanites' affluence, their consumption patterns and the technologies adopted for generating and using energy predominantly determine the anthropogenic GHG emissions.

A vast majority of global urbanization is going to take place in large cities with a population between 5 to 10 million inhabitants (UN 2014). Therefore, amongst other issues, it is of particular interest to understand whether these large cities offer any economies of scale as they increase in size i.e. as cities grow in terms of their population, will their emissions also increase proportionally? To address such questions a new science of cities called “Urban Scaling” has emerged in the recent years (Batty 2012; Bettencourt et al. 2007). This approach draws parallels between the allometric scaling in biological systems to that of cities. Assuming a power law correlation and relating a city indicator such as gross domestic product (GDP) to the population of the city, urban scaling depicts how these indicators scale with population size and whether large cities are more efficient in comparison to smaller cities. The slope of a linear regression between the logarithms of population and GDP determines whether large cities are more (or less) efficient compared to smaller cities. A slope ($\beta < 1$) indicates large cities typically generate lower GDP while a slope ($\beta > 1$) indicates large cities typically generate more GDP in comparision to smaller cities. There exists a general consensus in the application of urban scaling that large cities are typically more efficient with respect to GDP, employment, patents (all with $\beta > 1$), and urban infrastructure provision where $\beta < 1$ (Ribeiro et al. 2017; Lobo et al. 2013; Arbesman et al. 2009; Bettencourt and Lobo 2016). Consequently, researchers have applied urban scaling to city emissions to determine whether large cities are more (or less) emission efficient in comparison to smaller cities.

However, recent literature aiming at finding whether large cities are more emission efficient compared to smaller cities has three major drawbacks. Firstly, most of these studies are limited to urban systems in developed regions of the world. Secondly, the results of these studies are sometimes contradictory. For instance, a study by Fragkias et al. (2013) showed an almost linear scaling of emissions with population while another study by Oliveira et al. (2014) showed a super-linear scaling of emissions with population size. Interestingly, both these studies are done for cities in the USA. Similar contradictory results are also identified with respect to scaling of transport energy consumption with population size (Glaeser and Kahn 2010; Louf and Barthelemy 2014). Thirdly, an in-depth understanding about the inherent factors leading to such scaling parameters of emissions with population size is missing in these studies.

Given the strong global urbanization trend of the large cities globally most of which will take place in developing countries, and the current global emissions attributed to urban systems, there undoubtedly is a need to understand whether such a trend will make these cities more (or less) emission efficient. Merging the concept of the Kaya Identity with that of urban scaling (further details in Chapter 2) will give better insights whether large cities are more emission efficient and an in-depth understanding about the intrinsic socioeconomic and technological drivers that lead to such scaling parameters. Such an analysis will give further insights into the focal areas for mitigation actions in these cities.

1.3 Urban Density and GHG Emissions

The quest for identifying an ”Ideal urban form” in terms of city population has been illusory since the perceptions about quality of urban life have changed drastically from the time of Plato to Le corbusier until the modern day’s conventional wisdom (Batty 2015). However, population density as one of the distinct urban form characteristic of cities that distinguishes them from their rural counterparts is identified to have a significant influence on the functionality, economics and sustainability of cities (Glaeser and Kahn 2010; Roberts 2007). However, there exits a dichotomy within the urban planning debate whether compact cities function better or are more sustainable in comparison to sprawled/dispersed cities. Breheny (1996) categorized the protogonists who are in favour of a compact city as centralists and those who are aganist it as decentralists. Indeed, urban scholars such as Jacobs (1961) and Glaeser (2011) have advocated that population density and diversity play a crucial role in innovation, improving prosperity and livability in cities. However, contemporary research has also shown that population density might have a siginificant impact on other factors concerning sustainable development such as as traffic congestion, air pollution (Lohrey and Creutzig 2016), public health (Frank and Engelke 2001) and micro-climate (Zhou et al. 2004; Rode et al. 2014). Therefore, apart from population size, affluence, and technology, of particular interest is an in-depth understanding about the influence of population density on urban energy consumption and the subsequent emissions.

The seminal work by Newman and Kenworthy (1989) identified the influence of population density on per capita gasoline consumption. This study stated that sprawled cities in the USA such as Houston and Phoenix have a much higher per capita gasoline consumption compared to that of denser Asian settlements such as Hong Kong and Singapore. This work led to copious research in the field of urban planning especially in the field of urban transportation. Influencing travel demand by altering the built environemnt is one of most researcher subjects in urban planning (Ewing and Cervero 2010). A plethora of other studies also show the significant influence of population density in curbing urban GHG emissions. For instance, Brown et al. (2009) found that the 100 metropolitan areas in the USA with highest density have lesser carbon footprints than the average carbon footprint of entire USA. Similarly, Glaeser and Kahn (2010) also found that urban areas in USA generally have siginificantly lower GHG emissions than suburban areas. A recent study by Facchini et al. (2017) on the energy metabolism for 27 megacities concluded that population density has a significant inluence in decreasing total per capita energy consumption. Studying the factors influencing direct energy use in 7,000 local areas in England, Baiocchi et al. (2015) found that density is one of the crucial factor driving local energy use.

However, some studies found that population density doesn't play a crucial role in curbing GHG emissions and identified other factors which influence urban GHG emissions. Baur et al. (2014) using a comsumption based emission inventory investigated the influence of population density on per capita GHG emission efficiency for 62 European cities and concluded that it is household size and affluence that play a significant role in determining GHG emission efficiency in European cities and not population density. Similarly, a study on household carbon footprints by Jones and Kammen (2014) using the household demand for goods and services concluded that increasing population density will not decrease the household carbon footprint. Employing innovative multivariate statistical technique on the data used in the study by Newman and Kenworthy (1989), Mindali et al. (2004) found that total urban density has no direct influence on the per capita energy consumption and highlighted various other relationships between energy consumption and density attributes. Ewing and Cervero (2010) did a meta-analysis of more than 200 studies to find the key factors influencing urban Vehicle Miles Travelled (VMT) in USA and found that destination accessibility and street design network instead of population (and job) density play a crucial role in determining VMT.

As mentioned in Section 1.1, population density plays a crucial role in determining urban energy metabolism and subsequent the emission profiles of cities. Despite this, a general conclusion about the influence of population density on GHG emissions efficiency could not be drawn from the existing literature because of to two major reasons: (1) there exists no universal definition for what qualifies a given settlement as urban (UN 2014) and (2) a lack of comparable GHG emission inventory for cities. Most of the existing studies use city specific GHG emission inventories to quantify this relationship acknowledging the differences in spatial scales (urban extents) and emission estimation i.e. accounting methods, scope of GHG's and emission sources (Dhakal 2010; Fong et al. 2014; Kennedy et al. 2009; Satterthwaite 2008; Wintergreen and Delaney 2006). Therefore, a systematic analysis using a consistent definition for estimating urban extents and a standard GHG emission inventory (although subject to data availability at such detailed spatial resolution) will provide insights about the influence of population density on emission efficiency. Lack of data on energy consumption and GDP at such detailed spatial extents limited the analysis in Chapter 2 to the exisiting city specific data. Further details are discussed in Chapter 5.

Population density exerts a significant influence on the two most prominent sectors which are directly influenced by urban planning namely the building and transport sectors (Dodman 2009; Steemers 2003). Therefore, there is a need to analyze the influence of population density on emission efficiency in these sectors using a standard procedure for calculating urban extents and a consistent GHG emission inventory. Such an analysis will give better insights into finding effective land use and transportation solutions to mitigate urban GHG emissions.

1.4 Urban Resource Consumption

Irrespective of size and density, the alarming levels of urban resource consumption and waste discharges affect land use, biodiversity, and hydrosystems that threaten not only local but also global sustainability (Satterthwaite 1997; Grimm et al. 2008). The socioeconomic benefits that cities globally offer come at certain environmental costs. For example, it is projected that the global urban land cover will triple by 2030 compared to the land cover in the year 2000 (Seto et al. 2012) and 80 % of this urban expansion in Africa and Asia will happen on crop lands affecting agrarian livelihoods (Bren d'Amour et al. 2016). A study by McDonald et al. (2014) depicted that large cities in the world move roughly 500 billion liters a day from an upstream contributing area which is about 40 % of global land surface. Acknowledging the linear metabolism of contemporary cities which is manifested by large scale resource consumption and environmental pollution, the concept of circular metabolism where every undesirable output can be used as an input into the production system has been introduced by writers such as Girardet (1996).

Studies on urban metabolism which involve large scale quantification of resource flows and waste generation in cities and analyzing the pathways of materials, energy and pollutants enables local policy makers to adopt adequate management systems and technologies to improve urban resource efficiency (Newman 1999). Since its inception by the influential work of Wolman (1965), the concept of urban metabolism has lead to copious amounts of research in the field of urban sustainability (Zhang et al. 2015). Kennedy et al. (2011) highlighted how such a large scale energy and material flow analysis can have practical implications in urban sustainability reporting, GHG accounting, urban design and policy analysis. Urban metabolism is influenced by a number of factors such as urban form, affluence, local climate, stage of development, fuel prices and local demography (Pincetl et al. 2012; Kennedy et al. 2007).

Acknowledging that mere quantification of large scale resource and waste flows in cities is not enough to practically improve local sustainability, Newman (1999) suggested an extended metabolism model for human settlements which merges the resource (and waste) flows within a city with the dynamics of settlements and their livability. This extended urban metabolism model defines sustainable urban development as reduction of resources and waste generation while improving the urban livability. Minx et al. (2011) further extended this concept by including local drivers, patterns and lifestyles as the key factors determining urban quality and livability within the extended metabolism model. This process which is charecterized by improving socioeconomic conditions while decreasing the environmental burden is referred to as "de-coupling" (Swilling et al. 2013) and cities which enable better socioeconomic conditions whilst reducing their environmental burden are called "eco-efficient" cities (UNESCAP 2011).

Despite being a fundamental concept to build sustainable cities and communities, the concept of urban metabolism is applied to very few cities globally largely owing to data constraints (Kennedy et al. 2007; Minx et al. 2011). Apart from it's application to the specific cities such as the study by Newman (1999) on Sydney and 5 cities by Goldstein et al. (2013), there are very few studies which applied the concept of extended metabolism to many number of cities. Applying this concept to a larger number of cities where consistent data is available provides further insights whether large cities are more eco-efficient in comparison to smaller cities and the crucial role population density, economic structure and affluence play in determining a city's eco-efficiency. Moreover, such an exercise will enable policy makers to identify best performing cities in terms of their metabolic efficiency. This procedure, which is characterized by systematic search for efficient procedures and best practices for complicated problems leading to enhanced performance, is often referred to as "Benchmarking" in operations research (Dattakumar and Jagadeesh 2003; Elmuti and Kathawala 1997; Moriarty 2011). The concept of benchmarking so far has been applied to cities to identify best practices with respect to urban competitiveness (Arribas-Bel et al. 2013; Charnes et al. 1989; Jiang and Shen 2013; Kresl and Singh 1999), urban infrastructure service delivery (Fancello et al. 2014; Matas 1998; Pina and Torres 2001) and urban energy consumption and GHG emissions (Ahmad et al. 2015; Dhakal 2009; Hillman and Ramaswami 2010; Keirstead 2013; Kennedy et al. 2009; Sovacool and Brown 2010).

Since cities are primary drivers of global environmental change (Pincetl et al. 2012; Seto and Satterthwaite 2010), benchmarking eco-efficiency of cities could foster peer-to-peer learning of good practices for sustainable urban development between local policy makers. Further, a study by Marans (2015) depicted that the quality of life and liveability has a strong influence on urbanites' perception. Therefore, there is a need to relate urbanites' perception about the quality of life with eco-efficiency of cities to understand whether the most eco-efficient cities are well perceived by their citizens and to identify the crucial factors determining urbanites' perception about quality of life.

1.5 Research Questions

Acknowledging the crucial role of cities in mitigating climate change and ensuring sustainable development and drawing motivation from the gaps in the state-of-the-art research on emission and ecological efficiency, the overarching research question of this thesis is as follows:

> "What is the influence of urban form, economic geography and technology on GHG emissions and what are the fundamental characteristics of eco-efficient cities?"

The aim of this thesis is to identify factors contributing to city efficiency from two perspectives: GHG emission efficiency and ecological efficiency. While the emission efficiency part of this thesis addresses the influence of population size, density and other intrinsic factors such as economic geography and technology on city emissions, ecological efficiency addresses the issues concerning urban sustainability given the current resource consumption and socioeconomic structure in cities. With this motivation, this thesis aims to address three major research questions (RQs):

> RQ1: Are largely populated cities more emission and energy efficient in comparison to smaller cities and which intrinsic economic and technological drivers determine such emission and energy efficiency in large cities?
>
> RQ2: What is the influence of population density on urban GHG emissions?
>
> RQ3: Which cities are eco-efficient, what are their characteristics and how does eco-efficiency of cities relate to the public perception about quality of urban life?

1.6 Research Approach and Thesis Overview

The above research questions were addressed using a multitude of analytical and geo-spatial approaches at various spatial resolutions across various countries. An overview of the research approach (Figure 1.1) used to address each of the aforementioned research questions is given below.

RQ1 was addressed in Chapter 2 using emissions, energy consumption, population and GDP data for a set of 61 global cities. While the energy consumption data is taken from Creutzig et al. (2015), data on emissions is gathered from various sources including city specific reports (compiled by organizations such as ICLEI, CDP and C40 cities) and data which is published

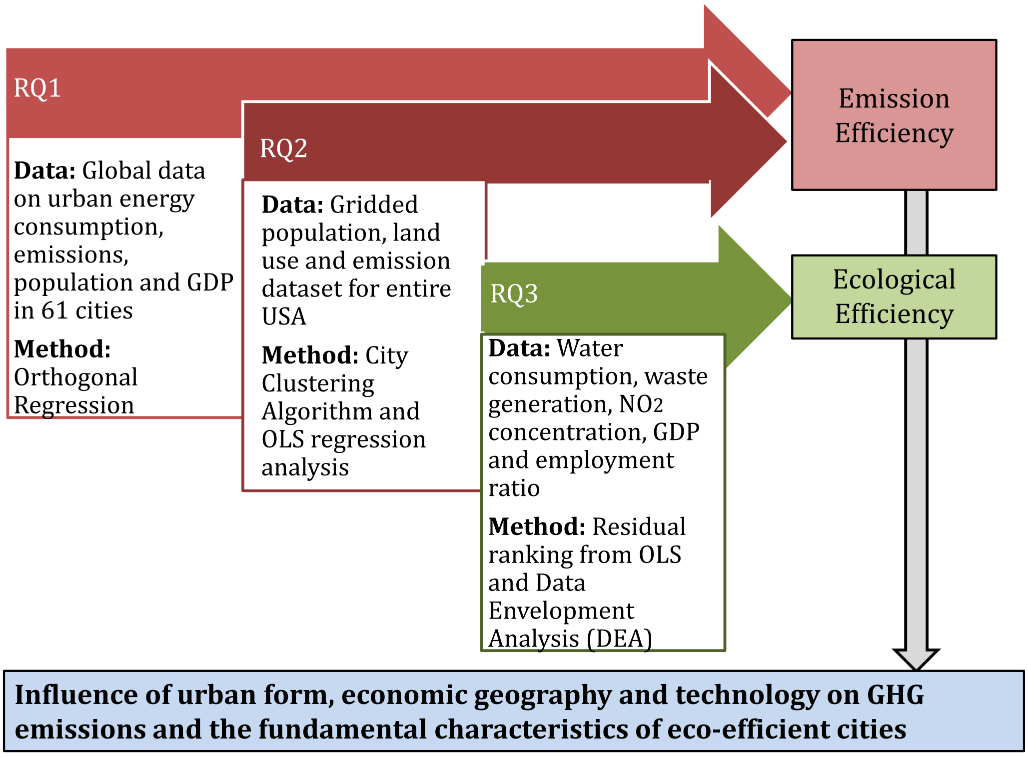

Figure 1.1: Data and Methods used to address each RQ in this thesis leading to the guiding research question.

in peer reviewed (journal) publications. In order to identify the intrinsic socioeconomic and technological factors that determine the scaling of emissions with population, the well-established Kaya Identity is transferred to urban CO_2 emissions. Originally, the concept has been proposed to separate global CO_2 emissions into contributions from global population, GDP per capita, energy intensity, and carbon intensity (Raupach et al. 2007; Yamaji et al. 1993). Relating the Kaya Identity to urban scaling led to an *Urban Kaya Relation*. Although studies on urban scaling use ordinary least squared regression analysis (OLS), this study used the orthogonal least squared regression analysis to obtain robust results of the scaling parameters within the Urban Kaya Relation.

RQ2 was addressed in Chapter 3 using three major steps: (1) superimposing the gridded population data on two gridded land use datasets namely Global Land Cover (GLC) data and Global Rural-Urban Mapping Project (GRUMP) land use data (both available at $\sim$1 km^2 resolution) to map the location of populated settlements in the entire USA; (2) downscaling the gridded

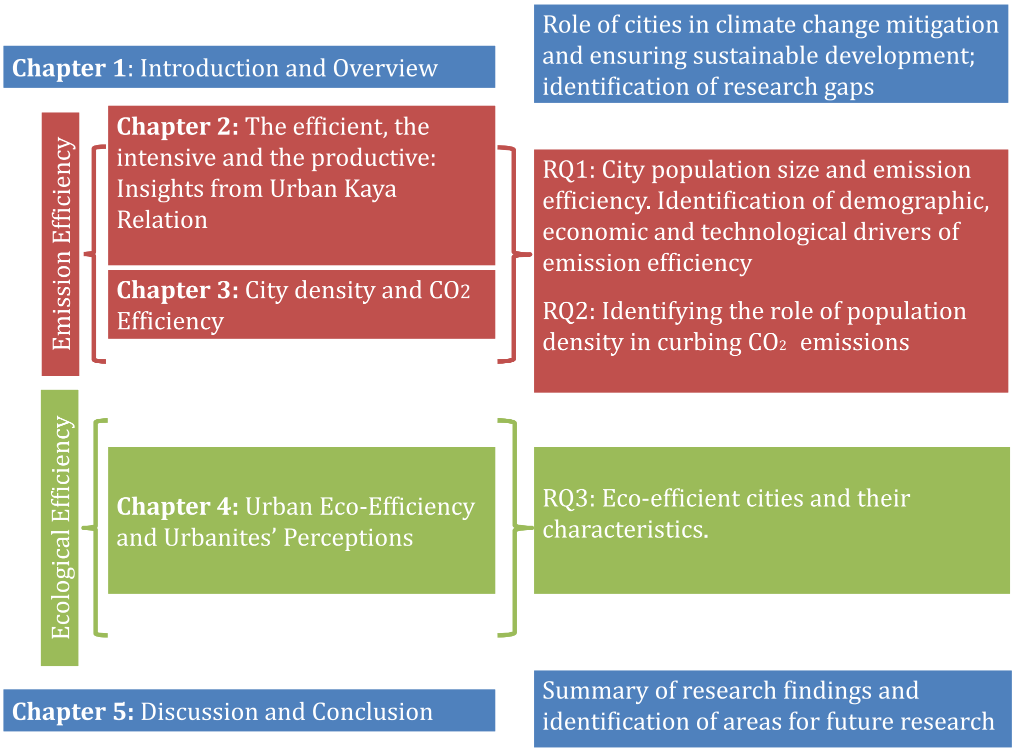

Figure 1.2: A schematic diagram presenting the overview and topics dealt with under each chapter in this thesis. While Chapter 2 and Chapter 3 addresses the RQ1 and RQ2 concerning the "Emission Efficiency"; Chapter 4 addresses the RQ3 concerning the "Ecological Efficiency" in this thesis.

building and transportation CO_2 emissions ($\sim$10 km^2 resolution) and superimposing the building and transport sectoral CO_2 emission data to the populated settlements obtained in step 1, (3) application of City Clustering Algorithm (CCA) at various threshold distances on this superimposed gridded dataset in order to ensure comparison of building and transport emissions for city clusters with similar urban extents. Applying these three steps led to identification of various city clusters at varying threshold distances (1–10 km), their sectoral emissions, extents, population and subsequently their population density separately for GRUMP and GLC land cover datasets. Using two different land use datasets enabled this study to check the consistency of the influence of population density on sectoral CO_2 emissions on a per capita basis.

RQ3 addressed in Chapter 4 ranks the 88 most populated European cities based on their socio-economic and environmental burden/resource consumption indicators for the year 2011. The environmental burden/resource consumption indicators considered in this study are the annual average urban waste generation, water consumption and NO_2 concentration. The socioeconomic outputs considered in this study are GDP per capita in power purchasing parity and the employment ratio. All the data used in this study is compiled from the urban audit database of the EUROSTAT (Dijkstra and Poelman 2012). Two different non-parametric methods were used in this chapter to rank the eco-efficiency of these 88 cities namely: (1) an OLS regression residual ranking and (2) a ranking based on Data Envelopment Analysis (DEA). Further, this study analyzed the correlations between the eco-efficiency ranking and the percieved quality of urban life ranking for a subset of 45 cities to check whether the objective eco-efficiency rankings are aligned with the public perception ranking in these cities. Figure 1.1 gives an overview of the data and methods used in each research question leading to the guiding research question.

Finally, specific answers to the research questions RQ1-RQ3 obtained from Chapters 2-4 are discussed in Chapter 5. While Chapters 2 and 3 focus on the aspect of emission efficiency in cities addressing research questions RQ1 and RQ2, chapter 4 focusses on ecological efficiency addressing RQ3. Figure 1.2 shows how all the five chapters of this thesis are interlinked. Chapter 5 also provides policy implications of the main research findings of this thesis while addressing the overarching research question.

Chapter 2

The efficient, the intensive and the productive: Insights from the Urban Kaya Relation[1]

Abstract

Urban areas play an unprecedented role in potentially mitigating climate change and supporting sustainable development. In light of the rapid urbanization in many parts on the globe, it is crucial to understand the relationship between settlement size and CO_2 emission efficiency of cities. Recent literature on urban scaling properties of emissions as a function of population size have led to contradictory results and more importantly, lacked an in-depth investigation of the essential factors and causes explaining such scaling properties. Therefore, in analogy to the well-established Kaya Identity, we develop a relation combining the involved exponents. We demonstrate that application of this *Urban Kaya Relation* will enable a comprehensive understanding about the intrinsic factors determining emission efficiencies in large cities by applying it to a global dataset of 61 cities. Contrary to traditional urban scaling studies which use ordinary least squares regression, we show that orthogonal regression is necessary when complex relations among scaling exponents are to be investigated. We discuss the potential of the Urban Kaya Relation in mainstreaming local actions for climate change mitigation.

[1]This chapter is submitted as a research article to the journal of royal society Interface as Gudipudi,R.; Rybski,D.; Lüdeke,M.K.B. ;Zhou,B.; Liu,Z.; Kropp,J.P. (2017): The efficient, the intensive and the productive: Insights from the Urban Kaya Relation,Interface,[submitted]

2.1 Introduction

Harbouring more than 50 % of the global population (UN 2014), contemporary cities generate 80 % of the Gross Domestic Product (GDP) while consuming approximately 75 % of energy supply and releasing approximately three quarters of global CO_2 emissions (Seto et al. 2014). Their unprecedented scale and complexity led to the development of a science of cities (Batty 2012). Drawing parallels between the allometric scaling in biological systems to that of cities, it has been studied how certain socioeconomic and environmental indicators in cities scale as a function of city size by means of the *urban scaling* approach (Bettencourt et al. 2007). Since a large fraction of the global population is expected to live in cities by end of this century (Batty 2011), contemporary and future cities will play a pivotal role in global sustainability and climate change mitigation. Given this strong global urbanization trend, one of the crucial questions that needs to be addressed is whether large cities are more or less emission efficient in comparison to smaller cities.

The application of allometric scaling to cities (often referred to as "urban scaling") has triggered copious research in the contemporary science of cities, see e.g. (Samaniego and Moses 2008; Arbesman et al. 2009; Alves et al. 2013; Pan et al. 2013; Yakubo et al. 2014; Alves et al. 2015; Bettencourt and Lobo 2016). Urban scaling relates a city indicator (e.g. total urban energy consumption) with city size (e.g. population). Assuming power-law correlations, the analysis depicts how these indicators scale with population size and whether large cities are more or less efficient. A sub-linear scaling (i.e. slope $\beta < 1$) indicates that large cities consume less energy given their size, while a unit slope ($\beta \simeq 1$) depicts proportionality, and a super-linear scaling ($\beta > 1$) indicates that large cities consume more energy given their size.

The state-of-the-art research aiming at identifying whether large cities are more energy and emission efficient led to contradicting results and have been largely limited to the cities in the developed world. For instance, studies on total CO_2 emissions for cities in the USA showed not only an almost linear (Fragkias et al. 2013) but also a super-linear scaling (Oliveira et al. 2014). A similar study for European cities depicted a super-linear scaling (Bettencourt and Lobo 2016). Studies on household electricity consumption in Germany and Spain revealed an almost linear scaling (Bettencourt et al. 2007; Horta-Bernús and Rosas-Casals 2015). With respect to energy consumed and the subsequent emissions from urban transportation at a household level in the USA, Glaeser and Kahn (2010) found a sub-linear scaling between population size and gasoline consumption; while Louf and Barthelemy (2014) showed a super-linear scaling of emissions with population size. A similar study done on British cities by Mohajeri et al. (2015) found a linear scaling between transport emissions and population size while finding a super-linear relationship between emissions and the total street length. Most of the existing studies followed different city definitions and chose different indicators to analyze scaling. However, little is known regarding the underlying systematic dynamics that govern these properties. Therefore, in this paper we develop a framework to investigate the intrinsic factors that determine scaling properties of urban emissions.

We tackle the problem from a different perspective and transfer the idea of the well-established Kaya Identity to urban CO_2 emissions leading to an Urban Kaya Relation. Then the scaling of CO_2 emissions with city size can be attributed to the scaling between population, GDP, energy, and emissions. To the best of our knowledge, such an attempt to obtain a deeper insight into the scaling of emissions with population using indicators in the Kaya Identity is unprecedented. Further, we apply Urban Kaya Relation to a global dataset of 61 cities. The objective of applying the Urban Kaya Relation to this global dataset is to demonstrate its applicability and draw some exploratory empirical conclusions about factors contributing to emission efficiency in large cities globally. Recent literature has identified that the energy consumption and the subsequent emissions depend on the city type i.e affluent and mature cities in developed countries versus cities in transition countries with emerging and nascent infrastructure (Creutzig et al. 2015; Seto et al. 2014). Therefore, we apply the Urban Kaya Relation to these cities separately.

2.1.1 Urban Kaya Relation

The *Kaya Identity* has been proposed to separate global CO_2 emissions into contributions from global population, GDP per capita, energy intensity, and carbon intensity (Yamaji et al. 1991; Raupach et al. 2007). It relates CO_2 emissions (C), population (P), GDP (G), and energy (E) according to

$$C = P \times \frac{G}{P} \times \frac{E}{G} \times \frac{C}{E}\,. \tag{2.1}$$

While the GDP per capita (G/P) is a common quantity, the energy intensity (E/G) can be understood as the energy necessary to generate GDP, and the carbon intensity (C/E) as the efficiency in energy production and consumption (technological). Equation (2.1) is an identity since it cancels down to $C = C$. As outlined above, here we are interested in how the urban CO_2 emissions scale with urban population size, i.e.

$$C \sim P^{\phi}\,. \tag{2.2}$$

The value of ϕ tells us if large or small cities are more efficient in terms of CO_2 emissions. Without loss of generality, we propose that the other quantities also exhibit scaling, i.e.

$$G \sim P^{\beta} \quad (2.3)$$

$$E \sim G^{\alpha} \quad (2.4)$$

$$C \sim E^{\gamma}\,. \quad (2.5)$$

E.g., it has been reported that GDP scales super-linearly ($\beta > 1$) with population (Bettencourt et al. 2007). In a sense, the exponents β, α, γ take the role of GDP per capita, energy intensity, and carbon intensity in the original Kaya Identity, Eq. (2.1).

Combining Eq. (2.2)-(2.5) leads to

$$\phi = \beta\,\alpha\,\gamma\,. \quad (2.6)$$

Thus, in analogy to the original Kaya Identity, Eq.(2.6) provides an *Urban Kaya Relation* according to which the exponent relating emissions and population is simply given by the product of the other involved exponents. This permits us, to attribute non-linear scaling of emissions with city size, Eq. (2.2), to potential urban scaling of GDP with population, energy with GDP, or emissions with energy. For the sake of completeness in Appendix A.1 we also provide another two complementary forms of Kaya Identities and corresponding Urban Kaya Relations.

However, the exponent ϕ is usually obtained from the data and a linear regression $\ln C = \phi \,\ln P + a$, where a is another fitting parameter. Equations (2.2)-(2.5) represent idealizations and in practice correlations are studied which can come with more or less spread around the regression. Ordinary Least Squares (OrdiLS) might make sense, when dependent and independent variables are clearly defined, e.g. in the case of GDP vs. population it might be preferable to minimize residuals of GDP. Here we found that applying Ordinary Least Squares to $C \sim P^{\phi}$ and $P \sim C^{1/\phi^*}$ generally leads to $\phi \neq \phi^*$ (Fluschnik et al. 2016; Rybski et al. 2017) so that also Eq. (2.6) would not be valid. In our context, however, dependent and independent variables need to be exchangeable and we obtained more robust results ($\phi \simeq \phi^*$) by applying *Orthogonal* Least Squares (OrthLS). Therefore, we apply OrthLS throughout the paper. In OrthLS the distance between the regression manifold and the points to be approximated is measured perpendicular to both the axis in contrast to approximation along the axis of dependent variable in OrdiLS. Technically, we use the `prcomp`-function in `R` (version 3.2.3). In order to quantify the uncertainty of the estimated exponents, we explore bootstrapping, i.e. 20,000 replications.

2.2 Data

The major pre-requisites while investigating the scaling effects of urban energy consumption and emissions are (a) a consistent definition and demarcation of cities from their hinterlands and (b) a consistent accounting approach to quantify the energy consumption and subsequent emissions (Seto et al. 2014). The analysis conducted in this paper is limited to 61 global cities, i.e. the union of cities for which the 4 quantities are available, i.e. (i) total final energy consumption, (ii) CO_2 emissions, (iii) GDP, and (iv) population. Although, the data used in this analysis might be inconsistent owing to the challenges mentioned above, we used it as a showcase to demonstrate the applicability of the Urban Kaya Relation. The limitations of the data and its implications on the exploratory results are discussed in the Section 2.4.

The population, GDP, and total final energy consumption data used in this study is taken from the Chapter 18 "Urban Energy Systems" of the Global Energy Assessment (Grubler et al. 2013). This database includes the per capita total final energy consumption of 223 global cities, their respective population and GDP for the year 2005. The data on emissions is compiled from various sources including city specific reports (compiled by organizations such as ICLEI, CDP, and C40 cities) and data which is published in peer reviewed journal publications (Shan et al. 2016).

The cities with available data are located in 12 countries. The GDP per capita of these countries shows two groups. One ranging from 740 USD to 4,700 USD and the other from 26,000 USD to 44,000 USD (year 2005). These two groups can be considered developing and developed countries and represent the Non-Annex 1 and Annex 1 countries as reported by the United Nations Framework Convention on Climate Change (UNFCCC), respectively. Amongst the 61 cities used in this analysis 22 cities are from the Annex I countries and 39 cities from Non-Annex I countries. The database consists of cities of varying population sizes across 6 continents including 7 megacities (with a reported population above 10 million). Within countries in Annex 1 regions, 7 cities from the USA, 4 cities from the UK, 2 cities from Germany, Spain, Australia, Italy, France respectively, and 1 city from Japan are considered in this study. With respect to cities in Non-Annex 1 countries 33 cities from China, 2 cities from India, South Africa, and Brazil were included.

On the country scale, CO_2 emissions per capita strongly depend on the development of the considered country, see e.g. Costa et al. (2011) and references therein. Here we pool together cities from many different countries, including from developing countries; as a consequence, the data needs to be normalized prior to the analysis in order to account for such baseline emissions.

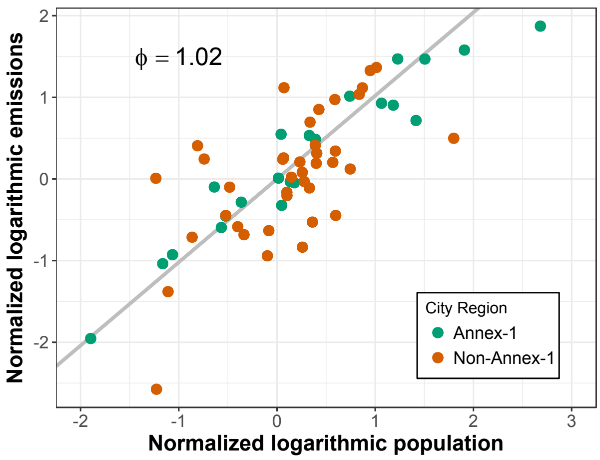

Figure 2.1: Scaling of CO_2 emissions with population size for 61 global cities. The data has been normalized by substracting average logarithmic values, see Section 2.2. The solid line is the regression obtained from *Orthogonal* Least Squares (Section 2.1.1) and the slope is $\phi \simeq 1.02$, see Table 2.1 for details.

Therefore, we employ a method that was recently proposed for urban scaling (Bettencourt and Lobo 2016) and normalize the data for each country by the average logarithmic city size ($\langle \ln P \rangle$) and indicator value (e.g. $\langle \ln C \rangle$) within our sample.

2.3 Results

We begin by looking at the scaling of emissions with population size for all the 61 cities considered in this study. The slope of this logarithmic orthogonal regression (see Figure 2.1) is almost equal to one ($\phi = 1.02$), however, the pattern of residuals is diverse as also reported in some earlier studies (Bettencourt and Lobo 2016). This clearly depicts the diversity in urban energy metabolism leading to varying emissions (Fragkias et al. 2013). This result shows that at a global scale, large cities are typically not more emission efficient compared to smaller cities. Further, in Figure 2.1 a distinction between the scaling of emissions with population size in developed countries (Annex 1 cities shown in green colour) in comparison to cities in developing countries (Non-Annex 1 cities shown in red colour).

For comparison, we also include the resulting exponents, when we employ OrdiLS to the scaling of the 61 cities. Table 2.1 includes the absolute difference between the prediction, Eq. (2.6), and the measured exponent ϕ. The obtained exponents deviate strongly when OrdiLS is used (instead of OrthoLS). As discussed at the end of Sec. 2.1.1, we attribute this discrepancy to different regressions when minimizing the residuals along any of both axis leads. In the case of

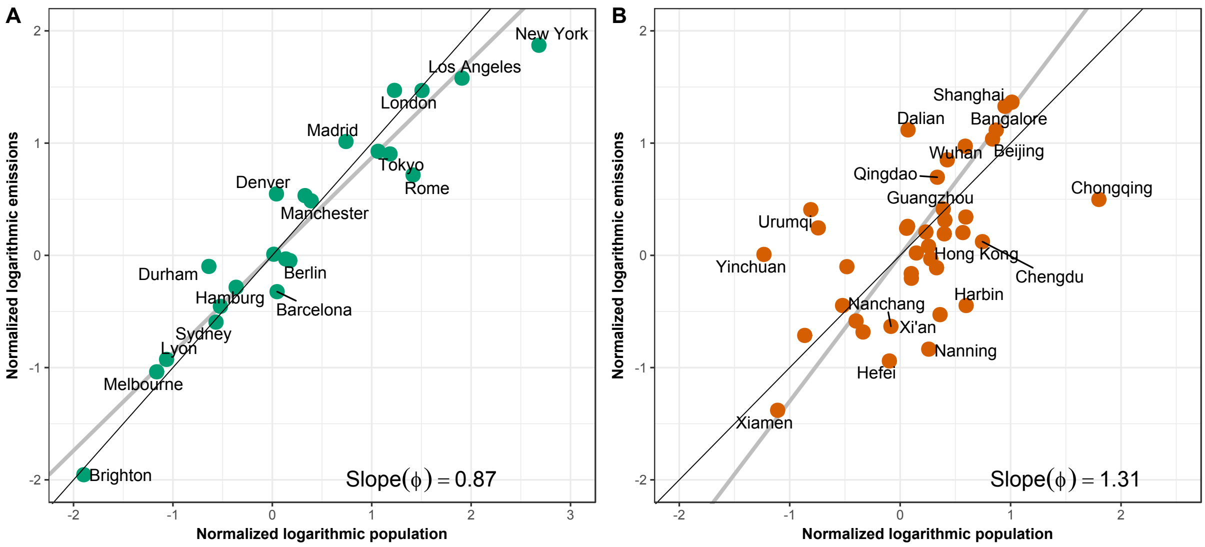

Figure 2.2: Scaling of CO_2 emissions with population for cities in Annex 1 countries (panel A) and in Non-Annex 1 countries (panel B). Each bubble reflects the emission intensity and GDP per capita for a given city in Annex 1 (panel A) and Non-Annex 1 countries (panel B), respectively. While the slope of the *Orthogonal* Least Squares for Annex 1 countries is found to be sub-linear ($\phi \simeq 0.87$), it is super-linear ($\phi \simeq 1.31$) with respect to cities in Non-Annex 1 countries. As in Fig. 2.1 the data of both axis has been normalized subtracting average logarithmic values, see Sec. 2.2. The grey line indicates a slope of 1 and is included for comparison.

OrthoLS, where the residuals are perpendicular to the regression, e.g. plotting G vs. P and P vs. G leads to the same result. Thus, we recommend to employ OrthoLS instead of OrdiLS when studying the Urban Kaya Relation. Moreover, for OrdiLS it has been shown that whether the estimated exponents are statistically different from 1 depends on the assumptions made (Leitão et al. 2016).

As a next step, we analyzed the scaling properties of emissions with size seperately depending on the economic geography (i.e. Annex 1 cities vs. Non-Annex 1) of the country in which these cities are located. In Figure 2.2 we see that the scaling of emissions with the population size indeed has a dependence on the economic geography of the country. We found a sub-linear scaling for cities in Annex 1 regions ($\phi = 0.87$) and a super-linear scaling for cities in the Non-Annex 1 regions ($\phi = 1.31$), see Table 2.1. The fit appears to be good for cities in Annex 1 regions which are broadly characterized as service sector oriented economies. However, in industry dominated Non-Annex 1 cities with widely varying infrastructure and energy intensity of production the goodness of fit appears to be relatively poor. This result shows either that the emissions data from Non-Annex 1 cities is not as accurate, or that population is a good proxy to estimate emissions for cities in Annex 1 regions while there seems to be other factors that influence emissions for cities in Non-Annex 1 countries.

Exponent: Equation: Scaling of:	ϕ Eq. (2.2) Emissions with population	β Eq. (2.3) GDP with population	α Eq. (2.4) Energy with GDP	γ Eq. (2.5) Emissions with Energy	$\lvert\phi - \beta\,\alpha\,\gamma\rvert$ Eq. (2.6)
All Cities	1.02 $\rightarrow$ [0.84,1.23]	1.16 $\nearrow$ [1.04,1.30]	0.89 $\searrow$ [0.69,1.09]	0.96 $\rightarrow$ [0.75,1.22]	0.03
Annex 1	0.87 $\searrow$ [0.76,0.97]	1.04 $\nearrow$ [1.00,1.07]	0.99 $\rightarrow$ [0.67,1.45]	0.79 $\searrow$ [0.54,1.15]	0.06
Non-Annex 1	1.31 $\nearrow$ [0.81,1.76]	1.40 $\nearrow$ [1.07,1.87]	0.78 $\searrow$ [0.54,1.00]	1.16 $\nearrow$ [0.90,1.48]	0.04
All Cities (OrdiLS)	0.80	0.98	0.64	0.67	0.38

Table 2.1: Scaling exponents and urban kaya relation. The Table lists the various estimated exponents and the last column shows how well the Urban Kaya Relation performs. The exponents are listed for all cities, cities in Annex 1 countries, and cities in Non-Annex 1 countries (see Sec. 2.2). All exponents have been obtained from Orthogonal Least Squares (see Sec. 2.1.1) except for the last row, where Ordinary Least Squares have been applied for comparison. The square brackets give 95 % confidence intervals from bootstrapping (20,000 replications). Inspired by the notation used in (Leitão et al. 2016) we put the following symbols. $\nearrow$, at least 66.6 % of the replications lead to exponents larger than 1; $\rightarrow$, 33.3 % to 66.6 % of the estimates are larger than 1, and $\searrow$, less than 33.3 % are larger than 1. While Eq. (2.6) works reasonably well for Orthogonal Least Squares, for Ordinary Least Squares the estimated exponents are incompatible (last row).

As a next step we looked at scaling of each of the indicators in the Urban Kaya Relation namely: the scaling of GDP with population (G/P) Eq. (2.3), scaling of energy intensity (E/G) Eq. (2.4), and carbon intensity (C/E) Eq. (2.5), in these cities. Table 2.1 lists the exponents of each of these indicators. From a global perspective, our results suggest that the almost linear scaling of emissions with population size could be attributed to the almost linear scaling of carbon intensity and the trade-off between scaling of GDP with population and the scaling of energy intensity (i.e. they compensate each other).

In the case of cities in Annex 1 countries, our results show that the large cities typically have lower emissions per capita compared to smaller cities because of the sub-linear scaling of the carbon intensity (Table 2.1). This can be attributed to the carbon intensity of the electricity generation supply mix, vehicle fuel economy and the quality of public transit in these cities (Kennedy et al. 2009). We found an approximately linear scaling of GDP with population. Our result shows that doubling the GDP in these cities will lead to an almost similar increase in energy consumption. Such a linear scaling can be largely attributed to the consumption patterns and infrastructure lock-in behavior in largely service based economies (Satterthwaite 2009; Creutzig et al. 2015).

We further checked if the sub-linear scaling of emissions with population for cities in Annex 1 countries could be attributed to a possible sub-linear scaling with respect to their total final energy consumption Eq. (A.1). Even in a completely decarbonized world, the question of energy efficiency will persist. Our results show that large cities in Annex 1 countries are not energy efficient (with respect to their population) ($\delta \simeq 1.04$) compared to smaller cities. This result indicates that although the per capita energy consumption in large cities is similar to that of smaller cities, it is the better technologies employed in larger cities that makes their per capita emissions lower than smaller cities.

With respect to cities in Non-Annex 1 countries, our results show that the super-linear scaling of emissions with population is due to two factors: (1) super-linear scaling of GDP with population and (2) super-linear scaling of carbon intensity. However, we found that doubling the GDP in these cities will lead to a less than double increase in energy consumption. This can be attributed to the prevalence of energy poverty in these cities (Satterthwaite 2009). Large cities in Non-Annex 1 countries benefit economically (more GDP) from the urban poor who consume less energy and have limited access to electricity. Therefore, large cities in this region are more energy efficient compared to smaller ones.

2.4 Discussion & Conclusions

To this day, the scaling properties of urban emissions with population size remain inconclusive. However, it is crucial to establish a framework to understand the guiding factors that govern them since urban areas are often identified as the focal spatial units for improving energy efficiency and climate change mitigation (Dodman 2009; Hoornweg et al. 2011a). Urban energy consumption and subsequent emissions is an outcome of urbanites' affluence and their consumption patterns (Satterthwaite 2008). Nevertheless, it is important to investigate whether the infrastructural efficiency of large cities will be manifested as emission efficiency gains. An in-depth investigation about the demographic, economic and technological drivers of urban emissions is necessary to identify the key entry points for mitigation actions at a city scale. By means of an exploratory analysis, we demonstrate that the Urban Kaya Relation can be used to address this issue adequately by attributing the scaling properties of emissions to the scaling of GDP with population (affluence), energy intensity (economic geography) and emission intensity (technology).

The data used in this study has three major constraints. Firstly, the sources for emission data is different from the source of energy consumption and GDP. Therefore, the urban extents and the population size might vary for few cities. Studies have shown that such city definitions will influence the scaling properties (Arcaute, Hatna, Ferguson, Youn, Johansson and Batty 2014; Cottineau, Hatna, Arcaute and Batty 2017). An illustrative example is the city of Chongqing. Secondly, since the data is from multiple sources, the accounting approach varied in most of cities. Inclusion (or exclusion) of emissions embedded in electricity generation will have a significant impact on energy and emissions attributed to building sector. Thirdly, the sectoral emissions and type of fuels used varies from city to another. The energy data from the Urban Energy Assessment (Grubler et al. 2013) study includes the total final energy consumption but excludes traditional biomass for few cities in developing regions. Data on emissions attributed to the industrial sector is inconsistent as it excludes industrial electricity and fuel usage in some cities. In the view of aforementioned data limitations, the broader conclusions drawn in this paper should be treated cautiously since the empirical part is rather intended as a proof of concept.

These data constraints also highlight the data needs. Therefore, we acknowledge the on-going efforts to develop a consistent emission framework by various international organisations[2] and make an appeal that such efforts should disclose data on energy consumption and GDP along with sectoral emissions and population. Application of Urban Kaya Relation on such a dataset will enable researchers to identify locally appropriate mitigation actions.

The urban scaling approach attributes city's extent as a (short-term) spatial equilibrium of the interplay between the density dependent socioeconomic interactions and transportation costs (Bettencourt and Lobo 2016). The universality of the scaling properties of socioeconomic (super-linear) and infrastructural components (sub-linear) in cities can be explained as an outcome of the increased interaction between citizens at a microscopic scale (Schlapfer et al. 2014) and it's combination with the fractal properties of cities (Ribeiro et al. 2017). However, unlike socioeconomic and infrastructure components, urban emissions are a result of various economic activities (e.g. location of industries) which consume resources and energy being often located beyond the urban boundaries but have an implication on emissions from electricity consumption. In such cases, population alone might not be a good predictor for emissions. This could be the explanation for the relatively poor fitting of the emission scaling properties of cities in Non-Annex 1 regions in comparison to cities in Annex 1 regions.

Our exploratory results show that large cities in Annex 1 countries have lower emissions compared to smaller cities, which gives a hint about the usage of more efficient technologies in electricity generation and by use of more emission efficient modes of public transportation. From a climate change mitigation point of view, the key challenge in these cities is to further

[2] http://www.ghgprotocol.org/

decrease their energy and emission intensity while ensuring economic stability. According to our exploratory results larger cities in emerging countries such as China, India, and Brazil typically have more per capita emissions compared to smaller cities. From one point of view, it may be good news that large cities in these regions are not emission efficient since much of the urbanisation in these regions is going to happen in small and medium size cities (UN 2014). Thus, despite being exploratory, our findings corroborate the results of previous studies which showed the significance of affluence on emissions (Martínez-Zarzoso and Maruotti 2011) and the influence of economic geography on the scaling properties of emissions with population (Rybski et al. 2017). Further support comes from a recent study, where a methodology other than urban scaling has been applied and completely different data has been used (Zhou et al. 2017).

Last but not least, we need to mention the role of urban population *density* as an important factor in determining the energy consumption and subsequent emissions (Doherty et al. 2009). On the one hand, it has been shown that urban CO_2 emissions from transport energy per capita decrease with population density (Gudipudi et al. 2016; Kennedy et al. 2009; Creutzig et al. 2015). On the other hand, there is a theoretical connection between urban indicators, population, and area scalings (Rybski et al. 2017; Rybski 2016). Combining density with the Urban Kaya Relation introduces further complexity which we leave to be addressed by future research.

Chapter 3

City Density and CO_2 Efficiency[1]

Abstract

Cities play a vital role in the global climate change mitigation agenda. City population density is one of the key factors that influences urban energy consumption and the subsequent GHG emissions. However, previous research on the relationship between population density and GHG emissions led to contradictory results due to urban/rural definition conundrum and the varying methodologies for estimating GHG emissions. This work addresses these ambiguities by employing the City Clustering Algorithm (CCA) and utilizing the gridded CO_2 emissions data. Our results, derived from the analysis of all inhabited areas in the USA, show a sub-linear relationship between population density and the total emissions (i.e. the sum of on-road and building emissions) on a per capita basis. Accordingly, we find that doubling the population density would entail a reduction in the total CO_2 emissions in buildings and on-road sectors typically by at least 42 %. Moreover, we find that population density exerts a higher influence on on-road emissions than buildings emissions. From an energy consumption point of view, our results suggest that on-going urban sprawl will lead to an increase in on-road energy consumption in cities and therefore stresses the importance of developing adequate local policy measures to limit urban sprawl.

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3.1 Introduction

While rapid urbanization has accelerated innovation and socio-economic growth on one hand, it has generated a multitude of global problems on the other hand ranging from climate change and its impacts on food, energy, water availability, public health and global economy (Bettencourt and West 2010). Consequently, sustainable management of urban areas worldwide is considered as one of the main challenges of the 21st century. It is well-known from various sources that cities consume between 67-76 % of the global energy supply and release 71-76 % of the carbon dioxide emissions (Seto et al. 2014). A major share of which can be attributed to building and transportation sectors, thus to particular structural features of a city. Finding effective integrated land use and transportation planning solutions to decrease fossil fuel consumption and consequently GHG emissions are key challenges to solve the problem of global warming.

However, tackling the above challenges needs a detailed and systematic analysis which is constrained by one major problem that is always prominent: There is no universal definition of what qualifies a given settlement as urban or rural (UN 2014). Environmental assessments become even more problematic when one needs to distinguish between administrative entities and/or suburbs, or to analyze twin cities. Thus, it is also difficult to relate carbon footprint of a city to its physical features and to derive conclusions about how urban structure needs to be designed to become more sustainable. For example, Parshall et al. (2010) highlighted that the methodological challenges in modelling energy consumption and CO_2 emissions at urban scale are extremely problematic, due to lack of a standard definition of what is urban and rural. However, there exists a general consensus that population density in settlements influences the on-road energy consumption and building emissions (Boyko and Cooper 2011; Dodman 2009; Jones and Kammen 2014; Lee and Lee 2014; Newman and Kenworthy 1989). Therefore, amongst others, population density is considered to provide a suitable indicator to measure the relationship between certain urban "functions" (for e.g. housing, traffic, recreational and institutional facilities) and their sustainability. Since urbanization is an inevitable global phenomena; from a local and international policy perspective; this fact stresses the importance of assessing the potential influence of population density in decreasing carbon footprint and improving energy efficiency.

Previous studies focusing on population density and their energy consumption and/or GHG emissions in cities can essentially be broadly categorized into 3 groups: (1) Studies focusing on the relationship between population density and transport related energy consumption (Breheny 1995; Kenworthy and Laube 1999; Mindali et al. 2004; Newman and Kenworthy 1989; Tiwari et al. 2011; Wang et al. 2014) (2) Studies focusing on the relationship between population density and household energy consumption (Ewing and Rong 2008; Larivière and Lafrance 1999; Martilli 2014; Ye et al. 2015) and (3) Cross sectoral studies focusing on population density, household carbon footprints and/or GHG emissions (Brown et al. 2009; Jones and Kammen 2014; Lee and Lee 2014; Myors et al. 2005; Norman et al. 2006; Steemers 2003; VandeWeghe and Kennedy 2008).

The methodologies used in most of the previous studies to find out the relationship between population density and energy consumption or GHG emissions, though internally consistent; vary significantly. Therefore the impact of population density on energy consumption in these studies exhibited conflicting results. For instance, study on household carbon footprints by Jones and Kammen (2014) using the household demand for goods and services concluded that increasing population density will not decrease the household carbon footprint although Brown et al. (2009) found that the top 100 metropolitan areas in the USA have lesser carbon footprints than the average USA carbon footprint considering the estimations of the transport carbon footprint of the metropolitan areas using the Vehicle Miles Travelled (VMT) data and the residential carbon footprint using the national electricity sales data for the metropolitan areas. Using existing urban GHG emission inventories to find out this relationship is also debatable because of the differences in spatial scales (urban extents) and emission estimation i.e. accounting methods, scope of GHG's and emission sources (Dhakal 2010; Fong et al. 2014; Ibrahim et al. 2012; Kennedy et al. 2009; Satterthwaite 2008; Wintergreen and Delaney 2006). A general conclusion about the influence of population density on GHG emissions therefore couldn't be drawn from the existing literature majorly owing to lack of a standard definition for urban areas and a comparable GHG emission protocol specifically for the urban areas until recently (Arikan et al. 2012).

The approach followed in this work systematically overcomes the aforementioned ambiguity in the definition of urban areas (and therefore their extents and population density) by applying a procedure called 'City Clustering Algorithm' (CCA) on gridded land use and population datasets. For further details see Rozenfeld et al. (2008). The CCA considers cities as adjacent populated clusters. The algorithm is an automated and systematic way of identifying adjacent populated clusters based on geographic location of people and combining them into one city cluster. The population densities of the resultant city clusters are comparable since the rationale behind identifying each city cluster is the same. The CCA method together with the availability of gridded sectoral emission data from the Vulcan Project (Gurney et al. 2011) paved road towards more systematic analysis on the influence of urban population density on sectoral emissions. By restricting the analysis to on-road and building (residential and commercial) sectors, the emissions were assigned to the populated settlements which are later aggregated to city clusters identified by the CCA. Consequently, our analysis clearly shows that there exists a fundamental relationship between population density and sectoral emissions on a per capita basis (which will be referred to as CO_2 efficiency from hereon). Our results show that doubling the population density will improve CO_2 efficiency in building and on-road transportation sectors at least by 42 %.

The paper is organized as follows: The data and methods chapter gives an overview about the data sets (land use, population and emission) used in this study, the rationale behind emission attribution to the populated settlements and the application of CCA. The results section shows the statistical significance of the relationship between population density in the city clusters and their CO_2 efficiency. The discussion section compares the results of our study with previous studies. The conclusion section identifies the policy implications of the research findings on cities globally depending on their current level of maturity. Insights on further research in this area are further elaborated in the conclusion section.

3.2 Data and Methods

3.2.1 Data Sources

The population count data used in this study is obtained from the Global rural-urban mapping project (GRUMP) for the year 2000 available at a spatial grid resolution of 1 km ×1 km (CIESIN et al. 2011). Since earlier work by Potere and Schneider (2007) indicated that the spatial extents of urban or non-urban land use varied depending on the methodology used to classify them; we extended our methodology and checked the consistency of the results for two different land use/land cover data sets namely: (1) The GRUMP classification of global land use into urban or non-urban at a spatial grid resolution of 1 km ×1 km (CIESIN et al. 2011) and (2) Global land cover 2000 (GLC) data available at 1 km ×1 km grid spatial resolution (Bartholome et al. 2003).

The emissions data used in this research is obtained from the Vulcan project (Gurney et al. 2011) which provides a consistent sectoral CO_2 emission data for entire USA at a grid resolution of 10 km ×10 km (which will be further referred as Vulcan grid). We restricted our analysis to on-road transportation and buildings (residential and commercial) sectors. However, it has to be noted that the CO_2 emissions from electricity are allocated at geocoded locations i.e. at source instead of allocating them at the point of consumption in the Vulcan grid. The building emissions in the Vulcan grid therefore predominantly include the CO_2 emissions related to combustion of fuels for heating purpose. The on-road mobile emissions are based on county-level data from the National Mobile Inventory Model (NMIM) County Database (NCD) for 2002 which quantifies the vehicle miles travelled in a county by month, specific to vehicle class and road type. The Mobile 6.2 combustion emissions model is used to generate CO_2 emission factors on a per mile basis given inputs such as fleet information, temperature, fuel type, and vehicle speed (Gurney et al. 2011).

3.2.2 Analytical Concept and Data Pre-processing

The data pre-processing done in this research comprised of three major steps. As a first step in data processing, we did a spatial overlay of the gridded population data separately on the GLC and GRUMP land cover datasets. The pre-conditions for the spatial overlay are: (1) the grid cell has to be classified as 'urban' and 'artificial surfaces/associated areas' in the GRUMP and GLC land cover datasets respectively and (2) population count of the grid cell attributed to urban/artificial surfaces land use in GLC and GRUMP land cover datasets is at least 1. As a result of the first step; we attributed population count to urban/artificial land use separately for GLC and GRUMP land cover datasets at 1 km $\times$1 km grid cells.

As a second step, we superimposed the sectoral emissions in the Vulcan grid on the spatial overlay obtained from the previous step. Since the emissions data is available at a different resolution (10 km$\times$10 km) compared to the spatial overlay in first step (i.e. 1 km $\times$1 km); there is a need to harmonize the datasets and bring all the datasets to same resolution. We harmonized the spatial resolution of these two datasets by the following assumption: since the study focusses only on building and on-road emissions i.e. settlements where people reside and commute; the energy consumption and the subsequent CO_2 emissions also originate from these settlements. Therefore, if a populated settlement intersects the Vulcan grid during the spatial overlay; we assumed that all the sectoral emissions in the Vulcan grid are emitted by the intersecting populated settlements. With this assumption we resampled the sectoral emissions in 10 km $\times$10 km Vulcan grid to 1 km$\times$1 km using nearest neighborhood method. The pre-condition for resampling are: (1) the Vulcan grid that attributes the emissions to the populated settlements should have non-zero residential emissions; (2) emissions should be always attributed to those cells which are classified as urban/artificial surfaces land use; (3) emissions attributed to the settlements should be proportional to the area of the settlements. As a result of the second step we have the sectoral emissions attributed to the populated settlements separately for GLC and GRUMP land cover datasets.

Lastly, we applied the CCA to the both land cover datasets separately to identify the unique settlement extents (called as city clusters from hereon), their corresponding population and sectoral emissions. The CCA defines a city as a cluster of connected populated cells with a maximum size using two threshold parameters: (1) A population threshold (p) which defines the minimum population of the grid cell and (2) A distance threshold (l) which defines the cut-off distance between two spatially contiguous cells. A grid cell (i) in the population grid is considered to be occupied if its population is more than the threshold population (i.e. $p_{\mathrm{i}} \geq p$) and if it is within the distance threshold (i.e. $l_{\mathrm{i}} \leq l$) to the next populated cell. In this study, we didn't define any population threshold (p), as we wanted to capture the relationship between population density and sectoral CO_2 emissions of all inhabited areas in the USA. We therefore applied CCA to all grid cells with non-zero population separately to both land cover data sets from 1 to 10 km threshold distance (l). The application of CCA is explained in Figure 3.1 where the blue color cells are exemplified as populated cells and the empty cells as white colored. Starting from an arbitrary populated cell which is converted to red color as shown in Figure 3.1(a), the algorithm starts iterative burning of all the neighboring cells that are within the given threshold distance (l) into one city cluster converting them to red color as shown in Figure 3.1(b) and Figure 3.1(c). The algorithm continues this iteration until all populated cells within the given threshold distance become one city cluster as shown in Figure 3.1(d). For further details on CCA, see Rozenfeld et al. (2008). As the sectoral emissions are always attributed to the populated settlements; the emissions of the city clusters are also aggregated proportionally. As a result of the third step, we obtained a number of city clusters (n) at varying threshold distances (1 to 10 km), their sectoral emissions, extents, population and subsequently their population density separately for GRUMP and GLC land cover datasets (which will be further referred as GRUMP and GLC data in this paper).

Since the criteria used to identify these city clusters is the same for all inhabited areas in the grid; their extents, population and subsequently their population density are also comparable unlike the traditional urban administrative boundaries. We used the population density of city clusters obtained from the CCA and their corresponding sectoral emissions to find out the influence of population density on CO_2 efficiency. Table 3.1 gives an overview about the datasets and methods used in this study.

3.2.3 Emission distribution in the selected datasets

Since the methodologies used to classify urban and non-urban areas vary from the GRUMP to GLC land cover data, the extents of the city clusters and therefore the emissions attributed

Data	**Sources**	**Spatial Resolution**	**Methods**	**Remarks**
Population count	GRUMP population count in USA for the year 2000: http://sedac.ciesin.columbia.edu	30 arc seconds (1 x 1 km)	Spatial overlay to attribute population to GRUMP urban extents and GLC urban and built up cells.	Since urban extents vary from one land use data to another; we tested our methodology and compared the results on two different urban land use/extent data sets.
Sectoral CO_2 Emissions	Project Vulcan for the year 2002*: http://vulcan.project.asu.edu/research.php	300 arc seconds (10 X 10 km) resampled to 1 X 1 km	Emission attribution to the populated settlements using nearest neighborhood method proportionally to their area.	The main assumption for emission attribution is that sectoral emissions originate from the populated areas. The resulting dataset consisted of building** (residential and commercial) and on-road emissions of all populated settlements in GRUMP and GLC urban/built up area cells.
Urban extents/-land use	GRUMP Urban Extents: http://sedac.ciesin.columbia.edu GLC: http://bioval.jrc.ec.europa.eu/products/glc2000/products.php	GRUMP: 30 arc seconds (1 x 1 km) GLC: 32 arc seconds (1 x 1 km)	Application of City Clustering Algorithm (CCA) to aggregate populated urban/built-up settlements into city clusters. The sectoral emissions are aggregated proportionally to city clusters.	This application ensured a consistent definition for identifying city extents. The resultant dataset consisted of city clusters from 1 to 10 km threshold distance; their extents, population density and sectoral emissions.

Table 3.1: Datasets and methods used in this study

* Only CO_2 emissions (not all GHG's) are reported in the project.

** Building emissions do not include emissions from electricity consumption which are reported at point of production.

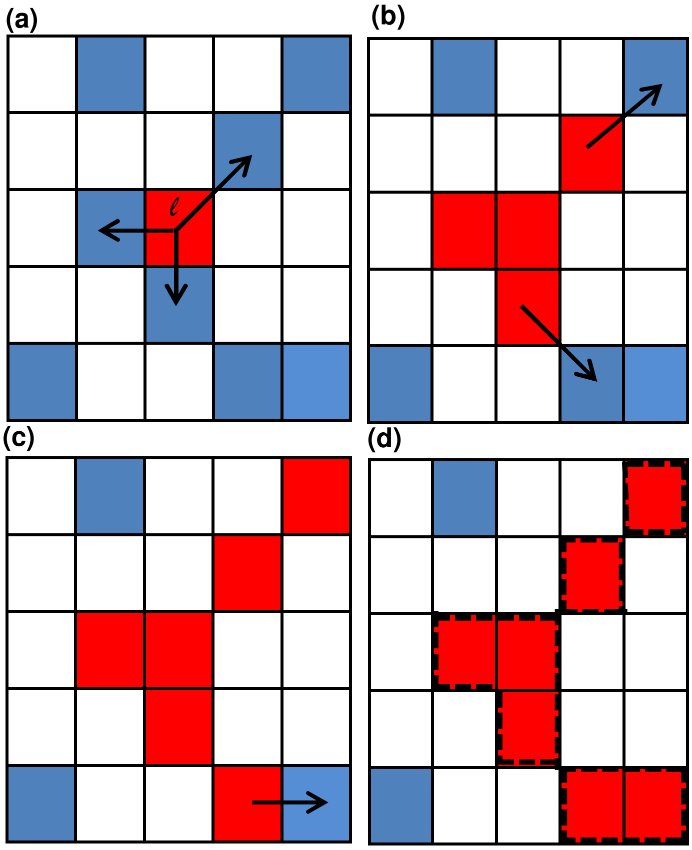

Figure 3.1: Application of CCA: (a) Burning an arbitrary populated cell from blue to red; (b) Identifying the nearest populated cells within the given threshold distance (l) and converting them into red color. (c) Iterative burning of all populated cells until all cells within the threshold distance (l) are burned. (d) Resulting city cluster at a given threshold distance (l).

to these areas also varied. The spatial extent of urban clusters plays a crucial role in defining the population density of the city cluster and therefore its relationship to the emissions per capita. Figure 3.2 illustrates how the on-road emissions are attributed to selected settlements which are adjacent to each other (populated settlements in New York-Philadelphia-Washington on the left and Chicago-Milwaukee on the right) in GLC (top) and GRUMP (bottom) land cover data prior to the application of CCA. It can be observed in Figure 3.2 that New York and Philadelphia are identified as separate extents in the GLC data whereas the GRUMP data identifies both of them as one urban extent even before the application of CCA. The same holds for populated settlements of Chicago and Milwaukee. After applying CCA in the GRUMP data at 1km threshold distance New York, Philadelphia and Washington are all combined into one city cluster. With respect to GLC data, such an inclusion of New York and Philadelphia in one cluster occurred only at 10 km threshold distance.

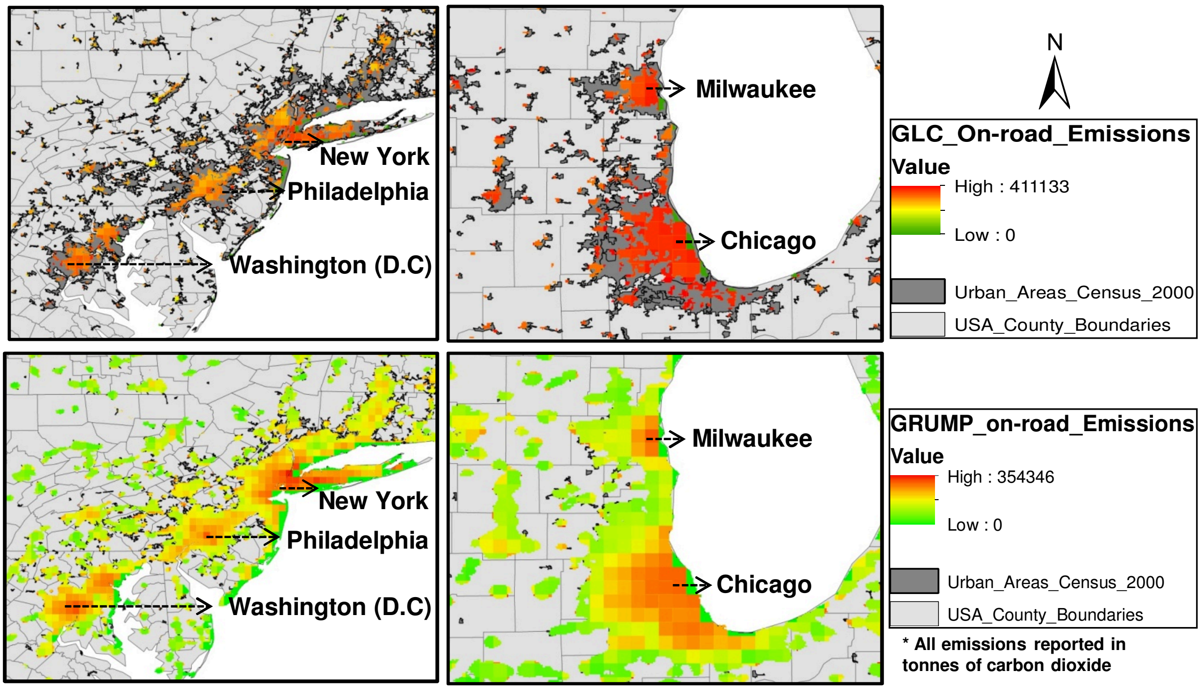

Figure 3.2: An illustration of spatial attribution of on-road emissions to land use classified as urban/artificial surfaces in GLC (top) and GRUMP (bottom) land cover data for selected settlements which are adjacent to each other prior to the application of CCA. The figure depicts how GRUMP urban extents mostly agree with the census defined urban areas while the urban extents in GLC land cover data are more much lesser. All emissions are reported in tonnes of CO_2.

At a threshold distance of 1 km i.e. the least logical threshold distance that can be applied in CCA, the total area of city clusters in the GRUMP data is approximately 9.6 times to that of the total area of urban clusters in the GLC data. At the same threshold distance; the sum of residential, commercial and on-road emissions under the GRUMP data are 1.4 times to that of GLC dataset. Figure 3.3 summarizes the key differences between the key parameters in GRUMP and GLC data at 1 km threshold distance. Since the extents of city clusters under GRUMP data are bigger when compared to that of GLC data; the total area of the city clusters Figure 3.3a, the total population of city clusters Figure 3.3b and the sectoral emissions attributed to these city clusters Figure 3.3c are also more in GRUMP data. As the threshold distance increased, the number of city clusters (n) decreased twice in GRUMP data when compared to the GLC data (n = 4,585, 3,285, 2,786 for GLC data and n = 5,182, 2,156, 1,538 for GRUMP data at 1, 5 and 10 km threshold distance respectively). Though the total emissions remained the same as the threshold distance increased (since the emissions are always attributed to the populated cells); the minimum, mean and maximum emissions in each sector varied significantly for both the data sets. For instance; the city cluster emitting maximum total on-road emissions for

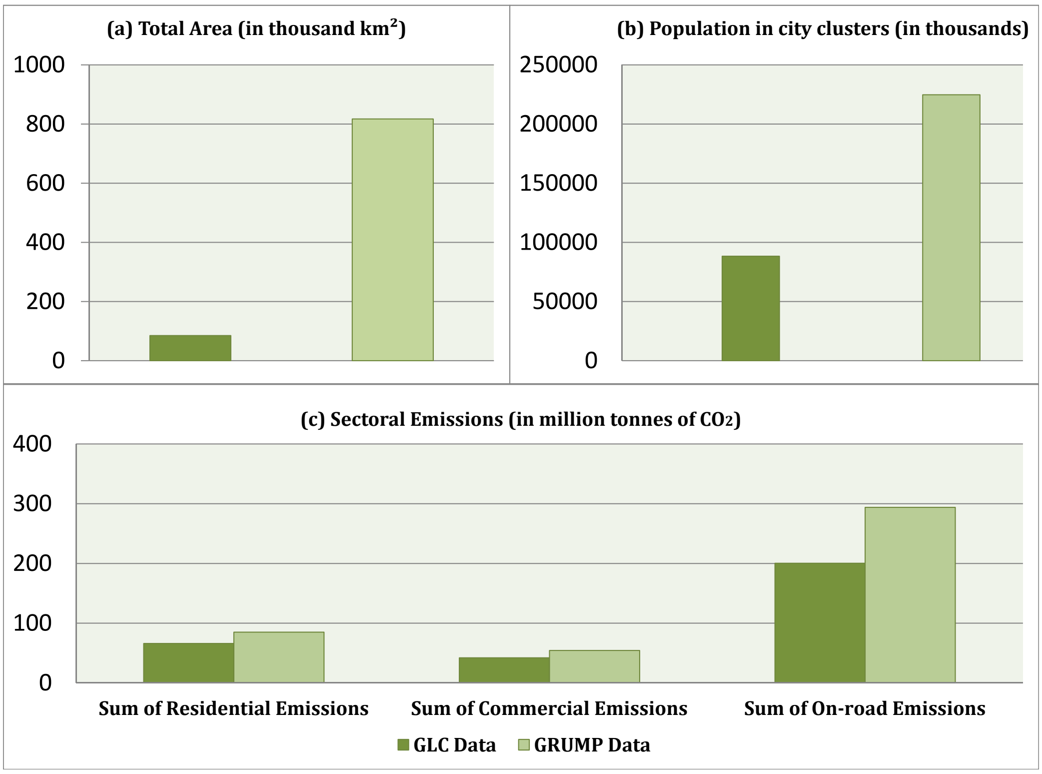

Figure 3.3: Comparison of key parameters after application of CCA at 1 km threshold distance in GLC and GRUMP data: (a) Total area (in thousand km^2) of city clusters. (b) Total population (in thousands) of city clusters. (c) Sum of residential, commercial and on-road emissions (in million tonnes of CO_2) of city clusters.

GRUMP dataset at 10 km threshold distance is 2.1 times when compared to 1 km threshold distance, indicating the expected increase in on-road emissions as city clusters increase in size. With respect to GLC dataset, this number is bit lower (1.9 times). The population density also varied significantly in the GLC and GRUMP data sets. The city cluster with maximum mean population density in GLC dataset at 1 km threshold distance (7,603 inhabitants per km^2) is almost double to that of GRUMP dataset (3,860 inhabitants per km^2).

3.3 Results

3.3.1 Sensitivity of the results to the datasets

We found out that irrespective of the land cover data set used; the total emissions (sum of residential, commercial and on-road emissions) always decreased with increase in cluster population density on a per capita basis. The results however altered in magnitude. We fitted a linear regression model between the total emissions per capita and the population density of all urban clusters for both datasets to find out the statistical relationship between the population density of the city clusters and their CO_2 efficiency using the following model:

$$\ln(CO_2/Population) = A + \beta \cdot \ln(Population/Area) \tag{3.1}$$

Where CO_2 refers to the sum of residential, commercial and on-road emissions; A is a constant, β is the slope of the linear relationship in log-log scale (in natural logarithm); $Population$ is the sum of population in each cell that form the city cluster and $Area$ is the extent of each city cluster.

Table 3.2 summarizes the results of the linear fitting at 1, 5 and 10 km cluster distance. Though there is no drastic change in the correlation coefficient (R^2) with increase in threshold distance, the slope (β) became steeper for both GLC and GRUMP datasets. However, the slope (β) varied from one dataset to the other. Therefore it can be inferred that as the size of the cluster increases, the rate at which per capita emissions decrease is sensitive to the land use dataset used. Considering the least slope (β) from the two land use datasets used in our analysis (GLC dataset at 1km cluster distance where β= -0.78) as shown in Table 3.2; our results showed that doubling the population density will increase the CO_2 efficiency at least by 42 %. At higher threshold distances in the GRUMP data we identified that a majority of cells merging at a certain density range (4-6 in natural logarithmic scale). This phenomenon can be attributed to the proximity of the city clusters in the north and west coast considering the methodology used to prepare the GRUMP urban extents (i.e. continuous night lights). In order not to over or under estimate urban extents, we show our results only for the 5 km threshold distance. Figure 3.4 shows the relationship between cluster density and total CO_2 efficiency for GLC and GRUMP data respectively at 5 km cluster distance.

Individual linear regression to find out the influence of population density individually on sectoral CO_2 efficiency (residential, commercial and on-road emissions per capita) revealed that

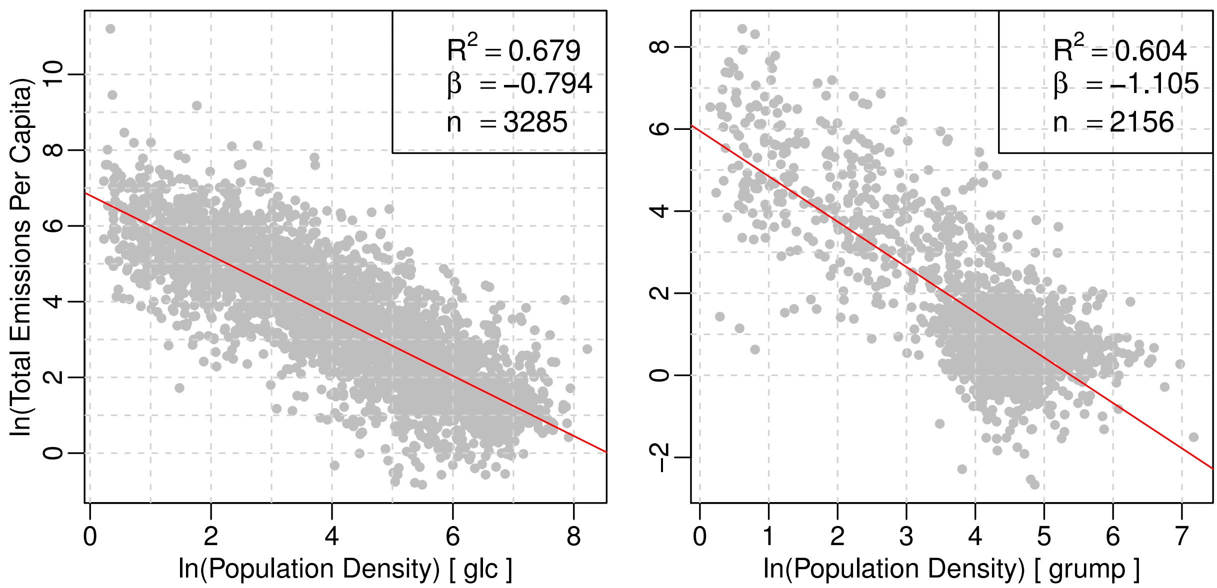

Figure 3.4: Relationship between population density and CO_2 efficiency at 5 km threshold distance for GLC (left) and GRUMP (right) data on a natural logarithmic scale.

	1 km			5 km			10 km		
	A	β	R^2	A	β	R^2	A	β	R^2
GLC	6.89	-0.78	0.69	6.8	-0.79	0.67	6.8	-0.82	0.71
GRUMP	5.17	-0.9	0.66	5.95	-1.1	0.6	5.95	-1.13	0.61

Table 3.2: Summary of the linear regression model for GLC and GRUMP datasets at 1, 5 and 10 km threshold distance.

increasing density majorly improves the CO_2 efficiency of on-road emissions compared to building (residential and commercial) sector. Our analysis (at 5 km threshold distance) showed that doubling the population density will improve the CO_2 efficiency (considering the least β values) at least by 43 %, 41 % and 36 % for on-road, residential and commercial emissions respectively. Table 3.3 shows how cluster population density influences sectoral emissions per capita in both the data sets at 5 km cluster distance.

	Residential		Commerical		On-road	
	R^2	β	R^2	β	R^2	β
GLC	0.5	-0.74	0.43	-0.63	0.68	-0.81
GRUMP	0.36	-0.93	0.39	-0.94	0.6	-1.14

Table 3.3: Results of the per capita sectoral emissions from the linear regression model for GLC and GRUMP datasets at 5 km threshold distance.

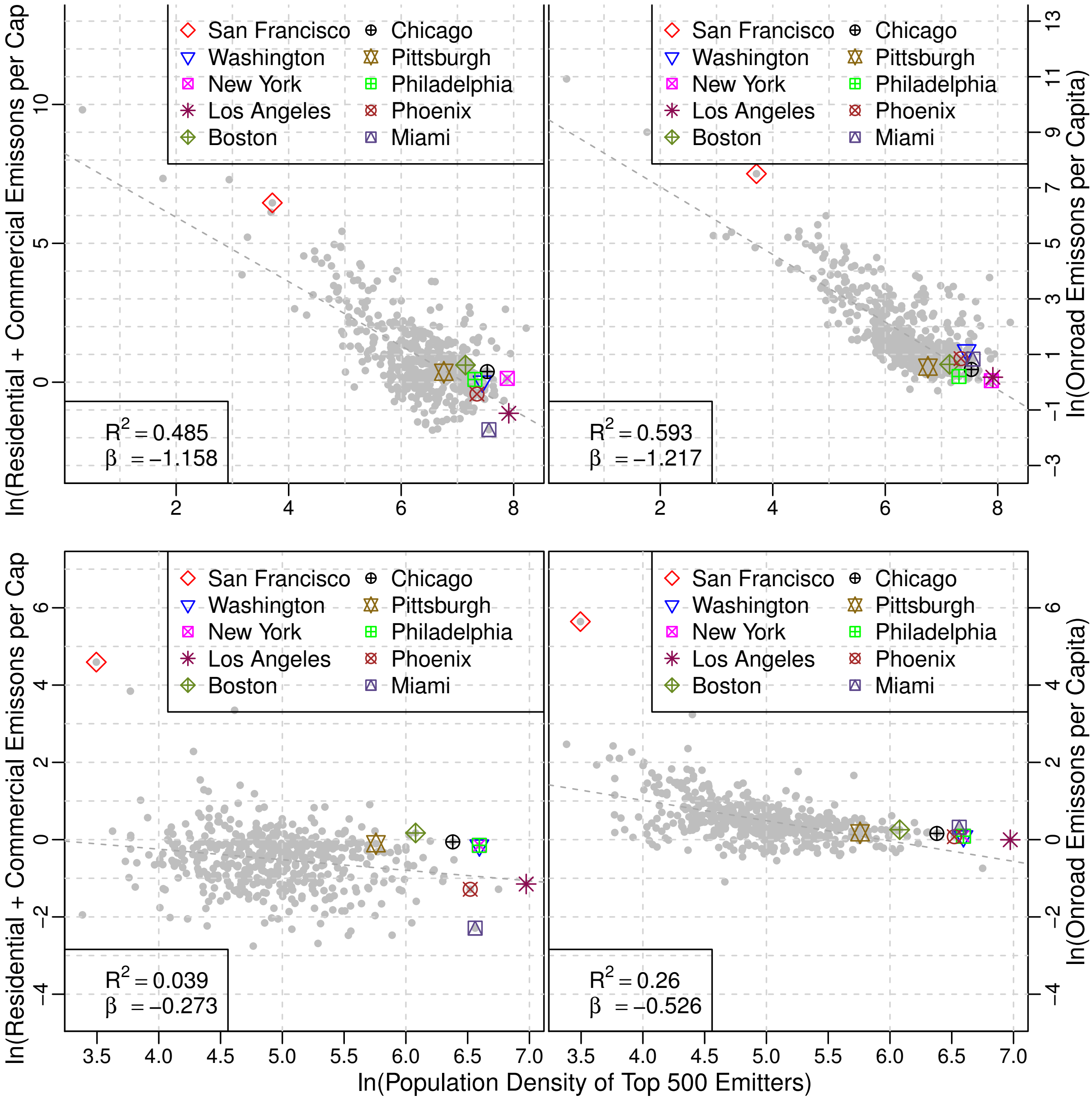

Figure 3.5: Relationship between cluster population density and sum of residential and commercial emissions per capita (left) and on on-road emissions per capita (right) at 5 km threshold distance for GLC (top) and GRUMP (bottom) datasets on natural logarithmic scale.

3.3.2 Influence of Population density on CO_2 efficiency in highest CO_2 emitting city clusters

To further investigate the major emitters of CO_2 and the influence of population density on their sectoral CO_2 efficiency; we made subsets of the top 500 emitting urban clusters for both

GLC and GRUMP datasets. We used the central latitude and longitude coordinates of the metropolitan statistical areas (MSA's) as defined by the Office of Management and Budget in the USA to identify the city clusters in selected metropolitan areas. Figure 3.5 shows the relationship between cluster population density, buildings (sum of residential and commercial emissions) and on-road emissions per capita for the top 500 emitting urban clusters for the GLC and GRUMP data at 5 km threshold distance.

It can be observed in the Figure 3.5 that all cities (except San Francisco) are identified in the lower-right corner which represents that most of the highly populated cities in the USA are also associated with higher population densities and relatively lower emissions on a per capita basis. From Figure 3.5 it should not be inferred that San Francisco urban cluster has lower population density and higher emissions per capita. The reason for high emissions at lower cluster distance in San Francisco occurred because of the resampling of emissions and lower population count in the city clusters as result of lack of continuous urban land (in this case islands). At higher threshold distances, San Francisco also has higher density and lower emissions per capita. Since the electricity emissions in the Vulcan emission data are geo referenced to the production sites, cities in the south such as Los Angeles, Phoenix and Miami have relatively less building emissions (due to lower demand for heating) when compared to Chicago or New York. As mentioned earlier, population density has much higher influence on the on-road emissions than building emissions per capita for both the data sets used. The building emissions per capita in the top 500 emitting clusters showed significant relationship to the population density in the GLC data (β = -1.15) when compared to GRUMP data (β = -0.27). This again could be attributed to the methodology used to identify urban extents in GLC and GRUMP landcover datasets.

Table 3.4 shows the top 5 urban clusters ranked based on their total emissions with their corresponding sectoral emissions. Though New York urban cluster is the top emitting urban cluster in both datasets, the per capita emissions of New York urban cluster is lower when compared to other urban clusters in the colder regions (lower per capita emissions in Los Angeles urban cluster is because the relatively lower building emissions per capita). New York urban cluster emits the highest on-road emissions but again on a per capita basis, is found out to be the lowest (except for Los Angeles – Riverside cluster in GRUMP dataset). The phenomena of decreasing on-road emissions with increase in population density can be observed in the table however no such trend can be seen with respect to building emissions.

City Cluster	Population density of the cluster	Sum of sectoral emissions	Total CO_2 emissions per capita*	Buildings sector CO_2 emissions per capita	On-road CO_2 emissions per capita
GRUMP dataset					
New York	2661	22.92	2.2	1.14	1.06
Los Angeles	2732	13.57	1.52	0.33	1.19
Chicago	1864	13.06	3.04	1.46	1.58
Washington (DC)	1516	9.7	2.81	1.01	1.8
Detroit	1259	8.1	2.9	1.16	1.74
GRUMP dataset					
New York,-Philadelphia-Washington	731	65.59	1.95	0.86	1.09
Los Angeles-Riverside	1068	22.79	1.31	0.31	1
Chicago-Milwaukee	589	20.77	2.11	0.94	1.17
Boston-Worcester	436	14.58	2.47	1.18	1.29
Detroit-Ann Arbor	491	13.8	2.51	0.96	1.55

Table 3.4: Ranking of the top 5 CO_2 emitting city clusters in GLC and GRUMP datasets at 5 km threshold distance.

* All emissions are in tonnes of CO_2 for the year 2002. The population density is expressed in inhabitants/km^2.

* Sum of the total emissions (in tonnes) from the residential, commercial and on-road sectors of the city cluster divided by the population of the cluster.

3.4 Discussion

This paper addresses the earlier challenges in finding out the relationship between population density and GHG emissions using the CCA approach of identifying the urban extents and gridded CO_2 emission data. Through our analysis we found out that population density is one of the vital factors that influence CO_2 efficiency in cities. We showed how the emissions per capita decrease as a general trend with increase in population density. However, as showed in the previous section, the results are sensitive to the input land cover data and the threshold distance used in the CCA. The selection of the land cover data and threshold distance should be therefore done cautiously while using the CCA approach in finding this relationship.

Urban areas are often blamed as the main reasons for global anthropogenic emissions (Hoornweg et al. 2011b) and are therefore identified as the key players in the global mitigation agenda (Dhakal 2010). While it is imperative that anthropogenic emissions concentrate at areas of human activity; the natural advantage cities offer is their relatively lower emissions on a per capita basis. Per capita emissions enable intercity comparison and benchmarking of policies and infrastructure services which can be adapted to other cities. Rapid urbanization in Asia and Africa augmented several national/state policies aiming at improving urban infrastructure in existing cities and building new cities. The findings of this study indicate that policies aiming at urban brown field regeneration (for existing cities) and compact urban development (for young cities) will lead to a significant decrease in their per capita carbon footprints. For the USA, Rybski et al. (2017) found linear or slightly sublinear correlations between population and emissions per capita. While lower emissions per capita for cities in developed regions can be attributed to larger efficiency of infrastructure as Bettencourt et al. (2007) also suggested; affluence, industrial activity and lack of basic infrastructure can be the main reason why cities in developing regions show higher emissions on a per capita basis.

Although this study is confined to inhabited settlements in the USA, the findings in the study are not unique to the cities in USA itself as they broadly reflect the general consensus in urban policy discourse globally (OECD 2012; Seto et al. 2014). However, the slope (β) of the log linear relationship between the emission efficiency and population density depends significantly on the urban form of the cities and their current building and on-road transportation infrastructure. The slope (β) might be pronounced more in case of cities in countries which exhibit more variance in population density profiles such as USA when compared to cities in countries which exhibit relatively less variance in population density profiles like those in Europe and Asia. Recent studies in European and Asian cities with relatively less variance in population density profiles found out that urban morphology, local climate, household size and personal wealth influence GHG emissions more than population density (Baur et al. 2014; Makido et al. 2012; Reckien et al. 2007). Therefore, it shouldn't be inferred that increasing population density will inherently decrease the building and on-road emissions especially for cities in developing countries where densities are already high. Even dense settlements with poor building insulation, lack of access to public transportation facilities and on-road infrastructure might lead to further increase in GHG emissions.

Oliveira et al. (2014) used the Vulcan emissions data, the GRUMP population data and the CCA to identify the relationship between city clusters population size and their total emissions. The authors argue that the population density is found to be constant after application of CCA and the study ultimately concluded that large cities emit more CO_2 when compared to smaller cities. We found out that population density was constant in their study since their study only considered urban cells (at 1 km^2 resolution) with more than 1000 inhabitants which excludes the low dense, automobile dependent, sprawled suburbs in the USA which are the main sources for on-road emissions (Gately et al. 2015; Jones and Kammen 2014). We found out that density is not constant if we apply CCA to all populated cells. Since the CCA identifies all populated cells within a given threshold distance as one city cluster, the resultant population density of the city cluster is only a weak measure of population density. Therefore the population density of Los Angeles cluster (2,732 persons/km^2) for example is more than the population density of the New York cluster (2,661 persons/km^2) since the extent of New York city cluster also includes the city cluster of Philadelphia.

Since, the electricity emissions in the Vulcan inventory are allocated at their point of production, one should be cautious in inferring from our analysis that cities like Los Angeles and Miami have lesser emissions per capita when compared to cities like New York and Chicago. As Zhou and Gurney (2011) explained, the per capita residential and commercial emission showed positive correlation with the heating degree days but not with the cooling degree days since the energy consumption for space cooling comes from electricity and the emissions are reported at source in the Vulcan grid. This is the main reason why we couldn't find any strong relationship between population density and CO_2 efficiency for the buildings sector for larger city clusters in the GRUMP dataset. A study by Akbari et al. (2001) on urban heat island effect in American cities showed that with each degree increase in temperature in cities lead to 2-4 % increase in electricity demand. Since the emission factor of coal driven electricity power plants are much higher than that of natural gas, it is expected that the overall carbon footprint of cities with higher cooling degree days will also be higher.

3.5 Conclusion and Policy Implication

In this era of rapid urbanization, resource consumption and GHG emissions associated with it; there exists a broader debate in contemporary research if large cities are efficient compared to smaller ones. However, urbanization as an inevitable phenomena, coupled with cumulative actions at local/city scale to curb GHG emissions play a significant role in global mitigation agenda. The findings of this research inherently imply that planning policies aiming at reducing urban energy consumption should contemplate on increasing population density coupled with stringent energy efficient building renovation/regulation codes, improving accessibility to public transportation and encouraging mixed land use. A recent study by Creutzig et al. (2015) have also highlighted the significant role played by urban form in mitigating energy consumption in cities where infrastructure is still nascent. Nevertheless, a practical repercussion while implementing such smart growth policies is the immediate increase in the local land prices. Urban intensification and improved access to public transportation triggers the highly speculative local land prices. This abrupt increase in local land prices displaces lower income families who live and work in the city to settle either in the suburbs or to migrate to the neighboring satellite towns; a phenomenon typically called "gentrification" in urban planning. This phenomenon is manifested more in developing and under developed countries with crippled local governance and lack of stringent enforcement strategies. Consequently, the objective of curbing on-road transportation emissions within the city is forfeited by the induced transportation emissions by relentless commute in and out of the city.

The findings of this study suggest that one can no longer view a city in isolation with clearly defined fictitious boundaries but rather as a dynamic cluster of entities constantly evolving in space and time. Therefore urban policies aiming at curbing the energy resources consumed by these clusters should not only aim at smart growth policies within the city but also at a broader metropolitan/regional level including the satellite towns which are well beyond the current city boundaries. Nevertheless, the ultimate objective of sustainable urban management could only be accomplished through stringent enforcement strategies and effective management of urban land use. Therefore there is a dire need for future research in this area to identify local urban policies that have addressed the issue of gentrification while implementing smart growth policies and whether they can be easily adapted to other cities.

Although, from a theoretical stance there is no vertical limit of building construction once all the safety measures are taken into consideration; increasing population density in urban areas is associated with two additional quandaries namely: the embedded emissions from buildings triggered by the urban heat island effect and the population density threshold beyond which the emissions from vertical transportation surpasses the emissions from lateral transportation. As the electricity emissions in the Vulcan grid are reported at source; this study couldn't find out the influence of urban heat island effect on building energy consumption in dense urban settlements. A more sophisticated emission inventory like that of the Hestia Project (Gurney et al. 2012) which calculates GHG emissions by fuel usage at building and street level might reveal much detail interactions between population density and sectoral GHG emissions.

Chapter 4

Benchmarking Urban Eco-Efficiency and Urbanites' Perceptions[1]

Abstract

Urbanization as an inexorable global trend stresses the need to identify cities which are eco-efficient. These cities enable socioeconomic development with lower environmental burden, both being multidimensional concepts. Based on this, we benchmark 88 European cities using (i) an advanced version of regression residual ranking and (ii) data envelopment analysis. Our results show that Stockholm, Munich and Oslo perform well irrespective of the benchmarking method. Furthermore, our results indicate that large cities are eco-efficient given the socioeconomic benefits they offer compared to smaller cities. We further analyse correlations between a subjective public perception ranking and our objective eco-efficiency rankings for a subset of 45 cities. This exercise revealed three insights: (1) public perception about quality of life in a city is not merely confined to the socioeconomic well-being but rather to its combination with a lower environmental burden; (2) public perception correlates well with both formal ranking outcomes, corroborating the choice of variables; and (3) the advanced regression residual method appears to be more adequate to fit the urbanites' perception ranking (correlation coefficient about 0.6). This can be interpreted as an indication that urbanites' perception is reflected more by the typical city performance and seldom with exceptionally performing cities (in this case, DEA would have better correlation coefficient). This study highlights that the socioeconomic growth

[1]This chapter is submitted as a research article to the Cities journal as Gudipudi,R. ;Lüdeke,M.K.B; Rybski,D.; Kropp,J.P. (2017): Benchmarking Urban Eco-Efficiency and Urbanites' Perceptions, Cities,[Submitted]

in cities should not be environmentally detrimental as this might contribute to poor perception about quality of urban life.

4.1 Introduction

Cities, like organisms, are the outcome of numerous bottom up evolutionary processes (Batty 2012). Thriving on natural resources, cities release pollution and waste as by-products. Harbouring more than 50 % of the global population, contemporary cities generate 80 % of the GDP while consuming approximately 75 % of energy supply and releasing bulk of environmental pollution (UN 2014; Seto et al. 2014). Projected to be crucibles for humanity by the end of this century, contemporary cities are acknowledged to play a pivotal role in global sustainability and climate change mitigation (Batty 2011; Creutzig et al. 2015).

Addressing issues concerning global sustainability with cities as foci relies heavily on the way they transform their energy and material flows at a local scale (Kennedy et al. 2015). Studies on urban metabolism address such issues concerning long-term sustainability by focusing on resource and energy flows in human settlements. The aim of sustainability according to previous studies on urban metabolism is to enhance socio-economic processes in cities while reducing the resource inputs and environmental pollution (Kennedy et al. 2011; Newman 1999). Parallels can be drawn between this definition and the concept of eco-efficiency in cities as defined by the World Business Council for Sustainable Development (UNESCAP 2011). Eco-efficiency couples economic and ecological performance with an aim to improve socio-economic value for urbanites' whilst reducing environmental burden and waste production.

The main objectives of this paper are twofold. The first objective is to rank the eco-efficiency of 88 European cities (which are amongst the 100 most populated European cities) based on their socioeconomic and environmental burden/resource consumption indicators. The second objective is to investigate the relation between objective eco-efficiency rankings and subjective ranking of urbanites' perception about quality of life for a subset of 45 cities. Our analysis is innovative in three ways. Firstly, we use comparable data for a relatively large set of European cities. Secondly, we attempt the validation of objective eco-efficiency rankings using subjective perceptions of quality of life. Thirdly, we employ two non-parametric benchmarking methods to show which cities are eco-efficient, which involves extending the well-established regression residual ranking procedure to more than one socioeconomic indicator using a non-parametric rank aggregation algorithm. To the authors' knowledge, such an attempt is unprecedented considering the indicator space and transparency of the eco-efficiency ranking procedures. The following subsections give an overview about the theoretical background of the two aforementioned objectives, literature review and the approach adopted in this paper.

4.2 Urban metabolism and factors influencing eco-efficiency in cities

Being a fundamental concept in developing sustainable cities, urban metabolism practically involves large scale quantification of energy and resource flows in cities (Kennedy et al. 2011). The seminal work of Wolman (1965) on city metabolism lead to copious research in this field. Kennedy et al. (2011) highlighted how this study resulted in two non-conflicting schools of urban metabolism. One school addresses urban metabolism in terms of energy equivalents from a systems ecology perspective. The other describes urban metabolism in terms of life cycle assessments of material flow analysis from an industrial ecology perspective. Both these schools on urban metabolism involve city scale quantification of inputs and outputs of materials, natural resources and energy balances.

Newman coupled the environmental and material resource flows in cities with the socioeconomic aspects that determine livability in his extended metabolism model see Newman (1999) (Figure 1). Similarly, Kennedy et al. (2007) stressed that urban metabolism is the summation of all the technical and socioeconomic processes that result in the growth and elimination of waste. Therefore, the goal of city sustainability is to reduce undesirable environmental burden and waste production while improving socio-economic processes. Relating the desirable outcomes with undesirable by-products, eco-efficiency of a city determines the efficiency of the urban metabolism.

Urban metabolism and the subsequent eco-efficiency is influenced by a number of factors such as urban form and structure, quality of physical infrastructure, local climate, social, cultural and transportation priorities of urbanites and political economy (Gandy 2004; Holmes and Pincetl 2012; Kennedy et al. 2007; Newman 1999; Weisz and Steinberger 2010). It is often challenging to have a consistent city level data covering all these aspects and limited studies on urban metabolism to a few case studies so far (Kennedy et al. 2007). However, benchmarking the eco-efficiency for a large set of cities where comparable data is available gives insights about the best performing cities and the factors contributing to such a performance. Having its roots in operational research, benchmarking is defined as a process characterized by the systematic search for efficient procedures and best practices for complicated problems (Dattakumar and Jagadeesh 2003; Elmuti and Kathawala 1997; Moriarty 2011).

The objectives behind previous applications of the benchmarking concept to cities varied significantly from identifying best practices with respect to: (a) urban competitiveness (Arribas-Bel et al. 2013; Caragliu and Del Bo 2015; Charnes et al. 1989; Du et al. 2014; Jiang and Shen 2013; Kresl and Singh 1999; Sáez and Periáñez 2015), (b) urban infrastructure (Fancello et al. 2014; Hilmola 2011; Lannier and Porcher 2014; Matas 1998; Novaes 2001; Pina and Torres 2001) and (c) urban energy consumption, sustainability and GHG emissions (Ahmad et al. 2015; Dhakal 2009; Hillman and Ramaswami 2010; Jiang and Shen 2010; Keirstead 2013; Munksgaard et al. 2005; Sovacool and Brown 2010; Yu and Wen 2010).

Obviously, the city rankings from the aforementioned studies depend on two aspects: (1) the benchmarking method and (2) the choice of indicators. In this paper, we address the former aspect by choosing two non-parametric ranking algorithms for our eco-efficiency rankings. This enables us to search for robust properties of city rankings which are independent to subjective weightage of indicators. We address the aspect of choice of indicators in this study by analysing correlations between objective eco-efficiency rankings and a subjective perception ranking about urban quality of life for a subset of 45 cities.

4.3 Quality of life in cities: Subjective versus Objective rankings

Cities bring people together, at the same location and time, to fulfil their functional/recreational needs, while city governments effect a range of activities to assist in the fulfilment of these needs (Grubler et al. 2013). In this regard, perceptions of quality of life, environment and ambient socioeconomic conditions reflect, in part, urbanites' views on the outcomes of city governance and performance.

Most quality of life city ranking studies focus solely on measurements of objective conditions (Okulicz-Kozaryn 2013), while previous analysis of links between objective measurement based quality of life rankings and subjective perception rankings has proved inconclusive (Kelly and Swindell 2002). Schneider (1975) argues that objective social indicators of quality of life in cities fail to capture urbanites' subjective perceptions, and the work of Cummins (2000) and McCrea et al. (2006) is consistent with this view. However, more recent work by Oswald and Wu (2010) finds that there does exist a correlation between objective and subjective rankings. Further, studies in the behavioral sciences literature generally conclude that quality of urban life is best represented by a combination of subjective and objective components (Marans 2015; McCrea et al. 2006).

In analyzing correlations between subjective perception ranking and objective eco-efficiency rankings in this paper, our purpose is twofold. Firstly, we use subjective perception of quality of life to validate the choice of objective indicators used in this study. We interpret good correlation as a sign that reasonable indicator combinations have been chosen. Secondly, we use subjective perception to determine which ranking method best captures urbanites' perception about a city's performance. It is expected that such an analysis might enable local decision makers in identifying the critical factors determining urbanites' perceptions about quality of life.

4.4 Data and Methods

4.4.1 Data

A major pre-requisite for city benchmarking exercise is a consistent definition of cities. The EUROSTAT's Urban Audit data base[2] available as a part of the new OECD-EC definition of cities (Dijkstra and Poelman 2012) enabled us to address this pre-requisite. Within this database, we identified three undesirable environmental burden/resource consumption and two desirable socio-economic indicators for the 88 most populated European cities for the year 2011. The indicator selection in this study is based on those suggested by Newman (1999) in his "extended metabolism model". We started the city selection by looking at the 100 most populated European cities and identified 88 cities where data on all these five indicators are available[3]. In instances where a certain indicator for the year 2011 is not available, the value for the 2010 (or 2012) is considered.

The environmental burden/resource consumption parameters that are included in this study are: (a) annual average NO_2 concentration (in μg/m^3) as an indicator for air quality, (b) annual solid waste generated (residential and commercial) per capita (in kilograms) as an indicator for resource consumption and (c) annual use of water per capita (in m^3) as an indicator for environmental burden. The socio-economic indicators that are used in this study include: (a) employment ratio (in percentage) and (b) GDP per capita expressed in purchasing power standard (PPS) which will be further referred to as GDP as indicators for socioeconomic well-being. Within these 88 cities, we identified a subset of 45 cities for which urbanites' perception about quality of life is available. The indicator "I am satisfied to live in this city: Completely Agree" within the perception survey on quality of life for European cities for the year 2013 is used to analyze correlations between the urbanites' perception ranking and the eco-efficiency rankings.

[2]Source: http://ec.europa.eu/eurostat/web/cities/overview

[3]Most cities in the UK and Ireland are not included because of lack of data on water consumption

Indicator	**Category**	**Average**	**Minimum**	**Maximum**
NO_2 Concentration (in $\mu g/m^3$)	Environmental burden/resource consumption	26.88	10.18 (Stockholm)	51.36 (Milan)
Waste generation (in kilograms per capita)	Environmental burden/resource consumption	467.2	239.38 (Sofia)	848.57 (Copenhagen)
Water consumption per capita (m^3)	Environmental burden/resource consumption	75.52	35.53 (Szczecin)	155.69 (Oslo)
Employment Ratio	Socio-economic	87.23	68.6 (Malaga)	97 (Oslo)
GDP per capita (in purchasing power standard)	Socio-economic	30,523	9,393 (Plovdiv)	51,382 (Munich)
"I am satisfied to live in this city: Completely Agree" for 45 cities	Urbanites' Perception in percentage points	45.33	20 (Palermo)	73 (Zurich)

Table 4.1: Descriptive statistics of the indicators used in this study for the year 2011.

All the aforementioned indicators except the indicator GDP are obtained from the data available under the category 'Cities/Local Administrative Units' spatial units in the urban audit database. The data on the GDP for these 88 cities is obtained from the spatial unit 'functional urban area' (as defined in the OECD-EU city definition) in the Urban Audit database[4]. The GDP reported here includes the income generated in the city together with its commuting zones. Since each city attracts commuters from neighboring towns who contribute to its GDP, this indicator provides a fair measure to depict GDP at city scale. Urban Audit data for European cities and a detailed description of the indicators used, their respective methodology can be found in the EUROSTAT urban audit website and methodological handbook (Eurostat 2014). To our knowledge this is the best available, sufficiently large and consistent dataset which allows for an indication of the dimensions covering eco-efficiency of European cities. Table 4.1 shows the descriptive statistics of the indicators used in this study.

[4]Source: http://ec.europa.eu/eurostat/web/metropolitan-regions/overview

4.4.2 Methods

The methods currently used for city benchmarking in the state-of-the-art research can be broadly divided into four categories:

(a) Per capita ranking measures in one dimensional indicator space (Dhakal 2009; Sovacool and Brown 2010)

(b) Ranking based on normalized and/or weighted measures in multi-dimensional indicator spaces (Jiang and Shen 2013; Singhal et al. 2013)

(c) Ranking based on deviations in ordinary least squares regression analysis (will be referred to as OLS hereafter) in one dimensional outcome space and multi-dimensional spaces of independent variables (Bettencourt and West 2010; Castillo et al. 2005; Glaeser and Kahn 2010; Larivière and Lafrance 1999; Matas 1998; Reckien et al. 2007) and

(d) Ranking based on Data Envelopment Analysis (will be referred to as DEA hereafter) in multi-dimensional input and outcome indicator spaces. (Charnes et al. 1989; Munksgaard et al. 2005; Sueyoshi 1992; Raab and Lichty 2002)

Keirstead (2013) did a detailed review of all the existing city benchmarking methods. The study concluded that searching for robust properties of city rankings that enable 'fair' comparisons is reasonable while using non-parametric methods such as OLS and DEA. In all other cases, virtually each ranking can be constructed by an appropriate choice of the parameters weighting the different indicators. Therefore we will use residuals in OLS and DEA to rank the eco-efficiency of the 88 cities in this paper. Here, the ranking is solely generated by the properties of the indicator space and the chosen method. It is in this spirit that these ranking methods are considered to be non-parametric.

While the OLS method has its foundations in econometric theory, DEA is based on mathematical programming techniques. In the OLS method, performance of each city with respect to each of its socioeconomic indicators (employment ratio and GDP) is compared with the average performance of cities with similar environmental variables. In DEA, a city's ranking is determined by comparing its performance with the best performing cities. While the DEA method can deal with multidimensional input and output spaces, the OLS method has been extended for that purpose as shown below.

4.4.3 City eco-efficiency rankings based on OLS and DEA

Eco-efficient cities maximize the socio-economic indicators given their environmental burden/resource consumption indicators. Therefore, the former are considered as dependent variables and the latter are considered as independent variables in the OLS method. The residuals with respect to each of the dependent variables in the linear regression manifold will determine the eco-efficiency of a city. The ranking of cities in the OLS method in this study followed two steps.

Firstly, we ranked the cities based on their residuals V within each dependent variable (E: employment and P: GDP/cap) separately given their independent variables (N: [NO_2], W: solid waste production and H: water consumption) as shown in eq. 4.1 and eq. 4.2.

$$\mathrm{V}_i^p = P_i - (\beta_0^p + \beta_1^p \cdot N_i + \beta_2^p \cdot W_i + \beta_3^p \cdot H_i) \tag{4.1}$$

Where, $i = 1, \ldots, 88$ is the number of the city and V_i^p is the residual of city i regarding P. The four parameters $\beta_k^p, k = 0, .., 3$ are chosen to minimize the sum of the squares of the residuals over all cities (the usual approach in multivariate linear regression).

Similarly, the residuals with respect to independent variable 2 i.e. employment ratio are calculated as:

$$\mathrm{V}_i^E = E_i - (\beta_0^E + \beta_1^E \cdot N_i + \beta_2^E \cdot W_i + \beta_3^E \cdot H_i) \tag{4.2}$$

Where V_i^E is now the residual of city i regarding E and the parameters $\beta_k^E, k = 0, .., 3$ are chosen to minimize the sum of the squares of the residuals across all cities. The method compares each city to the average performance which is reflected by the regression result. The larger (positive) the value of V_i^p and V_i^E the better is the eco-efficiency ranking of a given city. For further details on OLS ranking method, see Appendix A.2.

Secondly, the rankings under both dependent variables are further aggregated into a consensus ranking using a branch and bound algorithm (for details see Appendix A.2). The result is a new ranking which is closest to the two original rankings. As far as we are aware, such a non-parametric approach to solving the problem of multidimensional outcomes in OLS is unprecedented. We will refer to this consensus ranking as enhanced OLS ranking in what follows.

The efficiency of a city in DEA method is calculated based on the ratio of its outputs to its inputs. Since our objective is to characterize an eco-efficient city by high socio-economic measures and low environmental burden, the former were considered as outputs and the latter were considered as inputs in this study. DEA identifies the convex hull in data space which is spanned by the efficient cities and ranks the inefficient cities according to their (relative) distance to the hull. This hull is a piecewise linear manifold. Efficient cities which span the hull section an inefficient city is related to are called 'peers' (see Figure 4.1 for details). These are positive, efficient examples for the inefficient cities. Changes in the indicator values necessary to reach the convex hull for an inefficient city are called 'slacks'. Slacks allow us to identify the most critical dimension for improving efficiency. For further details please refer to Appendix A.2.

4.4.4 Methodological differences in ranking under OLS and DEA

Figure 4.1 illustrates the key differences between these two approaches for benchmarking efficiency in two dimensions for some hypothetical values. The cities represented by the green dots span the convex hull and are efficient (rank 1) in DEA. The distance from this hull (dashed green lines) determines the rank of a city in DEA (the smaller the better). In OLS the positive deviation from the solid black regression line decides the rank of a city (the more above this line the better is the ranking).

City B (rank 1 in DEA) has only a small positive deviation from the regression line resulting in rank 8 in the OLS method – here the methods deviate significantly. City A is ranked first in both methods: it spans the convex hull and has at the same time the largest positive deviation from the regression line. City C lies even below the regression line (resulting in a low OLS rank of 14) but gets a relatively good rank of 4 in DEA as there are only two other cities which are closer to the convex hull (we define the rank of the closest non-hull city as 2). In the chosen example city E has the most negative deviation from the regression line and, at the same time, the largest distance from the convex hull – so it is least ranked in both approaches. The red-dot cities with the green circles illustrate a specific property of the DEA approach which has no analogue in OLS. In DEA, cities F and B span the segment of the convex hull these red-dot cities with the green circles are related to. Therefore, cities F and B serve as peers or "reference cities" to these cities.

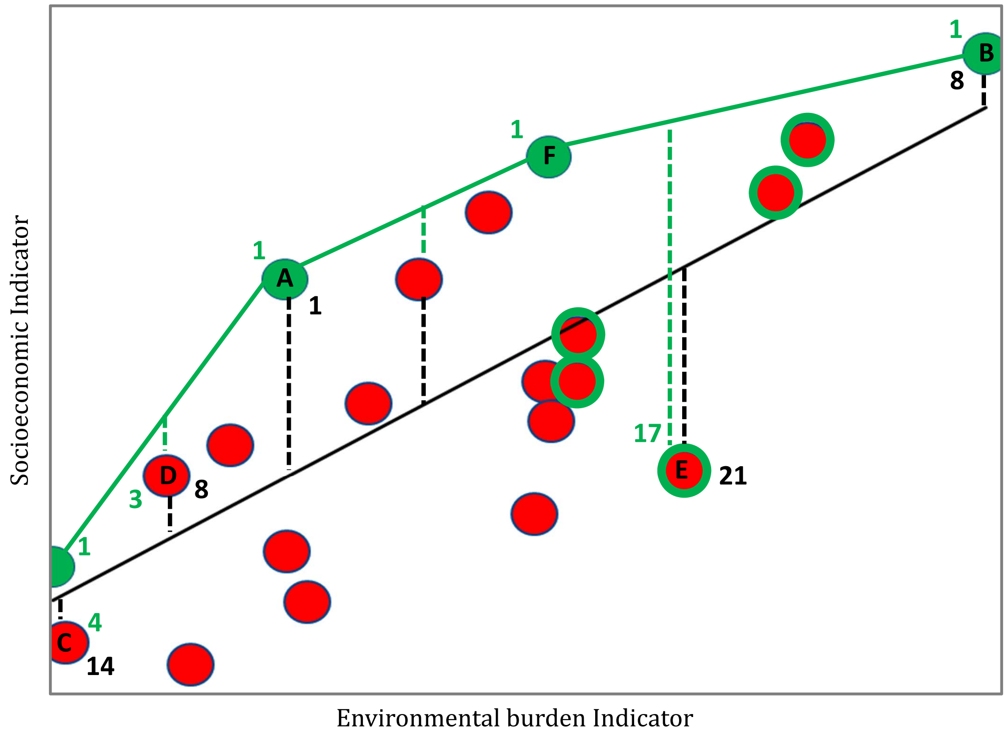

Figure 4.1: An illustration of the difference between OLS and DEA methods in two dimensions. Ranking of the cities in DEA and OLS methods are shown in green and black colors respectively.

4.5 Results

4.5.1 City ranking based on enhanced OLS method

As mentioned earlier, the OLS method ranks cities based on their residuals in the regression manifold. Figure 4.2 shows the city rankings of the 88 cities based on their residuals in employment ratio (Figure 4.2A) and GDP (Figure 4.2B). The results of the estimates (slopes) for the independent variables in the underlying multilinear regression are shown in Table 4.2. It can be inferred from the table that the regression manifold is strongly and positively influenced by NO_2 concentration followed by waste generation. This means that an average increase in GDP and employment will go together with an average increase in the NO_2 concentration and waste generation. The weak R^2 values shown in Table 4.2 depict the considerable variation amongst these cities with regard to the linear regression manifold which is the basis for our ranking. The 40 cities that deviate above the linear regression manifold with respect to GDP have an average

	Estimates of the Independent Variables			
Dependent Variable	NO_2 concentration (N)	Waste (W)	Water (H)	Correlation
Employment ratio in %	0.268	0.002	-0.036	0.083
GDP (per capita in PPS)	311.6	9.32	17.5	0.089

Table 4.2: Coefficients of each of the independent variables in OLS method.

GDP of 14,000 euros more than those cities that deviate below the regression manifold (the average GDP of all the 88 cities that are considered in this study is 30,523 euros). Similarly, the 52 cities that deviate above the linear regression manifold with respect to employment ratio in relation to the environmental burden have an employment ratio of 10 percentage points more than those that deviate below.

The rankings of the cities with respect to each of these dependent variables varied significantly. For instance, the city of Brussels while being ranked 13$^{\text{th}}$ with respect to GDP, is ranked 76$^{\text{th}}$ with respect to employment. Similar variations in rankings are observed for Dublin, Warszawa and Paris. However, there are also cities which are ranked poorly in terms of GDP while being ranked well in terms of employment ratio. For instance cities like Vilnius, Tallinn, Bucharest and Sofia are all ranked relatively better in terms of employment while being ranked relatively poorly in terms of GDP. This result shows that the importance of using both GDP and employment ratio as socio-economic indicators in eco-efficiency ranking.

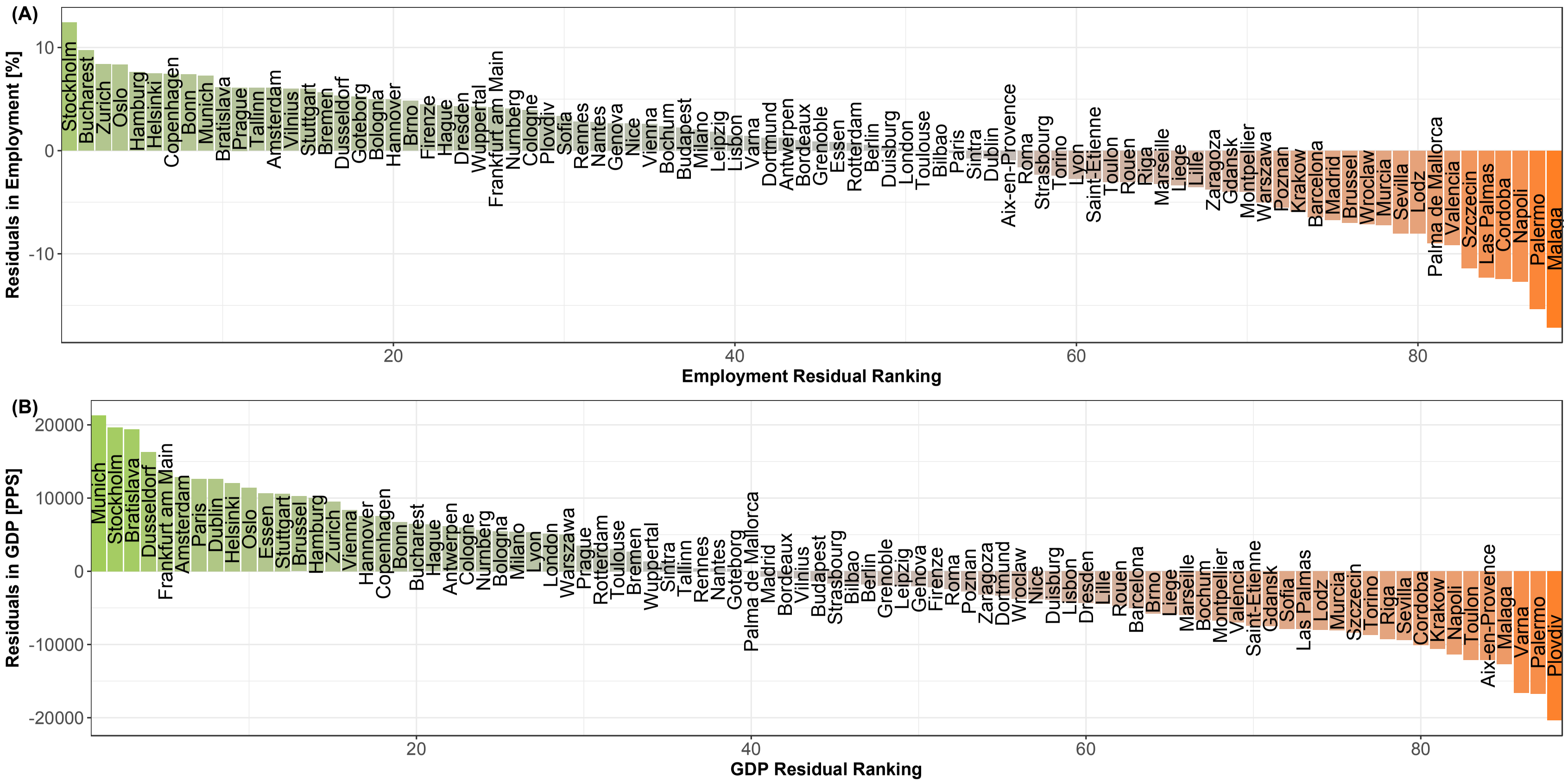

Figure 4.2: Eco-efficiency ranks for 88 cities based on their residuals in Employment (A) and GDP (B) under the OLS method. Cities are sorted based on their ranking from left to right. Stockholm is ranked 1st with respect to employment while Munich is ranked 1st with respect to GDP. Malaga and Plovdiv are least ranked cities with respect to employment and GDP respectively.

The enhanced OLS ranking post the rank aggregation algorithm using branch and bound method yielded 4 different ranking permutations in which 2 permutations ranked cities from 1 to 88. The only difference between these ranking permutations is the ranking of Malaga which is ranked 88^{th} in one permutation and 87^{th} in the other. The other two permutations ranked cities from 1 to 52 and 51 respectively (with ties in ranking). Since each of these permutations is Kemeny optimal (for further details refer to Appendix A.2), we considered the permutation which ranked cities without any ties. The results of the enhanced OLS method show that Stockholm, Munich, Bratislava, Oslo and Helsinki are the most eco-efficient cities. These cities perform better both in terms of employment and GDP. Malaga, Plovdiv, Palermo and Varna ranked as the least eco-efficient cities amongst the 88 cities in this study. These cities have either lower GDP or employment ratio compared to other cities. Enhanced OLS ranking all these 88 cities are shown in supplementary information while a graphic representation can be found in Figure 4.4 (values on the Y-axis).

4.5.2 City ranking based on DEA method

The efficiency of a city in DEA method is calculated based on the ratio of a linear combination of its socio-economic indicators to that of its environmental burden/resource consumption parameters. While the OLS method of residual ranking have unique city rankings (without ties), the DEA method identified 23 cities which are ranked 1^{st}. This is inherently because of the basic assumptions made under each method. As mentioned in the methods section, slacks determine the critical dimensions for improving efficiency of inefficient cities. Figure 4.3 shows the ratio of slacks in each variable to their present value. It can be observed in Figure 4.3 that the slack in GDP is a common factor determining inefficiency in most of these cities. The employment ratio in Brussels must be increased by 8 % in order to be on the convex hull whereas NO_2 concentration in Poznan has to be decreased by 12 % in order to be efficient. Plovdiv reportedly has a GDP of 9,393 in PPS and has to increase its GDP by almost 300 % in order to be an efficient city. Malaga, the least ranked city has to improve its GDP by 57 % while decreasing its waste generation and water consumption by 35 % and 7 % respectively.

There are two caveats in the eco-efficiency ranking under the DEA method. The first caveat is ranking under this method allows ties. In our case, there are 23 cities which are ranked 1^{st} under the DEA method. Literature in DEA has indicated methods such as super efficiency, cross efficiency and benchmark ranking method to further disentangle ranking of the efficient cities. However, each of these methodologies have their own set of assumptions which will influence the final ranking permutation. For further details see Markovits-Somogyi (2011).

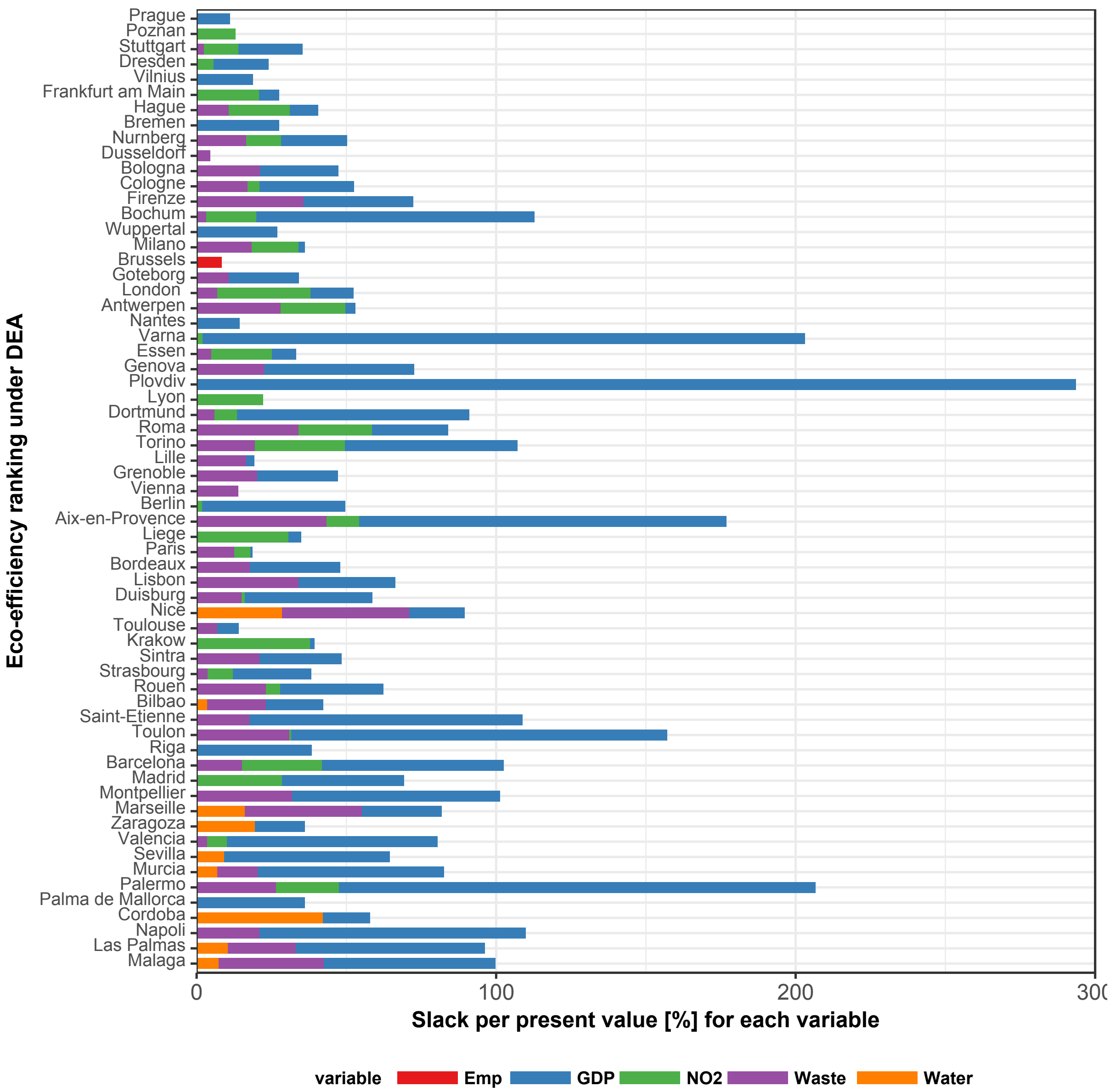

Figure 4.3: Eco-efficiency ranking of inefficient cities under DEA (from Prague which is ranked 2nd till Malaga which is the least ranked city) method and the percentage of slack per present value for each input and output variable.

For instance, the benchmark ranking method determines the ranking of the efficient cities based on the number of inefficient cities they serve as a peer. In our analysis, Munich serves as a peer to 48 inefficient cities. Hamburg and Bucharest serve as peers to 31 and 29 inefficient cities respectively. Therefore, these cities can be considered as the most eco-efficient cities under this method. Lodz, Warsaw, Dublin, Budapest and Rennes don't serve as peers to any inefficient cities except themselves. Therefore, there are still ties in this ranking permutation. Since the objective of this paper is to minimize subjective choices regarding the methods, we continued our further analysis with the original DEA result including ties.

The second caveat is that DEA ranking is highly sensitive to outliers (Banker and Chang 2006). Literature on detecting outliers depicted many methods to identify and deal with these outliers. A detailed overview of methodologies to detect outliers in DEA are mentioned in Ahamed et al. (2015). We addressed this issue in this paper in two steps. As a first step, we deleted one of the efficient cities and calculated the resulting eco-efficiency rankings. As a next step, we analyzed the Kendall Tau's correlation between the original ranking and the DEA result after deleting this city. Kendall Tau's correlation checks the number of concordant and discordant pairs within these two ranking permutations. Higher correlation signifies that the ranking permutations are almost similar while lower correlation signifies that the ranking permutations are dissimilar. We repeated that for all 23 efficient cities. Our results showed that the Kendall Tau correlation coefficient remained between 0.94 (after deleting Munich) and larger than 0.98 for 21 other deletions. Since Munich is identified as an outlier in our study, we had a closer look into the rankings before and after deleting Munich. Regarding the cities that span the convex hull, in this case, Munich is substituted by four inefficient cities in the original ranking. The relative ranking of the remaining inefficient cities in the original ranking remained exactly the same. This result shows that even the most pronounced outlier (Munich) has no significant influence on the interpretation of the resulting city ranking under DEA.

4.5.3 Comparison of enhanced OLS and DEA rankings

Figure 4.4(A) compares the ranking of 88 cities in DEA and enhanced OLS methods and Figure 4.4(B) shows the number of inefficient cities an efficient city in DEA serves as a peer. The objective of Figure 4.4(B) is to depict that a majority of cities which are ranked well under both methods serve as a peer to many inefficient cities under DEA method. The Pearson's correlation coefficient of the rankings under both methods is found to be 0.64. With few exceptions such as Marseille, Barcelona and Madrid, the ranking of all the cities above 1 million population remained between medium to best under both methods. Although the number of cities with

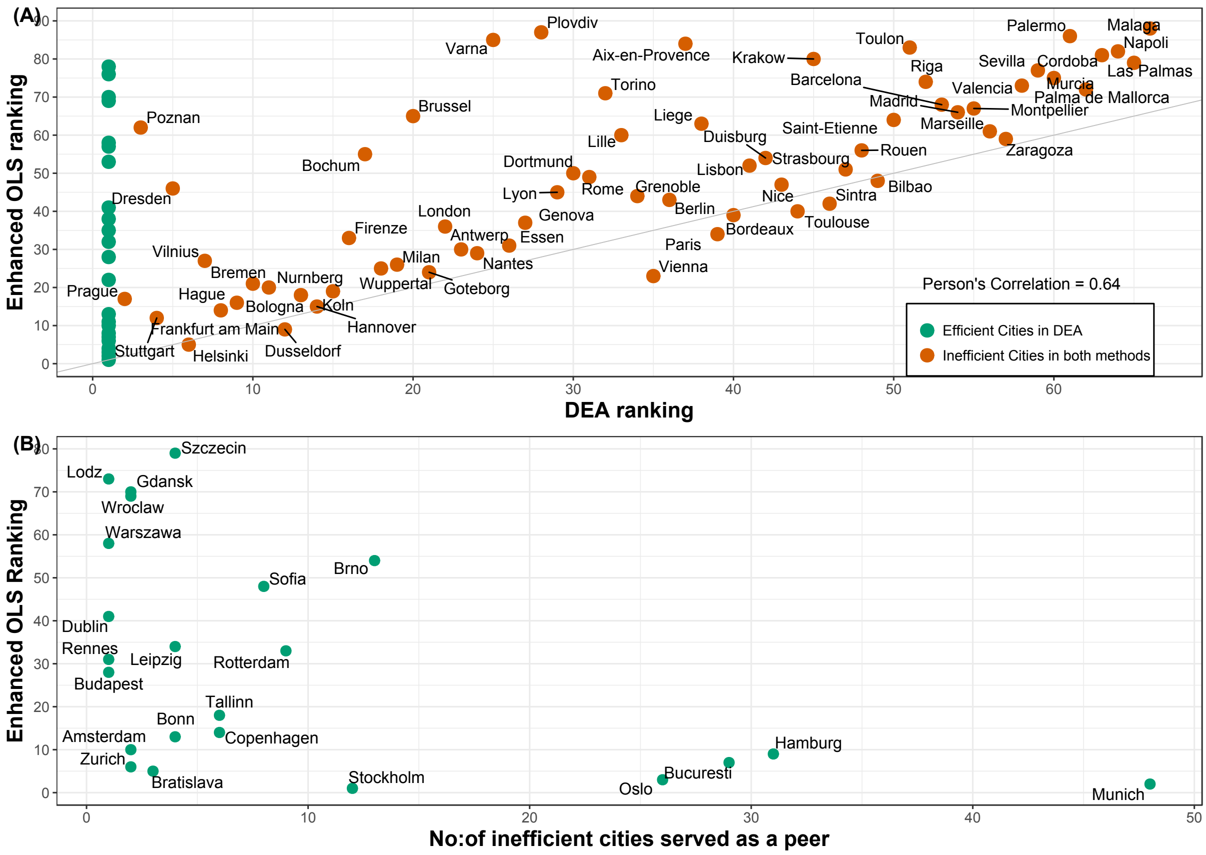

Figure 4.4: Comparison of city rankings in DEA and enhanced OLS method. Each dot represents the ranking of a given city in enhanced OLS and DEA method respectively. The grey line (with slope 1) in 4.4(A) shows how far the rankings agree under both methods. 4.4(B) shows that cities which are ranked well in OLS serve as a peer to many inefficient cities in DEA method.

more than one million population represents approximately only a quarter of the number of cities considered in this study, this result suggests that large cities per se are not detrimental to the environment considering the socioeconomic benefits they offer compared to smaller cities.

The 10 best performing cities under the enhanced OLS method are ranked as the most eco-efficient cities under the DEA method (except Helsinki and Duesseldorf which are ranked 6th and 12th under the DEA method). A comparison of the individual rankings of the two methods revealed that cities such as Stockholm, Munich, Oslo, Bratislava and Zurich are ranked as the best performing cities irrespective of the method used. Therefore these cities are the most eco-efficient cities according to this study. Cities such as Malaga, Palermo, Napoli, Cordoba and Las Palmas are ranked poorly under both methods and can be considered as inefficient cities.

As mentioned in the methods section, the eco-efficiency ranking of a city in DEA is based on the ratio of its socio-economic measures to its environmental burden. Therefore, despite performing poorly with respect to socio-economic measures, a city can still be efficient if it has lower environmental/resource consumption compared to other cities. This is because the efficiency of such a city is measured against the convex hull which is a piecewise manifold. OLS ranks city eco-efficiency based on its positive residual compared to one linear manifold defined by all cities. Therefore, cities such as Szczecin, Lodz, Gdansk, Wroclaw, Warsaw are ranked as the most efficient cities under the DEA method while being ranked poorly in the enhanced OLS rankings. On an average basis, the per capita water consumption and waste generation in these cities is 41 % and 34 % lower than all the other cities in this analysis. None of these cities serve as a peer for more than five cities under DEA method. For details, refer Figure 4.4(B). Therefore these cities can be considered as cities in the periphery of the indicator space in the DEA method and the convex hull is determined mainly by these cities in that indicator space. However, with respect to OLS rankings, these cities have negative residuals either in employment or in GDP (see Figure 4.2). Therefore, these cities are ranked poorly under the enhanced OLS method.

4.5.4 Comparison of public perception and objective city rankings

As a first step, we ranked each of the five indicators and the perception survey results separately in descending order by their given value. Cities which have higher NO_2 concentration, generate more waste per capita, use more water per capita, have lower employment ratio, have lower GDP are ranked last. As a next step, we ranked the eco-efficiency of these 45 cities using the enhanced OLS and DEA method based on all indicators and correlated each of these seven rankings with the perception ranking.

The correlation between the rankings of environmental parameters to that of the perception ranking is found to be low compared to that of socio-economic indicators (Table 4.3). The correlation of employment and GDP rankings is similar (0.48). We found that eco-efficiency rankings from enhanced OLS method to be strongly correlated with subjective perception ranking (0.61). Considering the ties in DEA ranking, the correlation between subjective perception ranking and DEA (0.47) is also relatively good. This result demonstrates that urbanites' perception about quality of life is determined by the combination of socioeconomic well-being and lower environmental burden. Further, we show that the correlation between perception ranking and enhanced OLS ranking is more than that of DEA. This result suggests that urbanites' perceptions reflect the eco-efficiency performance of their city compared to the typical performance of similar cities. This result illustrates that urbanites' perception about quality of life in their city is not influenced by a city which performs exceptionally well (Munich for instance).

Variable	**Correlation Coefficient**	**p-Value**	**95% Confidence Interval**	
			Lower	Upper
NO_2 Ranking	0.25	0.09	-0.04	0.51
Water Ranking	0.21	0.16	-0.08	0.48
Waste Ranking	0.03	0.82	-0.26	0.32
Employment Ranking	0.48	0.00***	0.22	0.68
GDP Ranking	0.48	0.00 ***	0.22	0.68
DEA Ranking	0.47	0.00 ***	0.2	0.67
Enhanced OLS Ranking	0.61	0.00 ***	0.39	0.77

Table 4.3: Results of the statistical analysis for the correlation between perception ranking with the ranking of the variables and objective eco-efficiency rankings. p-value significance codes : 0 = ***, 0.001 = **, 0.01 = *.

Since the OLS rankings are correlated the most to the perception rankings, we had a closer look at how the subjective perception ranking is interrelated to enhanced OLS rankings (Figure 4.5). Our results show that there are three groups of cities. The first group consists of cities where perception rankings are in line with the enhanced OLS rankings. Cities like Zurich, Copenhagen, Stockholm, Helsinki and Munich which are amongst the top five best ranked cities with respect to urbanites' perception are amongst the best ranked cities in enhanced OLS method. Similarly, cities such as Palermo, Napoli, Lisbon, Rome and Riga being the least ranked cities under public perception are also amongst the inefficient cities under OLS rankings.

The second group consists of cities which are ranked relatively better in the enhanced OLS method while being perceived poorly by their inhabitants. We observed such occurrences in almost all eastern and southern European cities where urbanites' perception is lower than those cities in western Europe. For instance, the city of Bucharest despite being ranked relatively well in the enhanced OLS ranking (15^{th}) is ranked very poorly (44^{th}) in perception rankings (a meagre 21 % of its inhabitants are completely satisfied to live in this city). Another example is the city of Bratislava which is also ranked well in enhanced OLS ranking (7^{th}) while being ranked 15^{th} in terms of urbanites' perception.

The third group belongs to cities such as Dublin, Warsaw and Gdansk. Despite being ranked poorly in the objective ranking, these cities are perceived relatively well (ranked 11^{th}, 17^{th} and 18^{th}respectively). Although the perception rankings of most of southern European cities are poor, the city of Malaga is found to be an exception. Despite being the least ranked city in enhanced OLS ranking (45^{th}), the city stands 22^{nd} with respect to perception rankings. Since

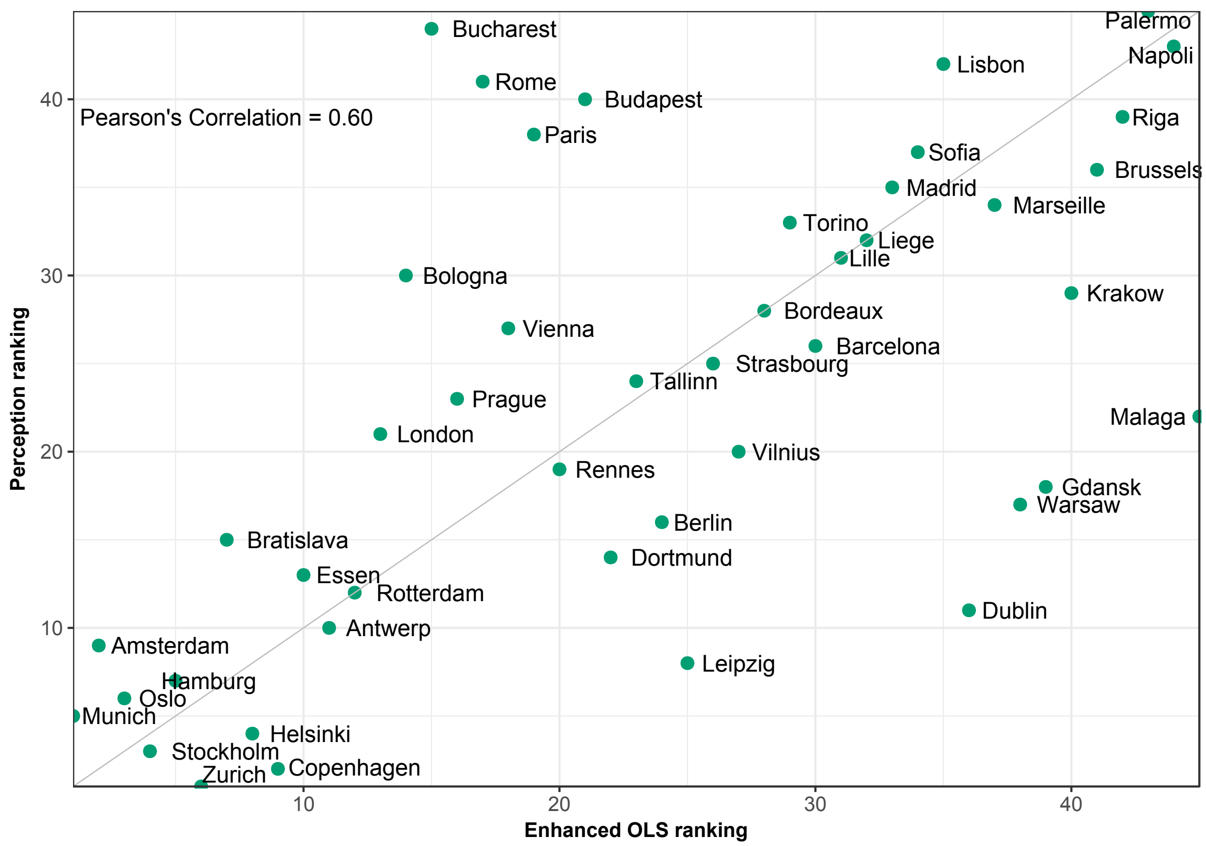

Figure 4.5: Comparison of enhanced OLS ranking with public perception ranking for the 45 cities. Each dot represents ranking of a given city in enhanced OLS ranking and urbanites' perception ranking respectively.

this analysis is done for a relatively smaller sample (45 cities), the slope of regression line depends on the few outliers (Malaga, Gdansk and Warsaw). In general, our results depict that public perception about the quality of life in western European cities is guided by the prevailing social, economical and environmental dimensions. There seem to be other factors (for e.g. political) that influence the public perception in southern and east European cities.

4.6 Conclusion

City benchmarking studies (for instance city rankings by The Economist Intelligence Unit (EIU) (2015) and the Mercer quality of living rankings[5] usually attract a lot of attention ranging from the scientific community to general public and the media. These rankings can influence the scale

[5]Available at: https://www.imercer.com/content/mobility/quality-of-living-city-rankings.html

and direction of public/private investment and inform city inhabitant understandings regarding urban quality of life.

Broadly all environmental indicators used in this study reflect either the environment burden and/or resource consumption. The NO_2 concentration can serve as a proxy for air pollution. Waste generated and water consumption can serve as a proxy for resource consumption and land/water degradation and air pollution in case a city lacks proper treatment and disposal facility. City efficiency benchmarking is highly sensitive to the selection of the indicators which define efficiency and the data quality. The eco-efficiency ranking of the 88 cities considered in this study will differ when more cities and more indicators are used in the analysis. In both cases such an inclusion will influence the number of cities deviating from the regression manifold in OLS method and the convex hull in DEA method. However, the biggest challenge here is the consistency of the indicators used to define eco-efficiency of cities. Lack of consistent and reliable data constrained this study to only three environmental/resource burden and two socio-economic indicators.

Our results show that cities with well-established urban economies such as Munich, Stockholm and Oslo are eco-efficient irrespective of ranking methods. The results of this study corroborate the hypothesis that the stage of city development influences the metabolic process (Kennedy et al. 2007) and the subsequent eco-efficiency of a city. A majority of cities in southern and east European cities considered in this study face a bigger challenge to simultaneously improve their socio-economic conditions while decreasing their environmental burden. Although out of the scope of this study, an entry point for these cities to improve their eco-efficiency is to develop and implement city specific green growth policies (OECD 2011).

Urbanites' perception about the quality of life in a city is crucial for any city benchmarking study. The findings of this study reinforce that urbanites' perceptions about quality of life in a city is not confined merely to the socioeconomic opportunities it offers but more towards the core vision of sustainable urban development. The higher correlation between subjective perception and objective OLS rankings compared to DEA rankings in this study points towards a crucial trait in city efficiency benchmarking. We showed in this study that city's inhabitants don't compare their city with a best 'ideal city' but rather to average eco-efficiency of similar cities.

In summary, the main results of this study are twofold. Firstly, it is depicted that mature cities with well-established and diversified economic structures provide more socioeconomic opportunities and are found to be eco-efficient irrespective of the ranking method. Secondly, we show that urbanites' perception about quality of urban life reflects socioeconomic well-being coupled with lower environmental burden. Therefore, strategies to improve socioeconomic well-being in urban areas should not be environmentally detrimental as that will influence urbanites' overall perception about quality of urban life.

As cities play a pivotal role in ensuring global sustainability, we believe that the results showed in this study represent a step towards a scientific understanding of sustainable urban development. There are two main areas which this study identifies as future research. Firstly, to analyze the progress of urban eco-efficiency using more comparable indicators as cities evolve in space and time. Secondly, to check whether such a progress in urban eco-efficiency is in accordance with local efforts in improving quality of urban life using more recent data on urbanites' perception.

Chapter 5

Conclusions and Outlook

5.1 General Achievements

Acknowledging the unprecedented role contemporary cities play in climate change mitigation and sustainable development, this thesis focussed on analyzing the factors contributing to emission and resource efficiency in global cities. Diving deeper into the guiding research question "What is the influence of urban form, economic geography and technology on GHG emissions and what are the fundamental characteristics of eco-efficient cities?"; this thesis identified the crucial role of urban form, affluence, economic geography and technology in improving emisssion efficiency and identified factors contributing to eco-efficiency in cities. An in-depth understanding about the influence of these factors led to the identification of entry points for potential action. The following is a summary of the key results of this thesis:

1. Analysis of the Urban Kaya Relation enabled an in-depth understanding about the key factors that typically determine emission efficiency of large cities. This analysis depicted that there is a need to deploy better technologies to improve the emission efficiency of large cities at a global scale in order to compensate the impacts of increasing affluence. With respect to cities in the developed regions, emission efficiency of large cities can be further improved by addressing issues concerning lifestyle and consumption patterns since energy consumption in these cities increases typically with increase in affluence. Since doubling the GDP typically leads to less than double energy consumption, large cities in developing regions of the world show a leap-frogging potential into emission efficient cities by adopting better technologies and infrastructure for energy generation and consumption.

By providing a framework for mainstreaming mitigation actions through indentifying the intrinsic factors leading to emission efficiencies in large cities, the results of this study reinforce the results of Rybski et al. (2017) and Martínez-Zarzoso and Maruotti (2011). Moreover, the lock-in patterns of energy intensity for cities in the developed regions is highlighted in this study.

2. Combining landcover data and gridded emission inventory using geo-spatial techniques to attribute building and on-road transport emissions to all populated settlements in the USA with the City Clustering Algorithm (CCA) to have consistent urban extents; it was possible to find out the crucial role population density plays in improving CO_2 emission efficiency. Although there are other factors such as local climate, affluence and technology that determine building and transport emissions, the findings of this study highlight the potential over proportional increase in global urban on-road transport emissions as a consequence of the on-going urban sprawl. Therefore, compact urban development policies which encourage mixed landuse, improve accesibility to public transportation and enforce stringent building regulation codes are key entry points for improving emission efficiency in cities. Apart from providing a methodological foundation for future studies in this area, the results of this study supports the arguments by Creutzig et al. (2015) that, amongst others, compact urban form plays a significant role in realizing the urbanization mitigation wedge.

3. Ranking the eco-efficiency of the most populated European cities was accomplished by merging the concepts of urban metabolism with benchmarking. Within the cities considered in this analysis, the results depicted that Stockholm, Munich and Oslo are most eco-efficient cities since these cities enable better socioeconomic conditions given their environmental burden. On contrary, cities which lack a strong economic base such as Malaga, Palermo and Napoli are poorly ranked. This result hints at a possibility of improvement in urban environmental management as cities get richer. Further, this study highlighted that large cities, in general, are eco-efficient compared to smaller cities, a promising insight given the current urbanization trend. By extending the analysis to a large set of cities, the results of this study prove the hypothesis by Kennedy et al. (2007) that the stage of development influences it's urban metabolism.

4. It is often assumed that the prevailing socioeconomic conditions in a city predominantly determine urbanites' perception about quality of urban life. Analyzing correlations between the objective eco-efficiency ranking with the indicator ranking and ranking of the subjective urbanites' perception about quality of life revealed that this not the case. The

Study Results	Study Implications	Policy Recommendations: Developed Regions	Policy Recommendations: Developing Regions
Large cities in developed regions are typically more emission efficient compared to large cities in developing regions.	Technology and affluence play a crucial role in determining emission efficiency	Addressing issues concerning urbanites' attitude towards resource consumption	Leapfrogging potential can be realized by adopting better technologies and infrastructure
Population density plays a significant role in decreasing building and transport emissions (per capita)	Effective management of land use and stringent enforcement strategies are essential for emission efficiency	Curbing further sprawl and increasing share of renewables in building and transport energy in the existing low density areas.	Apart from curbing urban sprawl, encouraging non motorized transport and investing in sustainable urban transportation.*
Mature cities are more eco-efficient and urbanites' perception reflects a combination of socioeconomic wellbeing and less environmental burden	Large cities are typically more eco-efficient compared to smaller cities.	Adopting effective strategies which promote "Green Economy"	Simultaneous improvement of resource efficiency and socioeconomic regime*

*** Recommendations not based on the thesis but reflect the general consensus in state-of-the-art literature**

Figure 5.1: A summary of the key results of this thesis, their implications and the broad policy recommendations. * These recommendations are based on broader conclusions derived from this research work)

results showed that urbanites' perception about quality of urban life is not confined to the socioeconomic benefits that urban areas offer but rather to their combination a lower environmental burden which is the core feature of sustainable development. The results of this study drawn from European cities corroborate the results of a study on cities USA (Cloutier, Larson and Jambeck 2014) that the percieved quality of urban life reflects a combination of socioeocnomic well-being coupled with lower environmental burden.

Thus, the methodological framework used to address each of the research questions posed in section 1.5 made it feasible to identify the focal areas for potential actions in improving emission and resource efficiency in cities. However, it has to be mentioned that improvements in urban efficiency will be realized only when addressed from dual point of view. Firstly, from a top-down urban governance point of view, there is a dire need for urban governments to adopt appropriate local policy measures for effective management of urban land use and identify various financial mechanisms, appropriate technologies and infrastructure for energy generation and consumption.

Secondly, from a bottom-up point of view, it is essential to address urbanites' lifestyle and behavioural attitudes towards resource consumption which plays a significant role in acheiving the goal of improving urban efficiency. A detailed overview of the key study results, broader study implications which are not emphasized in the individual chapters, and policy recommendations are shown in Figure 5.1.

The following sections will revisit the research questions RQ1-RQ3 posed in Chapter 1.5 and the results obtained in Chapters 2-4 to highlight the key contributions of this thesis to the on-going debate on factors influencing urban efficiency. Alongside, these sections discuss the scope and limitations of the methodologies used in this thesis and set the results into a broader context. Finally, identification of areas for further research and some concluding remarks are provided in Section 5.5.

5.2 Global Urbanization and its consequences on GHG emissions

The current global energy consumption and emissions attributed to cities raised questions if further urbanization will offer any economies of scale with respect to total final energy consumption and subsequent emissions. Although the state-of-the-art literature applied the concept of urban scaling to emission profiles of cities to identify whether large cities are more emission efficient compared to smaller cities, there exists a research gap with respect to identifying the prevailing intrinsic factors such as economic geography and technology that lead to such energy consumption and emission patterns. This issue has been addressed by the first research question RQ1:

> "Are largely populated cities more emission and energy efficient in comparison to smaller cities and which demographic, economic and technological drivers determine emission and energy efficiency in large cities?"

The objective of this research question is accomplished in Chapter 2 by merging the concept of urban scaling with the well-established Kaya Identity leading to an "Urban Kaya Relation". In contrast to other urban scaling studies which use ordinary least squared method to determine the scaling exponent of total urban emissions given their population size, this approach used the orthogonal least squared method to show the consistency of the different scaling parameters within the urban kaya relation. Splitting a global dataset of 61 cities based on the current development status of the country, this study identified the crucial role played by affluence and technology in determining the typical emission efficiency of large agglomerations.

The results of this study revealed that larger agglomerations in developed regions are typically more emission efficient compared to smaller cities (see Panel A in Figure 2.2). This is largely because of the sublinear scaling of emissions with energy consumption Table (2.1). However, the energy consumption in these cities increase proportionally with an increase in GDP clearly depicting a lock-in pattern of energy consumption (Table 2.1). By depicting this pattern, the results corroborate earlier arguments that affluence and consumption patterns play a crucial role in influencing the GHG emissions (Satterthwaite 2008). Therefore, there is a need for a paradigm shift in urbanites' attitude towards resources and energy consumption with increase in affluence to further improve the emission and resource efficiency of these cities.

Large cities in developing regions are typically emission inefficient compared to smaller cities (see Panel B in Figure 2.2). Unlike cities in the developed regions, the emission scaling properties of cities in developed regions depicted rich pattern of residuals. This can be largely attributed to the emissions from industrial sectors which are independent to the city population size. This study identified that the emission inefficiency of these larger cities is majorly because of two reasons: a more than proportional increase in affluence with population and emissions with energy consumed (Table 2.1). This result confirms a study by Dhakal (2009) which also identified that the emission inefficiency in large cities (predominated by Chinese cities in our analysis) can be attributed to the prevalence of industries which consume lot of energy and electricity, increase in affluence leading to increased usage of private modes of transportation and absence of efficient technologies in electricity generation. However, these cities show a leap frogging potential into emission efficient cities since doubling the GDP in these cities typically lead to a less than double increase in energy consumption (see Table 2.1). Recent literature has identified the potential mitigation wedge these cities offer in curbing urban energy consumption and GHG emissions (Creutzig et al. 2015). The key policy instruments to achieve this mitigation wedge include adopting cleaner technologies for electricity generation and mainstreaming investments in energy and emission efficient building and transportation infrastructure.

While the approach followed in this study revealed interesting insights about the factors driving emission efficiency in cities, it can be further improved in three different ways and is subject to data availability at detailed spatial and temporal resolutions. Firstly, much of the emphasis in this study is given to the typical behavior of the different scaling parameters within the Urban Kaya Relation. A quantitative assessment of the exceptionality of a given city (i.e. it's deviation from the regression line) as it is done in Chapter 4 will enable benchmarking of the emission efficient cities. Such an analysis can also identify the critical role of other factors such as population density, local climate, fuel price and household size in determining emission efficiency. Secondly, urban scaling approach used here is limited to one time step. Therefore, the dynamic nature of cities as they consume energy and grow in space and time while emitting GHG emissions is not completely captured in this study. Thirdly, recent literature highlighted that consistent defintion of urban extents and emission inventories are pre-requisites for these studies. Such an analysis with well-defined urban extents and a consistent emission inventory as shown in Chapter 3 will address some of the issues raised by recent studies which showed that the urban scaling laws vary with definition of urban extents (Arcaute et al. 2014; Cottineau et al. 2017).

In summary, this study has contributed to the on-going debate whether large cities are more emission efficient in comparison to smaller cities and highlighted their dependencies on the developmental status. Furthermore, it demonstrated that infrastructural and technological advancements are key to improve emission efficiency in cities. Amongst others, two major policy recommendations emerge from this study. Firstly, to identify appropriate measures and incentives which address behavioural issues of urbanites' towards resource and energy consumption. Secondly, to unlock the leapfrogging potential of cities in developing world by mainstreaming investments in cleaner technologies and provision of sustainable infrastructure.

5.3 Compact Urban Development and GHG Emissions

While the quest for identifying ideal city size in terms of population proved to be obsolete, recent literature identified population density to play a crucial role in determining urban livability and sustainability. However, there existed a dichotomy whether increasing population density will lead to a decrease in the overall urban energy consumption and susbsequent emission efficiency. Further, in the light of increasing urban sprawl as a global phenomenon (Angel et al. 2011), it is crucial to understand how such urban expansion will manifest in terms of sectoral GHG emissions at a city scale. With an objective to have an in-depth understanding on the influence of population density on building and on-road transport emissions, this issue is addressed as a part of second research question RQ2:

"What is the role of population density in improving GHG emission efficiency?"

This objective is accomplished by merging the concept of the City Clustering Algorithm (Rozenfeld et al. 2008) to have a standard definition of urban extents, with remote sensing techniques to attribute building and transport sector emissions to all inhabited settlements in USA. Further, this methodology is applied to two different land use datasets (namely GRUMP and GLC) to check the consistency of the results. Such a systematic analysis in this study enabled to have a deeper understanding about the significant role played by population density in improving building and transport emission efficiency on a per capita basis (see Figure 3.4). The results show that compact cities such as New York, San Francisco and Portland have lesser per capita building and transport emissions compared to sprawled cities such as Los Angeles, Atlanta and Houston. Further, this analysis depicted that population density plays a crucial role in improving on-road transport emission efficiency than building emission efficiency (see Figure 3.5). This result backs a study by Makido et al. (2012) on the influence of population density on building and transportation emissions.

On-road transport emissions account for almost one-third of total GHG emissions in USA (Gately et al. 2015). This can be largely attributed to the urban planning principles behind the so-called "modernist urban planning" which encouraged zoning regulations (i.e. dedicated land use such as residential, commercial and industrial area for a given area) which encouraged urban sprawl (Jacobs 1961) and the subsequent increase in private automobile based transportation (Glaeser and Kahn 2004). Despite being already charecterized as the most sprawled cities compared to other global cities (Kenworthy and Laube 1999), cities in the USA have experienced further increase in urban sprawl in the past decade (Hamidi and Ewing 2014). Since technological improvements within the vehicle fuel economy did not lead to a decrease in the total vehicle miles travelled (VMT) (Ewing et al. 2007), such an urban sprawl will further exacerbate on-road transport related emissions in these cities. Depicting that doubling the population density will improve on-road emission efficiency atleast by 43 %, this result corroborates with studies by Ewing et al. (2007) and Gately et al. (2015) which highlighted that policies aiming at compact development will lead to a decrease in overall VMT by 30 % and population density leads to a decrease in on-road emisisons per capita respectively for the cities in USA.

According to EPA, buildings (both residential and commercial) directly account for 12 % of the total GHG emissions (heating and cooking only) in the USA in 2014. The emissions from electricity consumption (including cooling) are reported at the electricity generation units and account for 30 % of the total GHG emissions in the USA. Apart from on-road emissions, the analysis of this shows that doubling the population density will decrease building emissions on a per capita basis. This decrease in per capita residential emissions can be largely attributed to the decrease in building floor area on a per capita basis (Timmons et al. 2016; Ewing and Rong 2008). These results corroborate with a global study by Güneralp et al. (2017) which identified efficiency gains with respect to building energy consumption in dense settlements.

At a global scale, the fifth assessment report of the IPCC (2014) estimated that buildings and on-road transportation are responsible for 19 % and 16 % of GHG emissions respectively. Using all the inhabitated settlements in the USA as a case study, the results of this study highilight the crucial role population density plays in improving emission efficiency. As mentioned in Chapter 2, technological advancements within the building and transport sectors will decrease the direct per capita energy consumption and emissions in cities. Nevertheless, urban sprawl will affect the surrounding crop lands and biodiversity which will aggravate in-direct emissions. Recent studies by Bren d'Amour et al. (2016) and Seto et al. (2012) highlighted these issues. Therefore, compact city development coupled with technological advancements is the key to improve urban emission efficiency.

However, increasing population density itself will not lead to gains in emission efficiency. For instance, the population density of the cities in developing world is higher than cities in the developed/industrialized nations. However, a majority of these cities often lack efficient public transportation infrastructure and are typically charecterized with increasing affluence as shown in Chapter 2. Such a scenario will encourage private ownership of vehicles leading to congestion and further exacerbate on-road emisisons (Wright and Fulton 2005). Moreover, compact development refers to higher average mixed land use and does not imply high rise settlements or uniformly high density (Ewing et al. 2007). Apart from these issues, fiscal measures also play a crucial role in improving urban emission efficiency. Since fuel prices play a crucial role in determining urban size and density directly and modal choices indirectly (Creutzig 2014), there is a possibility to address this issue from a optimum energy taxation perspective which ultimately encourages compact development (Borck and Brueckner 2016).

The findings of this study contribute to one of the most debated topics in sustainable urban development. Lack of consistent and detailed emission inventory at regular time steps limited the analysis of this study to inhabited settlements in USA only. An extension of this application to global cities is expected to give further insights about the influence of urban sprawl on building and transportation emissions especially in the developing regions. However, this study acknowledges that increasing population density alone is not sufficient to unlock such emission efficiency gains completely. This study reiterates that smart growth policies are the key instruments to address issues concerning climate change mitigation in cities. These policy instruments can be outlined in three perspectives. Firstly, from an urban planning point of view, adopting stringent land use policies and their enforcements which encourage brownfield development and mixed land use. Secondly, from a fiscal point of view, identification of optimum energy taxation and funding mechanisms which encourage public and non motorized transportation. Lastly, as highlighted in the previous section, from a bottom up perspective, identification of measures that shift urbanites' attitudes with regard to their lifestyle and energy consumption patterns.

5.4 Urban Resource consumption and sustainable development

The quest for socioeconomic growth in cities is accompanied with simultaneous increase in resource consumption and waste generation. Despite being fundamental to address urban sustainability issues, studies on urban metabolism are mostly limited to few case studies. Therefore, there is a need to improve current understanding on the interdependencies between socioeconomic wellbeing in cities and their resource consumption patterns. With an objective to identify cities which provide better socioeconomic conditions while consuming fewer environmental resources, this issue is addressed as a part of third research question RQ3:

"Which cities are eco-efficient and what are their characteristics?"

The answer to this research question is accomplished by using three environmental indicators (NO_2 concentration, per capita water consumption and waste generation) and two socioeconomic parameters (GDP per capita and employment ratio) for the 88 most populated European cities. Unlike previous benchmarking studies which are largely limited to one ranking method, we checked the consistency of the eco-efficiency ranking of these cities by using two different non-parametric methods. Further, analyzing correlations between the indicator rankings and eco-efficiency rankings with that of public perception ranking about quality of urban life enabled deeper insights into some of the fundamental issues concerning sustainable urban development.

The findings of this research (although limited to one time step) depict that mature cities with a diverse and well-established economic structure such as Munich, Stockholm and Oslo are eco-efficient cities irrespective of the benchmarking method. Cities in transition which largely depend only on one economic sector (in this case tourism) such as Malaga, Las Palmas, Napoli and Cordoba are ranked poorly under both methods. These cities face a bigger challenge to improve their socioeconomic wellbeing while decreasing their environmental burden simultaneously. Therefore, it is crucial for these cities to develop and implement city specific green growth policies (OECD 2011) in order to improve their eco-efficiency. Another key finding of this research is that large cities (with a population of more than a million) are more eco-efficient when compared to smaller cities. As shown in Chapter 2, as cities grow (in terms of their population), their affluence increases more than proportionally. Therefore, this result is in line with the argument that as cities get larger, their economic base diversifies providing more employment opportunities (Bettencourt et al. 2007). This is accompanied with simultaneous improvements in their resource efficiency.

Analysis of the ranking correlations revealed that urbanites' perception about the quality of life in a city is not merely confined to the socioeconomic well-being that a city offers. For instance, the city of Berlin despite being ranked poorly under both methods owing to it's current socioeconomic situation is perceived well in terms of quality of life. Leipzig despite being ranked 25^{th} is amongst the top 10 well perceived cities in terms of quality of life within the 45 cities considered in this city. Conversely, Paris, despite being ranked 16^{th}, is in 37^{th} place in terms of percieved quality of life. Within the 45 cities considered in this analysis, with few exceptions, cities which are ranked better in terms of their eco-efficiency are also well percieved and vice-versa. This result suggests that strategies of local policy makers to improve socioeconomic wellbeing should at least not be environmentally detrimental.

As highlighted in Chapter 4, city rankings are sensitive to the choice of variables and benchmarking methods. For example, the recent IESE Cities in Motion Index (IESE 2017) ranked Berlin as the best performing European city while it is ranked 43^{rd} out of the 88 cities considered in this study. Similarly, according to the IESE rankings, Stockholm is ranked 7^{th} while being ranked as the most eco-effcient city in this study. While the IESE rankings use more indicators than those used in this study, data inconsistency is highlighted by the authors' of the IESE study (IESE 2017). Moreover, as most of other city ranking studies, city rankings in this study is based on subjective weights given to each indicator. Therefore consistent and reliable information together with transparent benchmarking methods is a pre-requisite for such benchmarking exersices. Improving urban resource efficiency is one of the core objectives of the Europe 2020 strategy and is a part of its seven flagship initiatives (EEA 2015). While believing that the results of this study contribute to a more scientific understanding about factors contributing to improved eco-efficiency and urbanites' perception about quality of life, this study appeals to develop more consistent urban indicators such as energy consumption and GHG emissions using a standard protocol as proposed by Arikan et al. (2012) which will enable local policy makers to take informed decisions while improving their resource and emission efficiency.

Although not a part of this study, the urban metabolism in cities in developing countries is of great interest and concern especially with respect to those which are experiencing an increase in affluence while lacking basic infrastructure facilities. Myers and Kent (2003) highlighted the serious repercussions of increasing affluence and subsequent shifts in diet and personal transportation of over 1 billion new global consumers in 17 developing countries (most of whom are urbanites) on global environment and emissions. The lack of basic infrastructure in these cities can be percieved as an opportunity to incorporate strategies which encourage circular metabolism by adopting the measures taken at neighbourhood level in Stockholm and Frieburg (Spiegelhalter and Arch 2010). This can be achieved only when there is a giant leap in terms of the existing urban planning norms, involvement of all relevant stakeholders and a strong political will. It is expected that such strategies will enable these cities to completely unlock their leapfrogging potential as highlighted in section 5.2. However, such attempts should be accompanied with demand side interventions which are capable of affecting change in individual and household behavior in the key domains of energy, water, travel,and housing (Newton and Meyer 2012) which aim at improving the metabolic efficiency of these cities.

5.5 Outlook and Concluding Remarks

Cities are complex systems and data available to investigate the various factors that drive and sustain these complex systems eventhough improved lately for cities in developed world, is still scarce. Despite these challenges, this thesis paved way to an in-depth understanding about the factors contributing to emission and resource efficiency in global cities. Following the discussions about the scientific contributions on issues concerning emission and resource efficiency in cities, the outlook of this thesis is broadly framed into two perspectives: (1) prospective research and (2) practical efficiency improvements.

From a prospective research perspective, further studies should address two major issues. Firstly, the "Urban Scaling" approach enables researchers to identify the (in)efficiencies of various urban indicators given their population size and identifies city charecteristics which are particular and general in comparison to other cities. However, further studies should address four major concerns regarding these urban scaling laws. Firstly, some studies show that urban scaling laws are statistically obvious as they report extensive city-wide quantities rather than intensive per-capita quantities (Shalizi 2011) and fail to capture internal city dynamics (Sarkar et al. 2016). The second issue is the most common problem while dealing with urban assessments, i.e. defining urban boundaries. Therefore, urban scaling laws vary with the definition of urban extents (Arcaute et al. 2014). Using gridded emission data as it is done in Chapter 3 will address this issue adequately. Thirdly, as showed in Chapter 2, the scaling law might vary depening on the choice of regression model (ordinary versus orthogonal). Addressing these issues and relating them to the emission profiles of global cities will enable a deeper understanding about the crucial factors that affect urban emission efficiency. Lastly, since it is observed that population itself might not be a good predictor of emission and energy consumption for cities in developing regions, it is crucial to investigate the influence of other sectors such as industrial activity on these emission scaling deviations.

Secondly, despite improving urban emission efficiency (directly and indirectly), compact urban development might lead to other sustainability trade-off's with regard to air pollution, public health and other social aspects. Although technological advancements within the building and transport sectors will address few of these issues, there is a need to have a deeper scientific understanding about these trade off's and the multiple forms in which they manifest as urbanites' perception about quality of life. It is believed that relating urban form with resource and waste flows in global cities to affluence, prevailing infrastructure and technologies adopted for energy generation and consumption from a life cycle analysis point of view as suggested by Goldstein et al. (2013) will further improve the current understanding about urban metabolism and identify factors to decouple urban resource consumption with socioeconomic growth in cities. A starting point for such a scientific discourse can be the 'Sustainability Window' of urban form as suggested by Lohrey and Creutzig (2016).

Given the rate of global urbanization, the arduous task of achieving the Sustainable Development Goals (SDG's) predominantly becomes a task for decision makers at city level. Irrespective of the existing national mitigation policies, many cities in the developed world have already set stringent targets to improve their emission efficiencies. Augmenting emission and resource efficiency of the cities in developing countries is crucial and challenging at the same time as these cities mostly lack the technical, financial and institutional capacities to deal with the current urban dynamics. Dealing with these issues is crucial for these cities to unlock their leapfrogging potential completely. Acute poverty coupled with lack of basic infrastructure in these cities make them more vulnerable to the impacts of climate change. Therefore, a general rule of thumb in these cities is that every urban planning project that aims at climate change mitigation should also be resilient to the impacts of climate change and each climate change adaptation project should in principle mitigate climate change or at least be emission neutral. Irrespective of their current development status, cities need to identify various financial mechanisms/incentives to address urbanites' attitudes towards resource and energy consumption. Jacobson et al. (2017) recently developed renewable energy road maps to meet the energy requirements of 139 countries in the world and there exists enough scientific evidence that technologies to decarbonize the energy production and consumption already exist. Therefore, the pathway to sustainable urban development is mostly a social and political issue rather than being a technological challenge. Therefore, identifying and adapting available best practices with respect to innovative financing mechanisms involving all the concerning stakeholders for city wide mitigation and adaptation strategies can be a good entry point to address such political and social issues.

It is envisaged that this thesis will be of value for researchers working in the field of urban metabolism. It should encourage researchers from other disciplines to address the scientific challenges posed by cities as complex systems. Coupled with urbanites' lifestyles and attitudes, the land use and infrastructural decisions that local governments take today will have a significant long term influence on resource, energy consumption patterns and subsequent emissions. In conclusion, this thesis appeals local policy makers to apprehend these long term implications and ensure environmental protection while aiming for socioeconomic development.

Appendix A

Omitted Technical Details

A.1 Kaya II and III

It needs to be mentioned that there are another two identities complementary to the original Kaya Identity, Eq. (2.1), namely

$$\begin{aligned} C &= P \times \frac{E}{P} \times \frac{G}{E} \times \frac{C}{G} \\ C &= G \times \frac{P}{G} \times \frac{E}{P} \times \frac{C}{E}, \end{aligned}$$

or variations. We propose to denote Eqs. (2.1), (A.1), and (A.1), "Kaya I", "Kaya II", and "Kaya III', respectively. The identities Kaya II and III involve two intensities which do not appear in Kaya I, namely E/P and C/G, i.e. energy per capita and carbon per GDP, respectively. In the urban scaling picture these take the form

$$\begin{aligned} E &\sim P^{\delta} \\ C &\sim G^{\eta}. \end{aligned}$$

The relations corresponding to Eqs. (A.1) and (A.1) are

$$\begin{aligned} \phi &= \frac{\delta\,\eta}{\alpha} \\ \eta &= \frac{\delta\,\gamma}{\beta}. \end{aligned}$$

Other combinations of C, P, G, or E involve only two components each.

A.2 OLS and DEA methods for ranking city efficiency

Let's assume that the relationship between a socio-economic indicator i.e. GDP (dependent variable y_i,i=1,. . . ,88) and the environmental parameters i.e. NO_2 concentration, water consumption and waste generation (independent variables x_j,j=1,. . . ,88) of the cities considered in our study follow the functional form:

$$y_i = f_i(x; \beta_i) \tag{A.1}$$

Where, x is the vector of the independent variables and β_i is a vector of parameters to be estimated, in our case employing a multi-linear regression. The efficiency in the OLS method is determined by the regression residual. Therefore, if a given city k ($k = 1, \ldots, l$) has a larger (positive) residual than another city it is considered to be relatively more efficient. For a city k eq.1 can be written as:

$$y_i^k = f_i(x^k; \beta_i) + V^k \tag{A.2}$$

Where, V^k (regression residual) is the efficiency measure of a city k, y_i^k are the desirable socio-economic outcomes i and x^k are the environmental burden parameters of city k. The method compares each city to the average performance which is reflected by the regression result. The larger the value of V^k, the better the performance of the city. Since OLS residual ranking has to be calculated for each single dependent variable y_i, we aggregated the resulting rankings of all socioeconomic indicators using the branch and bound algorithm (D'Ambrosio et al. 2015). Further details of this rank aggregation method are mentioned below.

DEA defines the efficiency of a city k, $e^k \leq 1$, as the ratio of its weighted outputs y_i^k to its weighted inputs x_j^k:

$$e^k = \sum_{i=1}^{n} v_i^k \cdot y_i^k \bigg/ \sum_{j=1}^{m} u_j^k \cdot x_j^k \tag{A.3}$$

The city specific weights v_i^k and u_j^k are determined by maximizing e^k over (v_i^k, u_j^k) under the condition that the chosen set of weights keeps the efficiencies of all other cities below or equal 1. In case the side conditions allow $e^k = 1$ for the considered city it is part of the convex hull describing the manifold of best possible performance ("production frontier" in economy). In case $e^k < 1$, it is an inefficient city (measured by the distance to 1). The neighboring efficient cities which span the section of the convex hull the inefficient city is related to are called "peers". These cities are the "positive examples" the inefficient city might strive for. The changes in the x_i^k and y_i^k necessary to reach the convex hull, i.e. becoming efficient, are called "slacks" and allow for the identification of the most underperforming or critical properties causing inefficiency. The maximization has to be done for all cities, i.e. the resulting optimum weights are usually different. However, groups of inefficient cities which relate to the same efficient peers share the same weights describing a section of the convex hull. Without restrictions this piecewise linear construction of the hull comprises the variable returns to scale concept, a property clearly demonstrated in recent literature (Bettencourt et al. 2007; Bettencourt and West 2010) for city variables (super linear for socio-economic parameters and sub-linear for infrastructure parameters).

The problem can be transformed from difficult-to-deal-with ratio-maximization (see A.3) into a linear programming problem and then solved with standard procedures (Banker et al. 1984). In this paper this is done by using the R package called "Benchmarking" (Bogetoft and Otto 2011).

A.2.1 Rank Aggregation

Since ranking based on OLS method can only be done using one dependent variable, there is a need to aggregate the rankings obtained from both socioeconomic variables (employment and GDP) into a final ranking. This could be done by assigning weights to the respective residuals and adding them up. Such an approach would contradict the objective of this paper to avoid subjective or arbitrary elements in the ranking procedure. Therefore we used the Kemeny median ranking approach which results in a new ranking which is closest to all input rankings. In particular, the task is to search for a ranking which has the minimum average Kendall distance to all rankings which should be "aggregated". The Kendall distance between two rankings is defined by the number of pairwise permutations necessary to transform one ranking into the other. However, finding this optimal rank aggregation is a NP hard problem since the permutation space for optimal ranking for n cities will be $n!$ (D'Ambrosio et al. 2015; Dwork et al. 2001). Consensus ranking is one efficient procedure to solve the rank aggregation problem based on the maximization of the Kendall tau's correlation coefficient which is linearly related to the Kendall distance. A branch and bound algorithm is applied. Starting with initial guess new rankings are constructed along the permutation polytope. Here, branching is considered and branches are "cut" according to an evaluation criterion that shows if an optimum average Kendall tau can be reached or not by further extending this path. Technically, we applied the R package "ConsRank" (D'Ambrosio et al. 2015) to aggregate the individual rankings of employment and GDP in OLS method to derive the consensus enhanced OLS ranking for all the 88 cities. The result of the of the algorithm usually includes more than one permutation ranking each of which have the same Kendall tau's correlation coefficient which means each of these permutations are Kemeny optimal rankings. In such instances we considered the permutation which has the highest ranking discrimination in this study i.e ranking permutation without ties.

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