A Global Typology of Cities: Classification Tree Analysis of Urban Resource Consumption

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ABSTRACT

A study was carried out to develop a typology of urban metabolic (or resource consumption) profiles for 155 globally representative cities. Classification tree analysis was used to develop a model for determining how certain predictor (or independent) variables are related to levels of resource consumption. These predictor variables are: climate, city GDP, population, and population density.

Classification trees and their corresponding decision rules were produced for the following major categories of material and energy resources: Total Energy, Electricity, Fossil fuels, Industrial Minerals & Ores, Construction Minerals, Biomass, Water, and Total Domestic Material Consumption. A tree was also generated for carbon dioxide emissions. Data at the city level was insufficient to include municipal solid waste generation in the analysis. Beyond just providing insight into the effects of the predictor variables on the consumption of different types of resources, the classification trees can also be used to predict consumption levels for cities that were not used in the model training data set.

Urban metabolic profiles were also developed for each of the 155 cities, resulting in 15 metabolic types containing cities with identical or almost identical levels of consumption for all of the 8 resources and identical levels of carbon dioxide emissions. The important drivers of the differences in profile for each type include the dominant industries in the cities, as well as the presence of abundant natural resources in the countries in which the cities are the main economic centers.

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Chapter 1. Introduction and Background of the Study

1.1 Problem Statement

Modern society is faced with both resource scarcity and accumulating local, regional, and global pollutants. The most pressing pollution challenge is that of climate change, which will bring about temperature changes to which ecosystems (including human ones) will have to adapt. On the other hand, the resource scarcity challenge involves the rising demand for multiple resources, under a finite supply.

This work, and the field of urban metabolism in general, focuses on cities because the human population is undergoing intense and rapid urbanization, resulting in cities of unprecedented size and geographical distribution. It is, by now, an often-stated fact that over half of the world's population lives in cities. In particular, developing countries are predicted to experience the most significant urban growth in the next 50 years (United Nations, 2007), and this can be expected to result in shortages of basic social services, a significant increase in the demand for urban infrastructure, air and water pollution, and an ever-growing impact of cities on climate change. As cities grow, the flow of energy and material through them increases, and the different ways in which cities consume resources is as yet understudied. Here we examine the energy and material consumption of 155 cities of the world, spanning all geographical regions and levels of development.

Bigio and Dahiya (2004) articulated the concept of "livable cities" as a necessary partner of economic growth in successful urban development. The move toward these so-called livable cities necessitates development policies that promote efficiency in the use of water, materials, and energy, as well as waste reduction. Furthermore, Bigio and Dahiya (2004) state three broad goals of the urban environmental agenda: "improving the quality of life, improving the quality of growth, and protecting the quality of the regional and global commons from the spillover of pollution originating in urban areas".

The underlying hypothesis of this work is that it is possible to arrive at a typology or categorization of the world's cities based on their resource consumption (or metabolic) profiles. In other words, cities can be classified to one of a number of types of resource consumption, in which between-type differences among cities are significantly greater than within-type differences. The aim is to find independent variables that have the ability to predict the consumption type to which a city will belong. This understanding will aid the urban environmental agenda by informing the design of policies specifically targeted to the resource efficiency concerns of different types of cities.

The development of a "typology of cities" will be based on a finding of distinct metabolic profiles related to a limited number of attributes. These attributes (independent variables) will include those that most influence the consumption of urban residents: affluence, population, climate, and density. Krausmann et al (2008) have found that development status and population density are key variables that impact the metabolic profile, and climate certainly has an established effect on levels of energy consumption. Together these attributes substantially determine the bulk and character of urban resource consumption as driven by socio-economic activities.

In this work, a representative set of the world's cities will be classified to a number of urban metabolic profiles using classification trees. Classification is a classic data-mining task involving, in this case, data on consumption (dependent variables) that is divided into three consumption types (i.e., low, medium, and high for each dependent variable). Consumption data was used to train the classification model using known values of the independent (or predictor) variables. A representative sample of the world's cities that run the gamut of population, level of development, climate, and geography was selected as the training (and validation) set. The resulting model can thus be used to predict the consumption types into which other cities of the world will. This predictive capacity of the model will allow for typological classification of cities, even if consumption data for them is not directly available. By giving simple characterizations of the conditions that predict when a city falls within one consumption category or another, we can arrive at a typology of urban resource consumption.

1.2 Background of the Study

The urban sustainability movement is fundamentally concerned with securing the delivery of the quality of life that people desire when living in cities, while exceeding neither the carrying capacity of their hinterlands nor that of their regional and global resource supply networks. At the same time, a compromised urban environment and the vulnerability brought about by global climate change will themselves decrease the very standard of living that society seeks to achieve. Historically, quality of life in the developed world has been achieved by means of increased resource throughput. It is evident that as human society comes up against the 'limits to growth', resource throughput can no longer be the yardstick by which development is measured.

Progress toward sustainable cities requires the measurement of the current resource inputs and outputs of cities around the world. Cities are also well situated to gather and use this information in support of greater resource efficiency; both economic power and political decision-making are concentrated in urban areas. To enable policy-making in aid of urban sustainability, it is necessary to consider the different levels at which cities utilize resources. In this work, we posit that particular types of cities have different resource consumption profiles that support the economy and human activity. The various metabolic profiles distinguish the groups that make up the typology of cities.

The typology of cities is based on two primary ideas: first, that it is possible to track some of the most important of the resources that urban dwellers consume; and second, cities can be classified to different types based on their metabolic profiles. An understanding of which type a city belongs to can help urban planners and managers assess the population's ecological impact and focus on the resources that are consumed with greater intensity. By allowing for the comparison of a particular city's metabolic profile with that of other city types, especially at a similar or higher level of development, this typology offers a benchmark for ecological performance and identifies the greatest challenges to making a city more resource-efficient. Documentation of the current consumption profiles of different categories of cities also provides a baseline from which scenario-building can proceed.

The motivation of this study is the idea that if cities gather the proper data and these are used to inform resource management policy, their metabolic profiles may become less intensive with respect to the provision of a desired urban quality of life. In other words, the challenge is to find cities' strategic leverage points: rather than planning around the continuous growth of urban resource throughput, the city's metabolic character can provide an indicator to point to inefficiencies on which policy must focus.

1.3 Study Objectives

The objective of this thesis is to contribute to the efforts toward a comprehensive and holistic approach to the characterization of urban resource consumption, leading to better-informed urban development strategies. The optimization of resource consumption in cities has as its goals the improvement of the quality of life, efficiency of growth, maintenance of the quality of regional and global resources, and protection of the regional and global environmental sinks.

Urban environmental agendas can no longer be restricted to the so-called "brown agenda" (United Nations, 1992) of protecting urban water, soil, and air quality from contamination and pollution. Development objectives cannot be restricted to providing water supply and sanitation, upgrading slum neighborhoods, and introducing industrial pollution management, although these are important urban environmental concerns. Urban development scenarios that aim towards sustainability must also ensure minimized impact on natural resources at the regional and global scales, as well as prevent and mitigate cities' aggregate impact on climate change.

This work is motivated by the lack of understanding regarding categorical differences among cities in terms of energy and material fluxes. Most studies of material and energy use refer to the country level. However, this level of resolution of information fails to fully tap into to the capacity of cities to take action with regard to the resource efficiency of businesses, industries, and the populations that are concentrated in urban agglomerations.

Progress in urban resource efficiency depends upon effective management and targeted policy making. As cities continue to grow and become more complex, a typology of cities will become increasingly important for effective urban data collection and indicator evaluation. The classification of cities' resource consumption provides support for sound policies, allowing for more efficient performance evaluation. City 'sustainability indicators' have emerged as a core requirement for effective city management. While some indicators of consumption are already being used to measure city performance, they are not yet standardized, targeted, or comparable across cities and over time. Because municipalities' resources for collecting indicator data may be limited, a lack of focus on the most pressing resource inefficiencies limits the ability of cities to observe trends, share best practices and target their most pressing consumption issues. In recognition of this need, this work was carried out to provide cities with a standardized system for the estimation and prediction of their resource consumption typology. The intention is that this will allow cities to identify what data should be collected on a regular basis, and focus policy-making on the resources that the city uses most intensively.

Specifically, this thesis aims to specify and characterize the different types of urban metabolic profiles to which the cities of the world belong. It describes the resource consumption and carbon dioxide emissions of 155 globally representative cities and attempts to formulate a typology of cities based on their metabolic character. The different types can also be seen as representing cities in various stages of industrialization and development, and give valuable insight into the associated resource utilization of different modes of economic production.

In addition to providing a rational typology of urban metabolic profiles, this research also has as its objective the development of classification trees that can serve as predictive models to assist the urban metabolism research community when resource consumption data gaps exist at the city level. Based on the decision rules that emerged from the classification tree analysis for each distinct resource, the different levels of predictor variables that suggest low, medium, or high consumption were determined. Thus, cities whose predictor variable characteristics fall within certain ranges are expected to have certain levels of consumption of each resource.

1.4 Scope of Work

1.4.1 Metabolic profiles

This thesis uses classification tree analysis as a data-mining tool to categorize 155 representative cities' annual per capita consumption of the following:

i. Total Energy
ii. Electricity
iii. Fossil fuels
iv. Industrial Minerals & Ores
v. Construction Minerals
vi. Biomass
vii. Water
viii. Total Materials (DMC)

as well as their emissions of carbon dioxide. For the limited subset of cities for which municipal solid waste data are available, observations were made, but the sample was not large enough to allow for the construction of a classification tree.

Four of the materials groups that are included in this study (fossil fuels, industrial minerals and ores, construction minerals, and biomass) are in accordance with the main groups that are included in economy-wide material flow accounts (Eurostat, 2001). Water is not included in material flow analyses because the quantities of per capita water consumption tend to be orders of magnitude larger than all other flows. From an accounting perspective, this would reduce the granularity of material flow indicators with respect to all the other material groups. However, since this work is not concerned with accounting, but rather with disaggregated metabolic profiles, water is an essential material that must be included to give a comprehensive picture of the urban resource burden. The Total Direct Material Consumption category in this study excludes water, as in the Eurostat (2001) methodology.

Furthermore, because we are concerned with the aggregate impact of cities on global climate change, total energy consumption, electricity, and carbon dioxide emissions are also included in the metabolic profiles that define each city type. High values for one or a combination of the three aforementioned categories may indicate leverage points on which cities falling into a particular typology can focus their policy efforts. For example, if a certain city type has low total energy consumption but high carbon dioxide emissions, then this would be suggest that the energy supply mix that these cities rely on are carbon-intensive. Cleaner, alternative energy policies may then be indicated as a priority for these cities, as opposed to reduction in energy consumption.

1.4.2 Classification trees

Classification tree analysis is a primary method used in data mining. Trees are used to predict membership of cases (in this work, cities) in the classes of a categorical dependent variable, based on their measurements of one or more predictor variables.

The classification tree method has much in common with the techniques used in the more traditional data mining methods of discriminant analysis, cluster analysis, nonparametric statistics, and nonlinear estimation. This study makes use only of classification trees. The more traditional data mining methods typically have more stringent theoretical and distributional assumptions; however, as an exploratory technique, classification trees are far more flexible since they are distribution-free and non-parametric.

Classification trees are widely used in applied fields as diverse as medicine (diagnosis), computer science (data structures), botany (classification), and psychology (decision theory). Classification trees readily lend themselves to being displayed graphically, helping to make them easy to interpret. The binary recursive portioning format of the trees also provides insight into the structure of the data without requiring assumptions about distribution to be made.

Breiman et al. (1984) give a number of examples of the use of classification trees. The classic example is that of medical diagnosis. When heart attack patients are admitted to a hospital, dozens of tests are often performed to obtain physiological measures such as heart rate, blood pressure, and so on. A wide variety of other information is also obtained, such as the patient's age and medical history. These are the predictor (or independent) variables. Patients subsequently can be tracked to see if they survive the heart attack for at least 30 days. This outcome is the dependent variable. It is useful in developing treatments for heart attack patients, and in advancing medical theory on heart failure, if measurements taken soon after hospital admission can be used to identify high-risk patients (those who are not likely to survive at least 30 days). One classification tree that Breiman et al. (1984) developed to address this problem was a simple, three question decision tree (Figure 1.4.1). Verbally, the binary classification tree was described by the decision rule, "If the patient's minimum systolic blood pressure over the initial 24 hour period is greater than 91, then if the patient's age is over 62.5 years, then if the patient displays sinus tachycardia, then and only then the patient is predicted not to survive for at least 30 days." Classification trees were selected for this study precisely because such decision rules would be valuable in predicting what typology a city belongs to, based solely on readily available predictor variables.

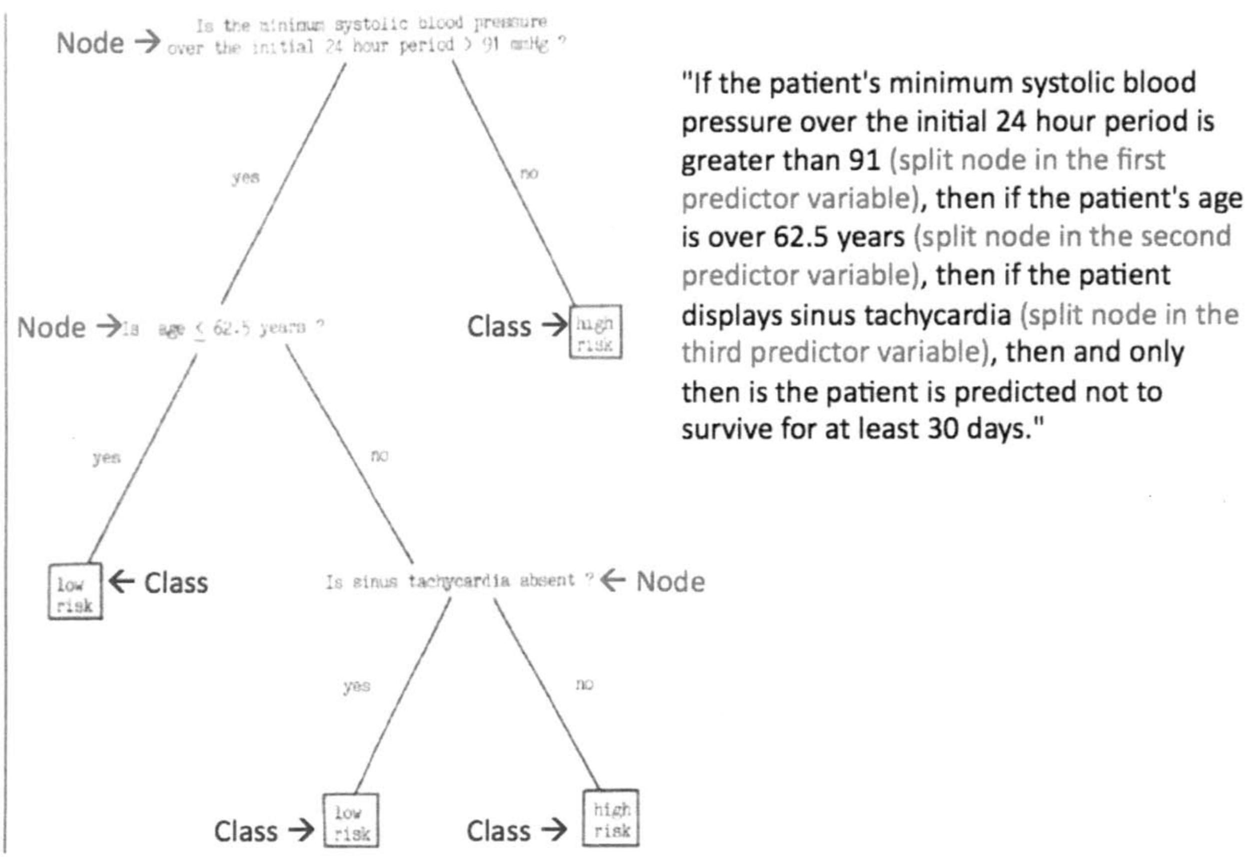


Figure 1.4.1 Breiman et al (1984) classification tree for heart-attack survival

Another aspect of the flexibility of classification trees is that they can be computed for categorical predictors (independent variables), continuous predictors, or any mix of the two types of predictors. In this study, population, density, and city GDP are all continuous variables. On the other hand, climate type is a categorical predictor. Additionally, any monotonic transformation of the predictor variables (i.e., any transformation that preserves the order of values on the variable) will produce splits yielding the same predicted classes for the cases or objects (Breiman et al, 1984). This makes classification trees robust to the assumptions that were necessary to estimate the values of predictor variables.

At this point it is useful to emphasize that the strength of city typology classifications is not their precision of measuring the quantities of particular resources that are consumed by cities. The typology's main motivation is to summarize the consumption of a variety of resources, provide an understanding of their *relative* magnitude and allow for a comparison of metabolic profiles across city types. The findings presented here, built exclusively on readily available data (both city-level and national), are primarily a first-order approximation of city types and metabolic profiles; however, they point to a method for more reliable assessment and application as a planning tool.

Classification trees are easy both to update as more refined training data become available, and to use when classifying cities that were not used as part of the model training set.

Chapter 2. Literature Review

2.1 *Urban Metabolism*

Urban metabolism as a research area has been building on the field of industrial metabolism since the mid-1960s, when Abel Wolman (1965) first applied the biological concept of metabolism to a hypothetical U.S. city of 1 million inhabitants. “Industrial metabolism” is a field of study in which the flow of materials and energy through a chain of extraction, production, use, and disposal are analyzed in order to arrive at some measure of the impacts of anthropogenic activity on the environment (Fischer-Kowalski, 1998).

The biological definition of metabolism refers to the biochemical reactions that living cells carry out in order to sustain the processes of life. These reactions convert raw materials from the environment into energy, proteins and other substances that living things need to maintain their bodily functions, grow and reproduce. Furthermore, metabolic reactions proceed down what are known as ‘metabolic pathways’, sequences of reactions that are ordered such that the product of a reaction is the input to the succeeding one (Odum, 1971). This concept heavily influenced the field of industrial metabolism, and was first applied in the development of eco-industrial parks, which are industrial complexes in which companies are co-located such that the product and even the waste of one manufacturing or industrial process is the input to another.

Fischer-Kowalski (1998) argues that ‘societal metabolism’ is the sum total not only of individual human beings’ biological metabolic processes, but also of the collective effort of human communities to ensure their survival and growth. Under this definition the total material and energy throughput of societies, as well as the self-organization that governs these flows, is then what constitutes societal metabolism.

In terms of urban metabolism, it has always been the surplus borne of human self-organization that has historically allowed for the formation of cities. When agricultural surpluses were great enough to allow for differentiation and the division of labor, urban agglomerations formed, in which workers involved in industry and non-farm work could be supported by the food grown in the surrounding rural areas.

In 2008, Krausmann et al stated that socio-ecological systems with similar energy sources and conversion technologies also share patterns and levels of resource use (metabolic profiles). In fact they termed these classes of systems with a common energy system as socio-metabolic regimes. They also posit that specific environmental impacts are attached to particular regimes. Hence it is clear that, for over two centuries, energy and the conversion technologies that various societies use to harness it have been important concepts in the analysis of societal metabolism.

Ayres and Kneese (1969) presented the argument that modern economies draw heavily on free environmental goods such as air and water, and that this results in market externalities, at the expense of environmental quality. They also presented the first material flow analysis of the United States, carried out for the years 1963 through 1965; they based the concept of material flow analysis on the fundamental law of the conservation of mass. In terms of socioeconomic systems, conservation of mass leads to the following equation:

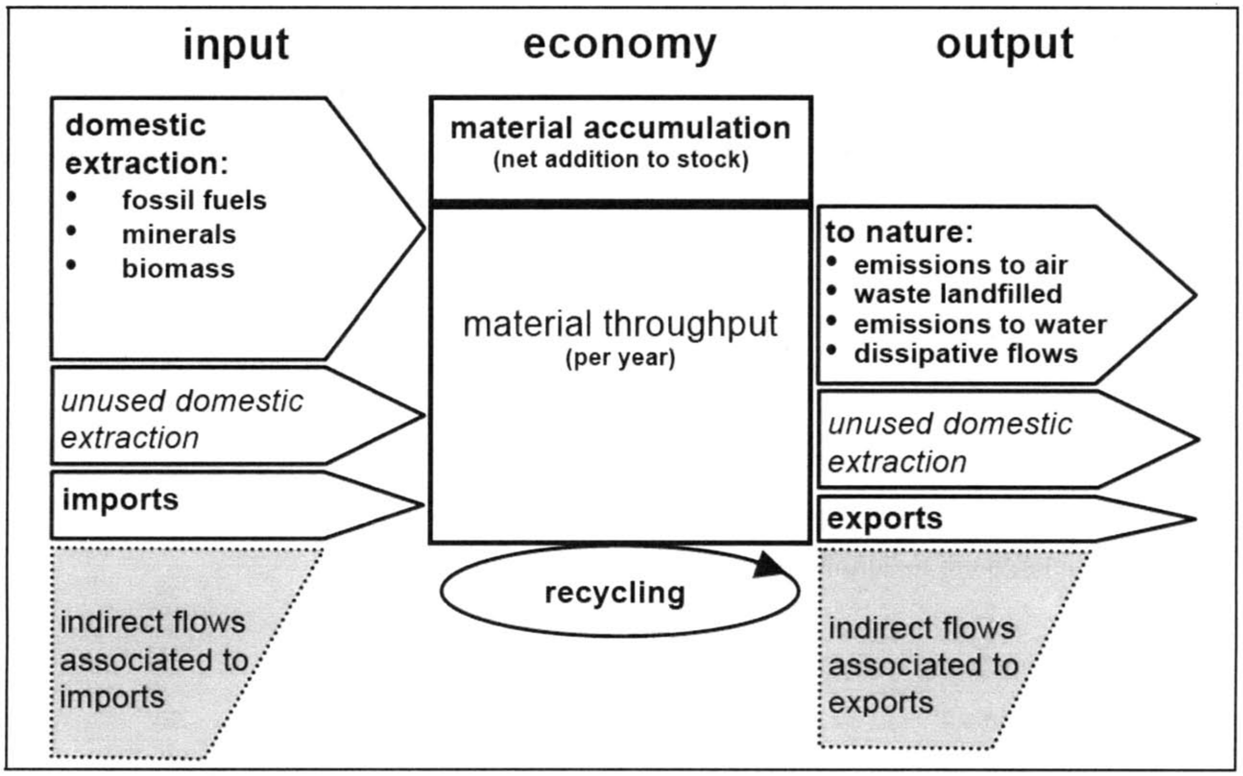
$$\text{Material and Energy Inputs} = \text{Outputs} + \text{Net Additions to Stock}$$

In the previously mentioned work, Ayres and Kneese also presented the only conditions under which the aforementioned environmental externalities would not occur: (1) all inputs to production are fully converted into outputs, with no unused residuals that are not permanently stored (at the expense of the producer); (2) all final outputs disappear when consumed; or (3) property rights are such that all affected environmental goods are privately owned, and these rights are tradable in competitive markets. Since full consumption and recycling of all matter are not achievable, materials balances are essential to determining anthropogenic impact on the environment, and are even useful in allocating responsibility for the flows that are extracted from and released to nature. Ayres and Kneese's work may be considered one of the pillars of industrial ecology, and certainly the fundamental basis of the industrial and urban metabolism fields.

2.1.1 Eurostat (2001) Material Flow Accounts Methodology

The Eurostat methodology for material flow accounting is the most widely used and standardized guide available, focusing on material flow accounts (MFA) and balances for a whole country or economy. Economy-wide material flow accounts and balances show the amounts of material inputs into a country, net additions to stock, and outputs to other economies or back to nature (Figure 2.1.1).

Figure 2.1.1 Scope of economy-wide material flow accounts (Eurostat, 2001)



Research from the past two decades resulted in the publication of 'Resource Flows: the material basis of industrial economies' (Adriaanse et al, 1997) and 'The Weight of Nations – material outflows from industrial economies' (Matthews et al, 2000), which were major moves toward harmonizing the approach to material flow analysis, and the works upon which much of the Eurostat methodology is based.

The need for material flow indicators on the national level came to the fore with the rise in prominence of eco-efficiency as a major environmental concern. In the United

Nations initiative on indicators for sustainable development, the material balance approach supports the derivation of material and resource consumption indicators. This is part of a long-standing push to integrate environmental and natural resource accounts with economic accounts, in order to arrive at a more holistic picture of national development. The rationale behind this is that if a country's economic growth is predicated on the exhaustion of national capital and the fouling of its environment by emissions and other types of output, then economic indicators alone will not reflect the tradeoff that has occurred with respect to long-term sustainability. Furthermore, MFAs can assist in providing indicators for resource *productivity* by relating aggregate resource use to GDP and other economic and social indicators. That is, what are the resources requirements associated with delivering a certain level of development, affluence, or lifestyle to a particular country, region, or society? The resource use indicators can also be used directly to inform resource and waste management policy-making.

Economy-wide MFA and balances are the primary analytical framework of societal metabolism. Material flow analyses are an established way to provide an aggregate overview of annual material inputs and outputs of an economy, including imports and exports. Various material flow-based indicators can be derived from the analysis. One of the most important of these indicators is Total Material Consumption (TMC), which is analogous to the national economic accounts indicator GDP.

Material inputs are classified into three main material groups:

- fossil fuels
- minerals (further subdivided into industrial minerals & ores, and construction minerals)
- biomass (from agriculture, forestry, fishing or hunting).

Material flow analyses that have been carried out to date have shown that water flows are typically one order of magnitude larger than all other materials. In order to deal with this issue, flows of water are calculated and presented separately.

Defining the system boundary is one of the most important issues in economy-wide material flow accounting. Because the focus is on national resource consumption and impacts, the convention has been to define the system boundary as follows:

a. by the extraction of raw, crude or virgin materials from the national environment and the discharge of materials to the national environment;
b. by the political (administrative) borders that determine imports and exports;
c. natural flows into and out of a country's geographical territory are excluded.

Material flows within the economy are not presented in economy-wide MFA and balances, although such flows would be of interest in industrial or urban metabolism studies that examine particular chains of production or specific cities, respectively.

The guiding principle of economy-wide material flow methodology is that the accounts and balances should be consistent with national economic accounts. These define the national economy as the "activities and transactions of producer and consumer units that are resident (i.e. have their center of economic interest) on the economic territory of a country". In order to maintain the consistency of physical accounts with economic accounts, the same residence principle is applied in material flow analyses. Thus, materials purchased (or extracted for use) by 'resident units' of a particular country, such as tourists abroad, are considered material inputs (and emissions abroad are considered material outputs) of the economy in which the tourists permanently reside. In practice, however, the Eurostat methodological guide suggests that information relating to tourism and international transport are disproportionately difficult to obtain. Thus, it is suggested that readily available national data should be used instead.

The following is a list of the aggregate resource indicators that are calculated based on material flow accounts and balances:

- Direct Material Input (DMI) – measures the input of materials for use in the economy, i.e. all materials that have economic value and are used in production and consumption

DMI (direct material input) = Domestic extraction (used) + Imports
= DMO + NAS (net additions to stocks)

- Total Material Input (TMI) – includes DMI as well as unused domestic extraction, i.e. materials that are moved by economic activities but that do not serve as input for production or consumption activities (mining overburden, etc.). Unused domestic extraction is also referred to as 'domestic hidden flows'.

- Total Material Requirement (TMR) – includes TMI as well as the (indirect) material flows that are associated with imports but that take place in other countries.

TMR (total material requirement) = Domestic extraction(used+unused) + Imports + indirect flows imported

- Domestic Total Material Requirement (domestic TMR) – includes domestic used and unused extraction, i.e. the total of material flows originating from the national territory.

Domestic TMR = TMI – Imports

- Domestic material consumption (DMC) – measures the total amount of material directly used in an economy (i.e. excluding indirect flows)

DMC (domestic material consumption) = Domestic extraction (used) + Imports – Exports

- Total material consumption (TMC) – measures the total material use associated with domestic production and consumption activities

TMC (total material consumption) = TMR - Exports - indirect flows exported

- Net Additions to Stock (NAS) – measures the 'physical growth of the economy', i.e. the quantity (weight) of new construction materials used in buildings and other infrastructure, and materials incorporated into new durable goods such as cars, industrial machinery, and household appliances.

- Domestic Processed Output (DPO) - the total weight of materials, extracted from the domestic environment or imported, which have been used in the domestic economy, before flowing to the environment. Included in DPO are emissions to air, industrial and household wastes deposited in landfills, material loads in wastewater and materials dispersed into the environment as a result of product use (dissipative flows). Recycled material flows in the economy (e.g. of metals, paper, glass) are not included in DPO. This indicator represents the total quantity of material leaving the economy after use either towards the environment or towards the rest of the world.

DMO (direct material output) = DPO (domestic processed output to nature) + Exports

In sum, the input indicators arising from material flow accounts and balances measure the physical bases that sustain a country's economic activity, including production for exports. These indicators reflect the dominant modes of economic production. As important as being able to show absolute amounts of input and consumption is the ability of indicators to express material efficiency (unit of GDP per unit of material indicator) or material intensity (material indicator per GDP).

2.1.2 Existing urban metabolism studies

Material flow analyses and balances for cities are rare and, as yet, unstandardized. There are some notable examples of urban metabolism studies that have been carried out to date, one case being that of Hong Kong. Warren-Rhodes and Koenig (2001) updated the pioneering Newcombe et al. (1978) study of Hong Kong's metabolism, analyzing trends in material consumption and waste discharges. Hong Kong is an extremely dense, highly developed coastal city whose economic base transitioned in the 1960s from being a major trading post, to light industry, and finally to service and financial industries in the 1990s. Rapid industrial and economic growth during these decades resulted in high pollution levels and resource intensity. The results of the Hong Kong study showed that per capita food consumption grew 20% from 1971 to 1997, water consumption increased by 40% during the same time period, and materials consumption grew 149%. On the output side, the 10% annual increase in per capita GDP was accompanied by 30% growth in total air emissions, 250% in CO_2, 245% in municipal solid waste, and 153% increase in sewage discharge. Regardless of these increases Warren-Rhodes and Koenig point out that, in comparison to other developed economies, Hong Kong has lower per capita infrastructure stock, and lower energy and materials use. The analysis of trends in Hong Kong's urban metabolism laid the foundation for speculating on the patterns of metabolism that other rapidly growing cities in China would experience.

Kennedy et al (2007) compiled data from eight urban metabolism studies to examine how the metabolism of cities has been changing over time. Material flow analyses from Brussels, Tokyo, Hong Kong, Sydney, Toronto, Vienna, London, and Cape Town revealed that metabolic rates have generally been increasing in these areas. There are some exceptions, however; per capita energy and water consumption in Toronto plateaued in the 1990s. Recycling programs in cities resulted in decreases in residential waste, but similar decreases were not experienced in the commercial and industrial sectors. Most notably, Kennedy et al called for research to be carried out to identify different classes of urban metabolism. They suggested that climate is a likely determinant of particular types of metabolism, along with a city's stage of development, among other factors. The identification of such a typology would assist urban policy makers in understanding the metabolism of the cities for which they are responsible.

Kennedy et al (2007) state that "It is practical for them to know if they are using water, energy, materials, and nutrients efficiently, and how this efficiency compares to that of other cities". This is a major motivating factor for the research that was conducted in the current work.

2.2 Existing typologies for the classification of countries and cities

A review of existing literature on typologies reveals that most of the research is based on categorizations at the national level, as opposed to the city level. A more urban-focused analysis is necessary to assist in finding solutions for municipal decision makers. Furthermore, typologies of countries and cities are not typically defined based on common patterns of resource consumption.

2.2.1 International development classifications

International development and multilateral agencies have historically developed very simple classifications for countries. They use these for operational, research, and lending purposes, and the groupings are based primarily on geographical regions and per capita income levels. The World Bank, for instance, classifies every economy based on its Gross National Income (GNI) per capita; countries are classified as low income, lower middle income, upper middle income, or high income. Table 2.2.1 shows the three groupings by which the World Bank classifies countries.

Table 2.2.1 World Bank country classifications

By Region	By Income (2008 GNI per capita)	By Lending
East Asia and Pacific	Low-income economies ($975 or less)	IDA
Europe and Central Asia	Lower-middle-income economies ($976-$3855)	Blend
Latin America & the Caribbean	Upper-middle-income economies ($3856-$11905)	IBRD
Middle East and North Africa	High-income economies ($11906 or more)	
South Asia	High-income OECD members	
Sub-Saharan Africa		

A country's lending classification defines the arm of the World Bank from which it is eligible to borrow. The IDA (International Development Association), for example, lends only to the world's poorest countries, including those that are at risk of debt distress. It provides interest-free credits and grants for programs that boost economic growth and living conditions in eligible countries (GNI per capita below an established threshold of US$1135 in fiscal year 2010), and is the major source for donor funds for projects that provide countries with basic social services. This service works in tandem with the International Bank for Reconstruction and Development (IBRD), which provides middle-income countries with capital investment and advisory services. In order to borrow from the IBRD, a certain level of creditworthiness is required. Blend countries including India, Indonesia and Pakistan, are those that are IDA-eligible based on per capita income levels, but are also creditworthy for some IBRD loans. The income categories also inform the operational lending preferences of the World Bank, for instance, certain income groups are preferentially given funding for civil works.

Classifications according to geographic regions are made only for low- and middle-income economies, also referred to as developing economies. However, development status does not correspond to particular income levels in all cases, and certainly can have many possible types of associated metabolic profiles.

The United Nations uses a similar classification system to the World Bank, in that it groups countries according to continental regions, geographical sub-regions, and selected economic and other groupings (Table 2.2.2).

Table 2.2.2 Selected economic and other United Nations country groupings

Developed regions Developing regions	In common practice, Japan, Canada and the United States, Australia and New Zealand, and Europe are considered "developed".
Least developed countries	
Landlocked developing countries	
Small island developing States	
Transition countries	Countries in transition from centrally planned to market economies.

It is clear that international development classifications are used primarily for economic analysis, lending, and operational purposes. They do not reflect the metabolic properties associated with countries at particular levels of income or development. Although these groupings may be a starting point for considering the characteristics that countries have in common, they have limited usefulness in the attempt to classify the material and energy requirements of different types of economies.

2.2.2 Evolutionary approaches to classification

Bai and Imura (2000) presented a model of urban environmental evolution that aimed to serve as an analytical framework for the comparison of East Asian cities. As a model of environmental evolution, four sequential stages were described: the poverty stage (poverty-associated issues), the industrial pollution stage (production-associated issues), the mass consumption stage and the eco-city stage (has neither poverty-related environmental problems nor production-related problems; minimal external environmental impacts related to consumption). These stages are not so much city types as they are descriptions of the major environmental problems confronting cities at different stages of urban development. The authors argue that for a particular city at a given time, one of these three types of issues gains dominance, until another group of issues becomes prominent in the succeeding stage of development. The eco-city stage is merely conceptual, and assumes that as the level of economic development increases, citizens will adopt more resource-efficient lifestyles and develop greater environmental consciousness. Bai and Imura (2000) conducted case studies on eight cities in order to present a stage model of urban environmental evolution in East Asian cities, but did not extend the work to the classification of a broader set of urban areas to each of the four stages.

Krausman et al (2008) likewise presented work that may be described as an evolutionary approach to the classification of national resource consumption profiles, i.e. from agrarian to industrial. They posit that the transition from agrarian to industrialized society is a process that is accompanied by distinct biophysical characteristics. They describe agrarian societies as those that are fueled by a solar-based energy system and rely on the energy conversion provided by plant biomass. In other words, solar energy flows are the main energy source, as opposed to fossil fuels. Conversion of solar energy into plant mass resulted in the availability of biomass to support human metabolism (as food), as construction material, and as the primary energy supply. Because of the constraints imposed by "bioconverters" (such as people and animals), the amount of useful energy that could be extracted from biomass was low, and this resulted in limited development within the agrarian regime. In agriculture-based economies, the main resource for production is human labor to cultivate food, animal feed, fibers, and biomass fuel. The sustainability issues that agrarian societies face are primarily related to long-term soil fertility and the sufficiency of food supply in the face of rapid population growth, as well as the effects of climate change on agricultural production.

Population growth is a major element in the positive feedback loop of labor-agriculture-population since the agricultural production process is labor-intensive, resulting in the encouragement of large family sizes and high birth rates.

Disruptive technological change came about due to the ascendance of coal as the main energy carrier in historical industrialization (Freese, 2008). The use of other fossil fuels and types of energy conversion gradually changed the metabolic profiles of transitioning industrial societies, e.g, in the case of England during the Industrial Revolution. Krausmann et al (2008) describe the transition to full industrialization as still being dependent on urban centers existing within a rural periphery. The rapidly growing population relied on the delivery of food from the agricultural hinterlands. The physical linkages between the rural farm areas and the urban/industrial centers were in the form of farm-to-market roads, which necessitated the increased use of construction materials. The basis of the entire industrial economy, therefore, is fossil-fuel energy and the levels of manufacturing and long-distance transport that are made possible by this system. These lead to significant growth in per capita material and energy use, as compared to that of agrarian societies.

Characteristic socio-metabolic profiles for industrialized societies were also described by Krausmann et al (2008), showing tremendous energy and materials usage. There is also a succeeding ("mature industrial") phase in which the service sector dominates national economies. At this later stage, resource- and emissions-intensive activities are shifted to countries that are entering or are in the industrialization phase, and this results in an apparent leveling off of energy and material use in the service economies, although absolute consumption remains high.

In their clustering analysis, Krausmann et al (2008) grouped 175 countries according to their stages in the transition process from the agrarian to the industrial regime (which essentially amounts to the country's development status – industrialized or developing). Population density is the other dimension along which countries were classified; it is a variable that reflects the per capita material and energy intensity of a given level of service delivery, and hence impacts an economy's metabolic profile. Low population density clusters were then subdivided into 'Old World' and 'New World' countries. This resulted in six contemporary "subtypes" of sociometabolic regimes: (1) High Density-Industrialized, (2) High Density-Developing, (3) Low Density-Industrialized-Old World, (4) Low Density-Industrialized-New World, (5), Low Density-Developing-Old World, and (6) Low Density-Developing-New World. Headline indicators of the metabolic profiles of these subtypes include Domestic Energy Consumption and Domestic Material Consumption, both measured on a per capita basis. General results were that developing countries derive a majority of their energy supply from biomass; for industrial countries approximately 75% of primary energy is fossil fuel-based. Most notably, average per capita material and energy consumption was found to be on the order of three to four times higher in industrialized countries than in the developing world.

The work of Krausmann developed a clustering based on the dimensions of level of industrialization and population density, and then examined metabolic characteristics based on those assumed clusters. It did not attempt to perform a clustering analysis *a priori* to determine whether the six groups were in fact those that resulted in the most significant metabolic differences across types. Furthermore, countries were allocated to particular clusters based on the independent variables of level of industrialization and population density, and then the variability of resource consumption profiles within each cluster was merely observed after the fact, to determine whether the countries grouped together in each cluster were reasonably similar in terms of resource consumption.

Chapter 3. Methodology

3.1 Data collection and sources

The aim of this work is to present an analysis addressing the differences in consumption levels across the world's cities, and to discuss the predictive applications of the resulting classification trees. Though the classification is supported with actual data indicated below, the resource consumption profiles and classification trees are not based on a rigorous data analysis at this time, but rather present a theoretical basis for doing subsequent statistical data analysis. Furthermore, the classification tree method is robust to variations in the magnitudes of observations, as long as the ordering across cases is maintained (Breiman et al, 1984).

3.1.1 Predictor (independent) variables

The basic assumption underlying this approach is that different levels of development, population size, density, and climate are indicators of different types of resource consumption. For the most part, these predictor variables are available for most cities in the world. Each of the following four independent (predictor) variables were gathered for the 155 cities in question:

- Population
- Population density
- Climate
- City GDP per capita.

The first two variables are readily available from UNdata, which is a data access system to United Nations statistical databases, which can be reached through a single entry point (http://data.un.org/). City population size and population density are available in the *Population of capital cities and cities of 100 000 or more inhabitants: latest available year (1988 – 2007)* document.

The climate type of each city was taken from the world map of the Köppen-Geiger Climate Classification, a Google Earth layer generated from shape files downloaded from http://koeppen-geiger.vu-wien.ac.at/ from the Department of Natural Sciences, University of Veterinary Medicine, Vienna.

The Köppen climate classification is one of the most widely used climate classification systems, first published in 1884 by the German climatologist Wladimir Köppen. Later changes to the system resulted from a collaboration with the German climatologist Rudolf Geiger. The system is based on the idea that native vegetation is the best expression of climate differences across the world. Hence, climate types are differentiated based on a combination of precipitation, average annual and monthly temperatures, as well as the seasonality of precipitation, which in turn are the major determinants of the dominant types of native vegetation in a region.

The Köppen climate classification scheme divides climates into five main groups and several types and subtypes. In this work, I used only the five main groups to differentiate cities (although none of the selected cities fall under fifth climate type, Polar).

- **GROUP A: Tropical/megathermal climates** – these are characterized by constant high temperature (at sea level and low elevations). All twelve months of the year have average temperatures of 18 °C (64 °F) or higher. Some examples of Tropical cities are:
    - Kuala Lumpur, Malaysia
    - Honolulu, Hawaii, United States
    - Conakry, Guinea
    - Mumbai, India
    - Jakarta, Indonesia
    - Lagos, Nigeria

- **GROUP B: Dry (arid and semiarid) climates** - these are characterized by the fact that precipitation is less than potential evapo-transpiration. Some examples of Arid cities are:
    - Dubai, United Arab Emirates
    - Niamey, Niger

- **GROUP C: Temperate/mesothermal climates**- these climates have an average temperature above 10 °C (50 °F) in their warmest months, and a coldest month average between −3 °C (26.6 °F) and 18 °C (64 °F). Some examples of Temperate cities are:
    - Athens, Greece
    - Cape Town, South Africa
    - Lisbon, Portugal
    - Los Angeles, California, United States
    - Madrid, Spain
    - Santiago, Chile
    - Tel Aviv, Israel
    - Victoria, Canada
    - Tbilisi, Georgia
    - Buenos Aires, Argentina
    - Durban, South Africa
    - Sao Paulo, Brazil
    - Melbourne, Australia
    - Curitiba, Brazil
    - Addis Ababa, Ethiopia
    - Bogota, Colombia
    - Mexico City, Mexico
    - Johannesburg, South Africa

- **GROUP D: Continental/Snow climate** - these climates have an average temperature above 10 °C (50 °F) in their warmest months, and a coldest month average below −3 °C. These cities are usually located in the interiors of continents, or on their east coasts, north of 40° North latitude. In the Southern Hemisphere, Group D climates are extremely rare due to the smaller land masses in the middle latitudes and the almost complete absence of land south of 40° South latitude, existing only in some highland locations. Some examples of Snow cities are:
    - Chicago, Illinois, United States
    - Toronto, Canada

- Belgrade, Serbia
- Bucharest, Romania
- Seoul, South Korea
- Beijing, China
- Minsk, Belarus
- Helsinki, Finland
- Boston, Massachusetts, United States

- **GROUP E: Polar climates - t**hese climates are characterized by average temperatures below 10 °C (50 °F) in all twelve months of the year.

City GDP values, on the other hand, were taken from various sources, including the Global City Indicators Program. The Program encourages member cities to measure and report a core set of indicators through the web-based database found at http://cityindicators.org. Global City Indicators provides a set of city indicators based on a globally standardized methodology, allowing for comparability of city performance and knowledge sharing. Other sources for city GDP values include individual municipal websites. Where the GDP data was not directly available at the city level, GDP of the urban population of each particular country was used.

3.1.2 Consumption (dependent) variables

In 2003, Myers & Kent discussed the influence of a newly affluent middle class on growing consumption in the developing world, as well as in newly industrialized countries. In their work, they pointed out what is one of the major bases of contemporary urban metabolism research: that "growing consumption can cause major environmental damage". They estimate that there are over 1 billion "new consumers", defined as people in developing and transition countries with an aggregate spending capacity equal to that of the United States, which equates to at least US$2,500 per capita at purchasing power parity. In particular, the new consumers possessed twenty percent of the world's cars in 2003, and that proportion is growing rapidly, an observation that is borne out by the acute and rapidly worsening road congestion in cities of the developing world. The dramatic rise in usage of personal automobiles is accompanied by significant growth in carbon dioxide emissions. It is, therefore, beneficial to characterize this and other environmental impacts in cities that have not historically been long-established centers of consumption.

The degree of affluence being discussed in Myers & Kent appears to be the threshold at which purchases of household appliances and televisions, air conditioners, personal computers, and other consumer electronics, a meat-based diet, and cars becomes widespread. Because of increased usage of household appliances and electronics, electricity use (generally fossil-based) in new consumer cities is also growing apace.

The incomes of these so-called 'new consumers' are significantly greater than national averages, income skewedness being a particularly pronounced phenomenon in developing countries. Furthermore, this rise consumption can be directly associated with urban areas, since cities tend to be where the upwardly-mobile professionals reside. The more sophisticated lifestyle, with the corresponding purchase of the symbols of affluence, is also more prevalent in the major cities. Thus, this growth in consumption is directly relevant to the study and characterization of the different types of urban metabolism throughout the world. This also underscores the need to include a significant number of developing and transition cities in the model training sample.

In the following paragraphs, I discuss the data sources for the per capita consumption values of each of the eight resources that are being tracked in this work, as well as carbon dioxide emissions.

i. Total Energy
ii. Electricity
iii. Fossil fuels
iv. Industrial Minerals & Ores
v. Construction Minerals
vi. Biomass
vii. Water
viii. Total Materials (DMC)

Data used for the dependent (consumption) variables consist of country-level data and individual city-level data. Country-level data for 175 countries from the Institute of Social Ecology Vienna (www.uniklu.ac.at/socec/inhalt/1088.htm) were used out of necessity to provide a general picture of the resource consumption of each city. A major obstacle in conducting this cross-city comparison was lack of complete consumption data at the city level and the comparability of the available data.

The national figures from the Institute of Social Ecology were the starting point for assessing city-level resource consumption. These national estimates are quite reliable, as official data on national production and the import and export of all major resources and goods are readily available.

Bettencourt et al (2007) presented analyses showing that certain processes (like consumption) related to urbanization are similar among cities, even across different countries. They show that power law functions of population size describe different urban phenomena. In their work, empirical evidence was presented regarding important socioeconomic and consumption indicators as scaling functions of city size that are quantitatively consistent. The most popular example of such a scaling function is Zipf's Law for the rank-size distribution of city population sizes.

Bettencourt et al (2007) gathered an extensive set of data, across various national urban systems, on phenomena that include energy consumption, economic activity, and infrastructure, among others. The power scaling laws take the form of (Bettencourt et al, 2007):

$$Y(t) = Y_0 N(t)^{\beta}$$

where N(t) = city population at time *t*

Y(t) = consumption of resources (such as energy, infrastructure, others), measures of social activity (such as pollution)

Y_0 = normalization constant

β = scaling exponent governing the relationship between population size and the behavior, Y(t).

Bettencourt et al found robust scaling exponents across different countries, levels of development, and time periods for a variety of indicators, including various consumption measures. This implies that cities that appear very different in form and geographic location are actually scaled versions of one another. The scaling relationship that I make use of in the present work is that associated with total electrical consumption (β = 1.07), a superlinear phenomenon that takes into account not only personal or household consumption, but also increasing returns with population size that reflect industrial and commercial consumption in cities. Because we adopt the β = 1.07 relationship for total consumption of particular resources by a city of population size N(t), then this leads us to the following method of estimating consumption at the city level based on national consumption values.

- For every city i, it is possible to determine how the consumption of a particular resource scales as a function of the city's Population, $N_i(t)$:

$$\alpha = (N_i(t)^{\beta})/N_i(t)$$

- For every city within a particular country, α varies from the largest value for the city with the highest population to the smallest value for the city with the lowest population. If α_0 signifies the scaling ratio for the largest city, then for all other cities i in the same country, α_i/α_0 is the ratio of consumption in city i to consumption in the largest city. This is how differences in consumption among cities in the same country were derived.

The method above was used for all of the resources (and carbon dioxide emissions) except Water. For water, per capita consumption data at the city level were extracted from http://www.ib-net.org, the website for the International Benchmarking Network for Water and Sanitation Utilities (IBNET). IBNET is an initiative to encourage water and sanitation utilities to compile and share a set of core cost and performance indicators, including consumption data for the water utilities serving most cities in the world.

Indirect assessments were necessary for resources other than water because the collection of local material consumption data is limited. Nevertheless, it is sufficient for a first-order approximation that can later lead to a more detailed analysis using the same methodology presented here.

After an extensive search for urban consumption data was carried out, it became evident that the sources listed above are the most reliable information sources available for a broad range of cities. It is recognized that not all data are as definitive as would be ideal. However, the degree of credibility must be balanced against the need to address the phenomenon of growing consumption that has great significance for the environmental sustainability and the quality of life in the cities of the world. The author believes that the development of a resource consumption typology and the methods of analysis that were used to arrive at the prediction model are useful in and of themselves, even though the data at the present time are not as accurate as would be ideal.

The data used for each of the classification trees are shown in Appendix A.

3.2 Classification tree analysis

The classification tree analysis in this work was carried out using R, a language and environment for statistical computing and graphics (http://www.r-project.org/). Using the rpart programs in R, I built classification models using a two-stage procedure; the resulting models are represented as binary trees. A tree-structured classifier is a decision tree for predicting a dependent variable from one or more predictor variables. In a typical classification problem (Breiman et al, 1984), there is a training sample $L = \{(X_1, Y_1), (X_2, Y_2), . . . , (X_N, Y_N)\}$ of N observations, where each $X_i = (x_a, . . . ,x_k)$ is a k-dimensional vector of predictor variables and Y is an independent variable that takes one of j values. The goal of classification methods is to construct a rule for predicting the Y value of a new observation given the values of the vector X. If the predictor variables are all ordered, i.e., non-categorical, some popular classifiers are linear discriminant analysis (LDA), nearest neighbor, and support vector machines. Although these classification algorithms often possess good prediction accuracy, they act like black boxes, in that they do not provide much insight into the roles of the predictor variables in determining the dependent variable.

A classification tree is an attractive alternative because it is easy to interpret. It is a decision tree obtained by recursive partitioning of the X-space, where an observation in a partition is predicted to belong to the Y class with minimum estimated misclassification cost. Classification trees have been demonstrated to possess high prediction accuracy compared to many other methods; see, e.g., Perlich et al. (2003), and Loh (2009). They do not require categorical predictor variables to be transformed.

All classification tree algorithms have to address two common problems: how to split a node in the tree and when to stop splitting it. The first problem is usually solved by means of a node impurity function, with the best split being the one that minimizes a function of the impurities in the subnodes. The second problem is addressed by first growing a large tree and then using cross-validation to 'prune' it to a smaller size.

One advantage of classification trees over traditional data mining techniques is that we can infer from the trees some insights about the importance of the predictor variables. For interpretability, the most desirable tree is one that is neither too small (because it provides little information) nor too big (because it can be challenging to follow the logic contained in several levels of splits).

A classification tree is built by the following process: first, the single independent variable is found which best splits the data into two groups. The data is separated, and then this process is applied recursively to each sub-group, and so on until no further improvement can be made. This results in a model that is almost certainly too complex, therefore, the second stage of the procedure consists of using cross-validation to trim back the full tree (Figure 3.2.1).

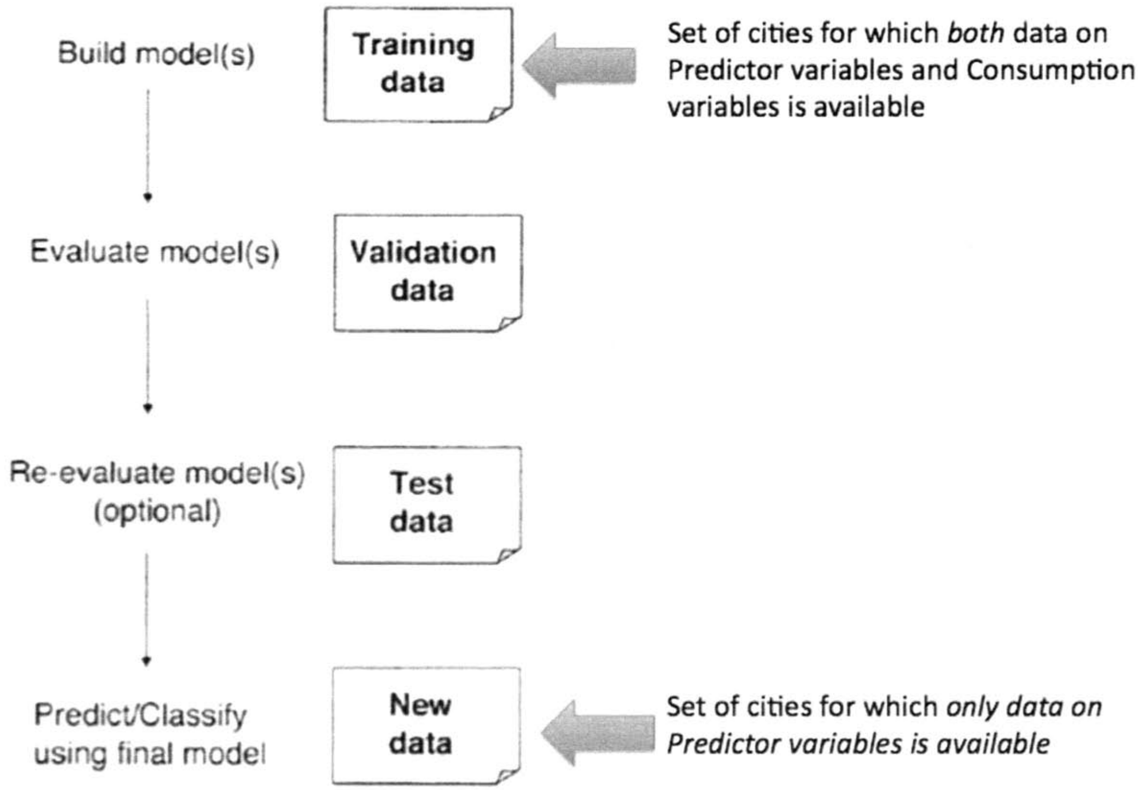


Figure 3.2.1 Flow diagram for building City Typology classification trees

The sample population consists of n observations (n=155 cities) from 3 classes of consumption of each type of resource (Low, Medium, High). A tree for a given resource breaks these cities into g terminal groups; to each of these groups is assigned a predicted class (this is the dependent variable, which takes on a value of consumption, either Low, Medium, or High).

3.2.1 Splitting criterion

Classification tree analysis uses one of several measures of impurity, or diversity, of a node as a splitting criterion (Breiman et al, 1984). We let f be some impurity function and define the impurity of a node A as

$$I(A) = \Sigma f(p_iA) \text{ from } i=1 \text{ to } C$$

where p_iA = the proportion of cases in node A that belong to class i. The goal is for $I(A) = 0$, indicating that node A is pure, or contains cases that all belong to a single class.

The Gini Index for a given node, A, is:

$$GINI(A) = 1 - \Sigma[p(i|A)]^2 \text{ over all classes } i$$

where $p(i|A)$ = the relative frequency of class i at node A

The maximum value of the Gini index is $(1 - 1/n_c)$, when observations are equally distributed among all classes (in our case, Low, Medium, or High). This implies the worst possible split, where n_c denotes the number of classes (in our case, 3). The minimum possible value of the Gini Index, on the other hand, is 0 when all observations belong to a single class. This implies that the split reveals the most amount of information about the data at that node.

When a node A is split into k partitions (child nodes), the quality of the split is evaluated as

$$GINI_{split} = \Sigma(n_j/n)GINI(j) \text{ from } j = 1 \text{ to } k$$

Where n_j = number of observations at child j

n = number of records at the parent node A

Again, the goal is to minimize the Gini Index of a particular split in order to obtain the purest child nodes. The Gini Index is the preferred splitting criterion for growing classification trees because it focuses less on reducing the misclassification rate of a data set, and more on the creation of pure nodes.

3.2.2 Cross validation

Using the Gini splitting criterion, I built classification trees to their entirety, for each resource under consideration. Complete trees are usually quite large and/or complex, and it is sometimes necessary to trim the nodes of the tree in a bottom-up fashion. The pruning process is a tradeoff between misclassification error in the validation data set and the size of the tree (number of terminal nodes).

Realistic estimates of the predictive capacity of a classification tree-based model must take account of the extent to which the model has been selected from a wide range of candidate models. I used the cross-validation approach to determine unbiased assessments of predictive accuracy.

The cross-validation error is relevant to predictions for the population from which the data were sampled. Cross-validation requires the splitting of the data into s subsets (in this case, s = 10). In building the classification trees, each of the 10 subsets of the data was left out in turn, the model was fitted to the remaining data, and the results were used to predict the outcome for the subset that was left out. One such division of the data is known as a fold, for each of the 10 subsets. At the s^{th} fold, the s^{th} subset has the role of test data, with the remaining data having the role of training data.

In a classification model, prediction error is usually determined by counting each incorrectly classified record. Cross-validation is an unbiased estimate of predictive power, because the model was developed independently of the data to which it is applied (the s^{th} excluded subset). However, the estimate is for a model that uses, on average, a fraction $(k - 1)/k$ of the data. An estimate of average error is found by summing up the measure of error over all observations and dividing by the number of observations. Once predictions are available for each of the subsets, the average error is taken as (total error)/total number of observations.

Cross-validation provides an evaluation of the variation in prediction error associated with various tree sizes. This is why it is typical to build a tree that has the maximum number of splits (or is over-fitted), and then to prune to a tree size that has close to the minimum cross-validated prediction error.

3.2.3 The cost-complexity parameter

Rather than controlling the number of splits directly, this parameter is controlled indirectly, via the quantity c_p (complexity parameter) that imposes a penalty for each additional split. Further splitting stops when increases in cost outweigh the reduction in lack of fit. A high value of the complexity parameter leads to a small tree (additional cost rapidly offsets additional increases in fit), while a low value leads to a complex tree. Thus, the choice of c_p is a proxy for the number of splits.

For each resource, I fitted a tree that was complete, i.e., one for which the Gini Index could not be improved by adding more splits. The cross-validated relative error was then plotted against c_p, and then the value of c_p for which the tree was optimal was determined. Having identified the optimal tree (with minimum cross-validation error rate), succeeding splits were then pruned off. The optimal tree is the smallest tree whose error is less than (minimum error + 1 standard deviation) (Breiman et al, 1984).

3.3 Categorization of urban metabolic profiles

The goal of this work is to find evidence showing that differences do exist in urban metabolic profiles, and to present a typology of cities based on the differences in these profiles. The following approach was adopted in developing the typology of cities:

- First, the levels of consumption (Low, Medium, and High) were taken for the eight resources, as well as carbon dioxide emissions, for every city under consideration.
- The resource consumption profile was developed for each city, reflecting the levels of consumption of the eight resources and carbon dioxide emissions.
- The 155 profiles of the cities were compared and grouped according to which profiles were either identical or without major differences in the consumption levels for each of the resources, and for carbon dioxide emissions. Note that only similarities in level of consumption of each type of resource were considered, without regard for the independent variables used in the classification tree analysis.
- Each group with identical resource consumption profiles constitutes one type of city, and the drivers that generate each distinct type of profile were analyzed.

The results of this categorization, as well as those of the classification tree analysis, are shown in Chapter 4.

Chapter 4. Results

4.1 Map of the 155 Representative Cities

The initial phase of this work involved the selection of a set of cities that spanned the entire range of the world's geography, affluence/level of development, population size, population density, and climate. Priority was given to selecting national capitals and major cities, although this set includes smaller cities as well.

Figure 4.1.1 situates these cities on a 'map', relating the Human Development Index (HDI) of the country in which a city is found to the city's population density, population size, and Koppen climate classification. At this point, no consumption variables have yet been introduced. We are merely observing which cities are similar, in terms of the selected predictor variables. The goal of the 155 Representative Cities Map is to visualize the way cities can be grouped based on the following variables:

- Population
- Population density, persons/sq.km
- Human Development Index
- Climate

I took a sample of 155 cities that run the gamut of these four characteristics, proportionally representing geographical regions according to the percentage of the world urban population residing there. Based on this representative sample, it was possible to discern a number of city types. In the interests of arriving at a limited number of groups, and recognizing that there may be significant variability among the cities in each group, the HDI – Population Density space was divided into Low, Lower Middle, Upper Middle, and High HDI, as well as Low, Medium, High, and Very High population density (Table 4.1.1). This division appears to reasonably capture the major concentrations of the cities on the map, whether by population size or climate. Figure 4.1.1 shows the map containing all the cities and their respective populations (denoted by the size of the circles), population density, Human Development Index, and climate (denoted by the color of the circles).

Figures 4.1.1a, 4.1.1b, 4.1.1c and 4.1.1d show the distribution of cities in this space according to climate type. Tropical cities are the most widely dispersed, appearing in all zones in which any city can be found; Temperate cities (although comprising the largest fraction of the 155 Cities) are found in slightly fewer groups. Arid cities are not represented in the Mid to Very High density – High HDI region, while cities with the Snow climate appear to be concentrated in the Low to Mid density – Upper Middle to High HDI area.

From Figure 4.1.1 it may be noted that in the High Density – High HDI region the cities are all Temperate, with the exception of Seoul (the most populous city in this group), which has a Snow climate. The Very High Density cities are all Tropical (and Middle HDI), with the exception of Cairo, which is an Arid city. Upon examination of the upper left and lowest left regions, we see that the High HDI – Low Density space is dominated by Temperate cities, while the Low HDI – Low Density space has almost exclusively Tropical cities. For the Low HDI range, the cutoff population density for this set of cities is approximately 15,000 persons per square kilometer; the maximum density for the High HDI range is approximately 20,000/sq.km. Two thirds of the cities in this sample (6 out of 9) with population ≥ 10 million people are located in the Middle density – Upper Middle HDI region, none of which are Arid.

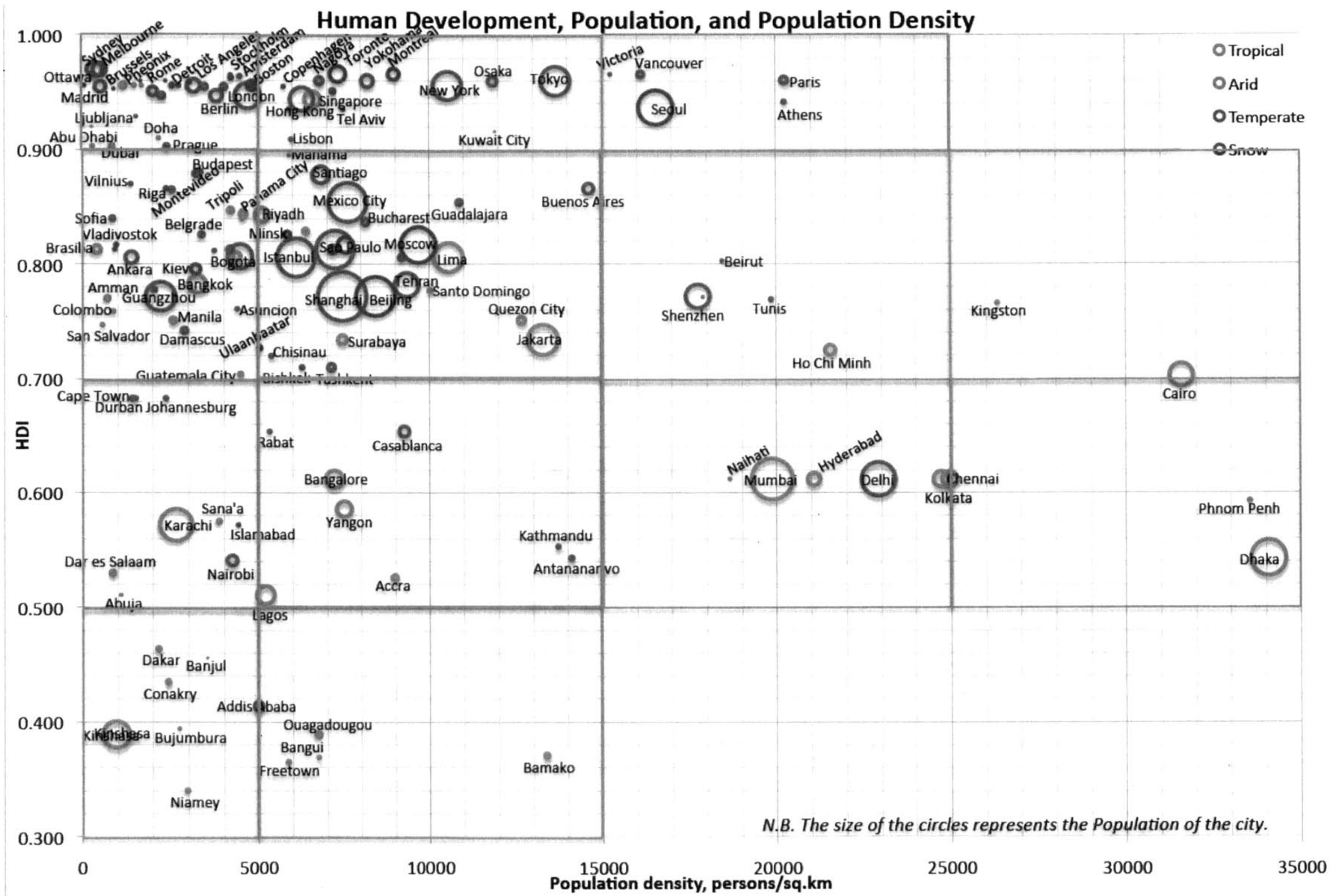


Figure 4.1.1. Map of 155 representative cities on the Human Development Index – Population – Population Density space

POPULATION DENSITY, PERSONS/SQ.KM

HDI	Low (0 – 5000)	Middle (5000 – 15000)	High (15000 – 25000)	Very High (25000 – 35000)
High (0.9 – 1)	Mostly **Temperate**, some **Tropical**, **Arid**, **Snow**; Interquartile Population Range: 400 thousand - 2M	Mostly **Temperate**, Some **Snow**, **Tropical**; Interquartile Population Range: 600 thousand - 4.7M	Mostly **Temperate**; One city >10M; Interquartile Population Range: 700 thousand - 2.2M	
Upper Middle (0.7 – 0.9)	Mostly **Temperate** and **Tropical**, some **Arid** and **Snow**; Interquartile Population Range: 500 thousand - 1.9M	Mostly **Temperate**, Some **Tropical**, **Snow**, **Arid**; Most of the cities>=10M belong to this type	**Temperate** and **Tropical**; Interquartile Population Range: 300 thousand - 3.1M	Mostly **Tropical**; One city>10M; Interquartile Population Range: 600 thousand - 7.7M
Lower Middle (0.5 – 0.7)	**Temperate**, Some **Tropical**, **Arid**; Interquartile Population Range: 600 thousand - 1.4M	**Tropical** and **Temperate**; Interquartile Population Range: 900 thousand - 4.7M	Mostly **Tropical**; Some cities~10M	
Low (0.3 – 0.5)	mostly **Tropical**; Interquartile Population Range: 400 thousand - 1.9M	Some **Tropical**, **Arid**; Interquartile Population Range: 700 thousand - 1.4M		

Table 4.1.1. Description of city groups on the Human Development Index – Population – Population Density space

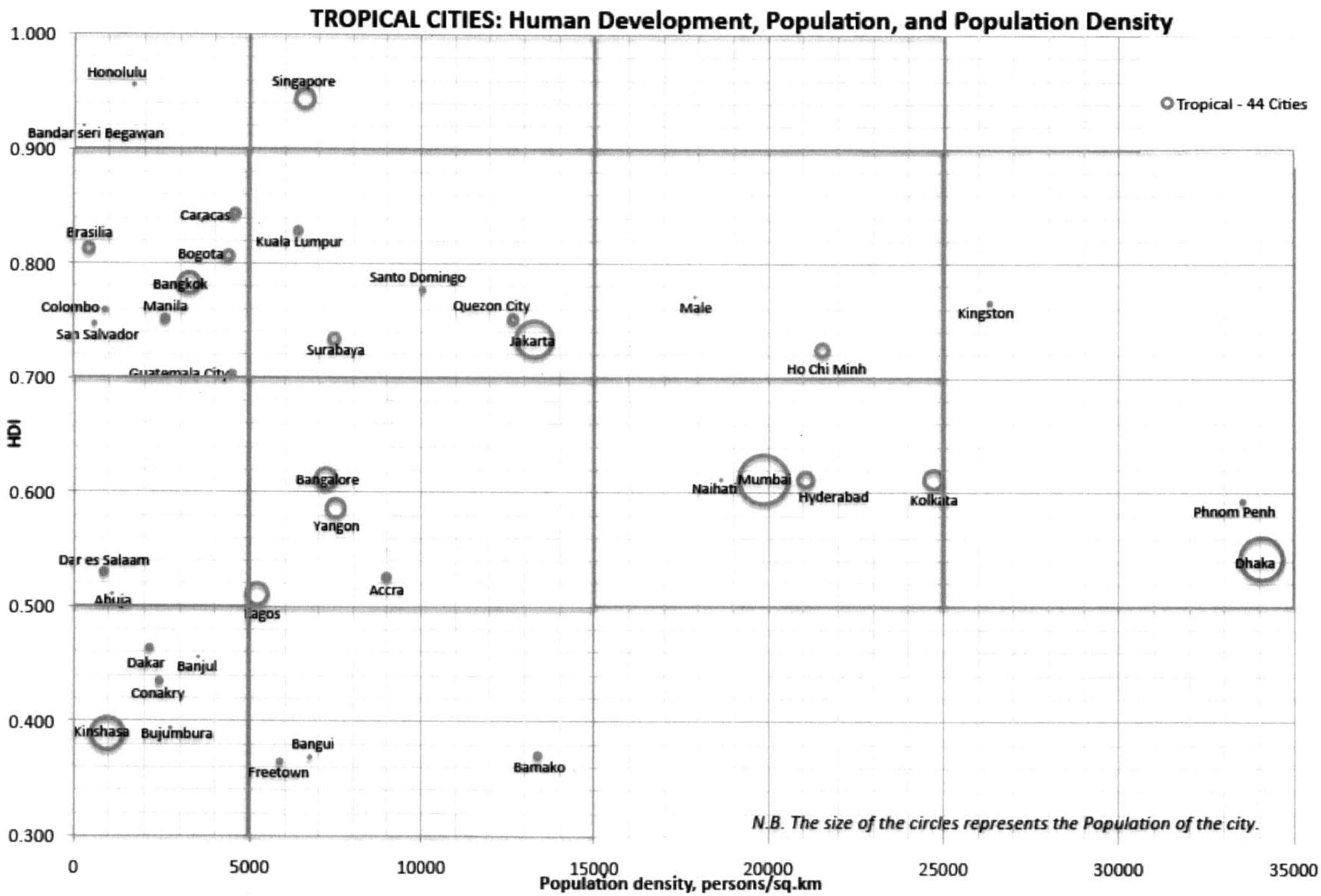


Figure 4.1.1a. Tropical cities on the Human Development Index – Population – Population Density space

Representation of Tropical cities in the High HDI range is limited, and occurs at densities below 10,000 per square kilometer. The majority of Tropical cities are found in the Lower Middle and Upper Middle HDI range, and span densities from Low to Very High. Three out of four of the Very High Density cities are Tropical. The Tropical cities with population ≥ 5 million are also concentrated in the Middle HDI – Middle to Very High density band. This suggests that the least developed countries in the tropics are still in the opening stages of large-scale urbanization, while the absence of Tropical cities with population ≥ 5 million in the High HDI band implies that there may be some factor that limits city size in highly developed countries. The upper left region of the map (Low Density – High HDI) contains Tropical cities with population less than 500,000. Detailed population distributions within each city group are shown in Figure 4.1.2.

Figure 4.1.1b shows the majority of Arid cities in the Low Density band (with HDI ranging from Low to High). As we observed with the Tropical cities, the largest of the Arid cities (population ≥ 5 million) are found in the Lower Middle to Upper Middle HDI range, across all population densities. Despite containing the fewest cities among the four climate types, Arid cities have greater dispersal across both population density and HDI than do the cities with Snow climates.

Figure 4.1.1c maps Temperate cities on the HDI – Population density space. These cities are concentrated in the Upper Middle to High HDI – Low to Middle density region, although dispersal of Temperate cities across this map is second only to that of Tropical cities. With the exception of Addis Ababa, there are no Temperate cities to be found in the Low HDI band (in this sample). Approximately half of the representative cities with population ≥ 5 million are temperate, and the largest city (Shanghai) is Temperate. Furthermore, half the representative cities with population ≥ 10 million are also Temperate; these cities are concentrated in the Upper Middle HDI – Middle density region. The Upper Middle to High HDI band is also dominated by Temperate cities.

In Figure 4.1.1d we see that the Snow climate cities are almost entirely in the Upper Middle to High HDI – Low to Middle density region, with the exception of Seoul, which is in the High density – High HDI space. Seoul is one of three Snow climate cities in the sample with population ≥ 10 million; the other two are Beijing and Moscow. In the Low density – Upper Middle to High HDI region, almost all of the Snow climate cities have population under 1 million.

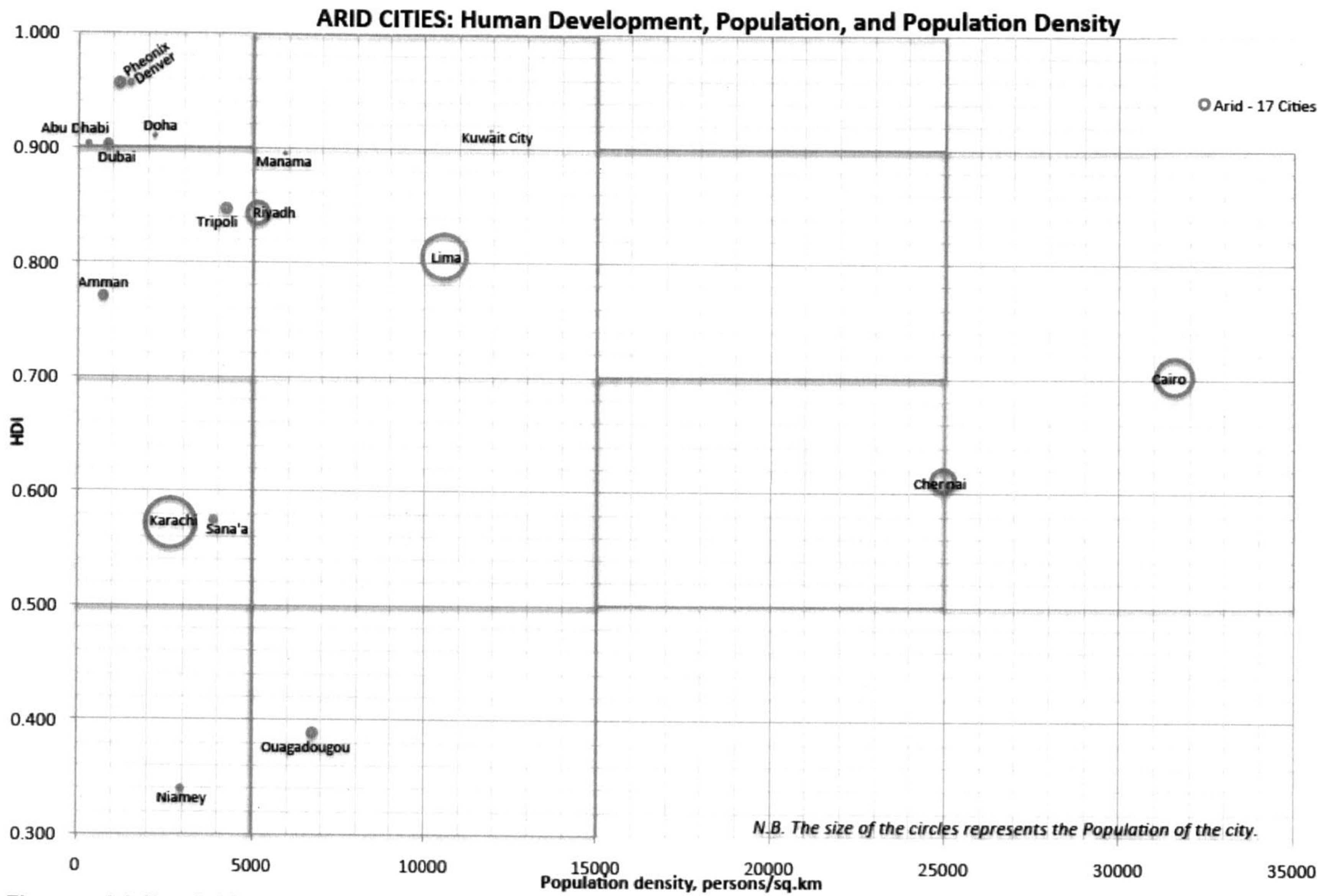


Figure 4.1.1b Arid cities on the Human Development Index – Population – Population Density space

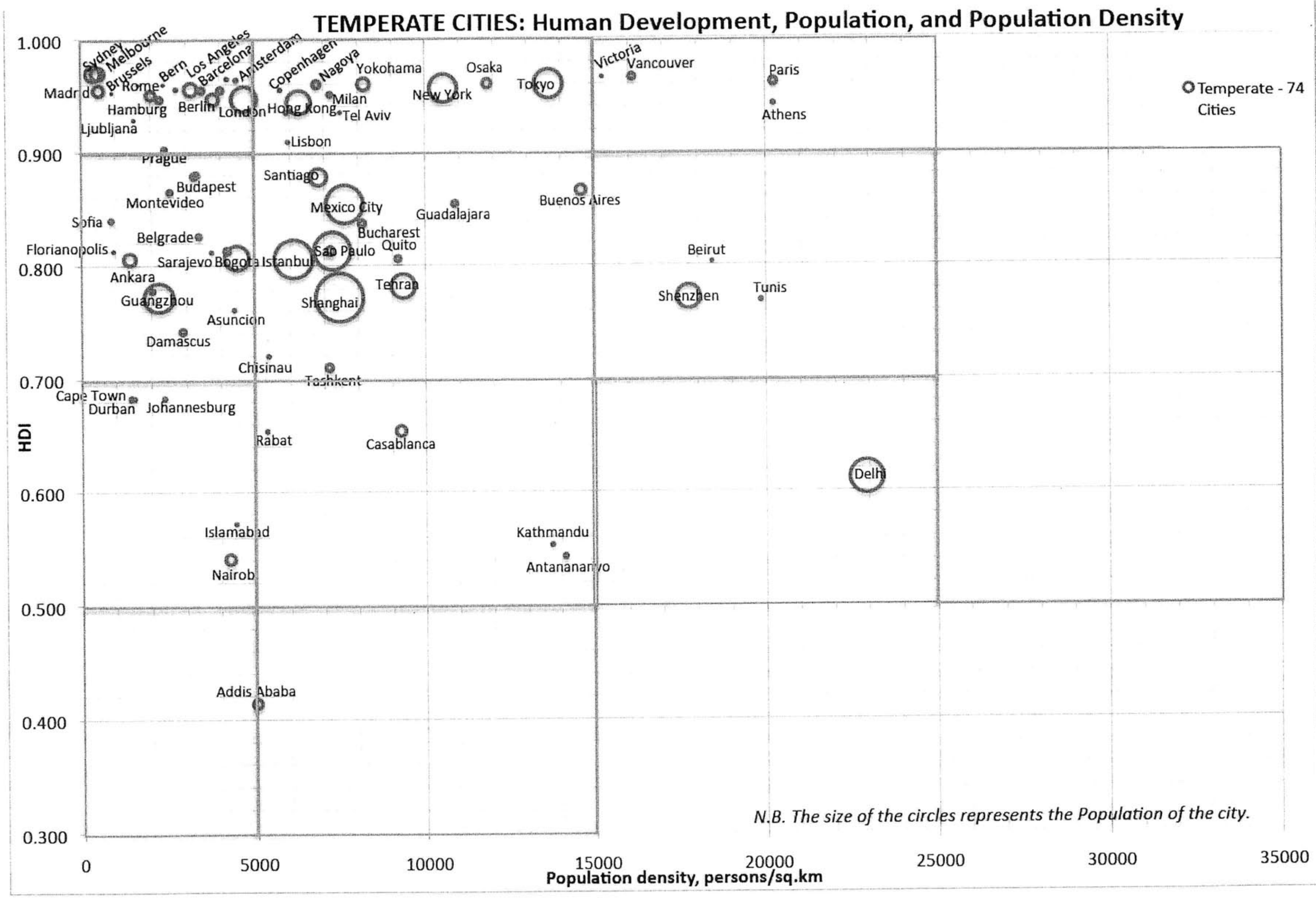


Figure 4.1.1c Temperate cities on the Human Development Index – Population – Population Density space

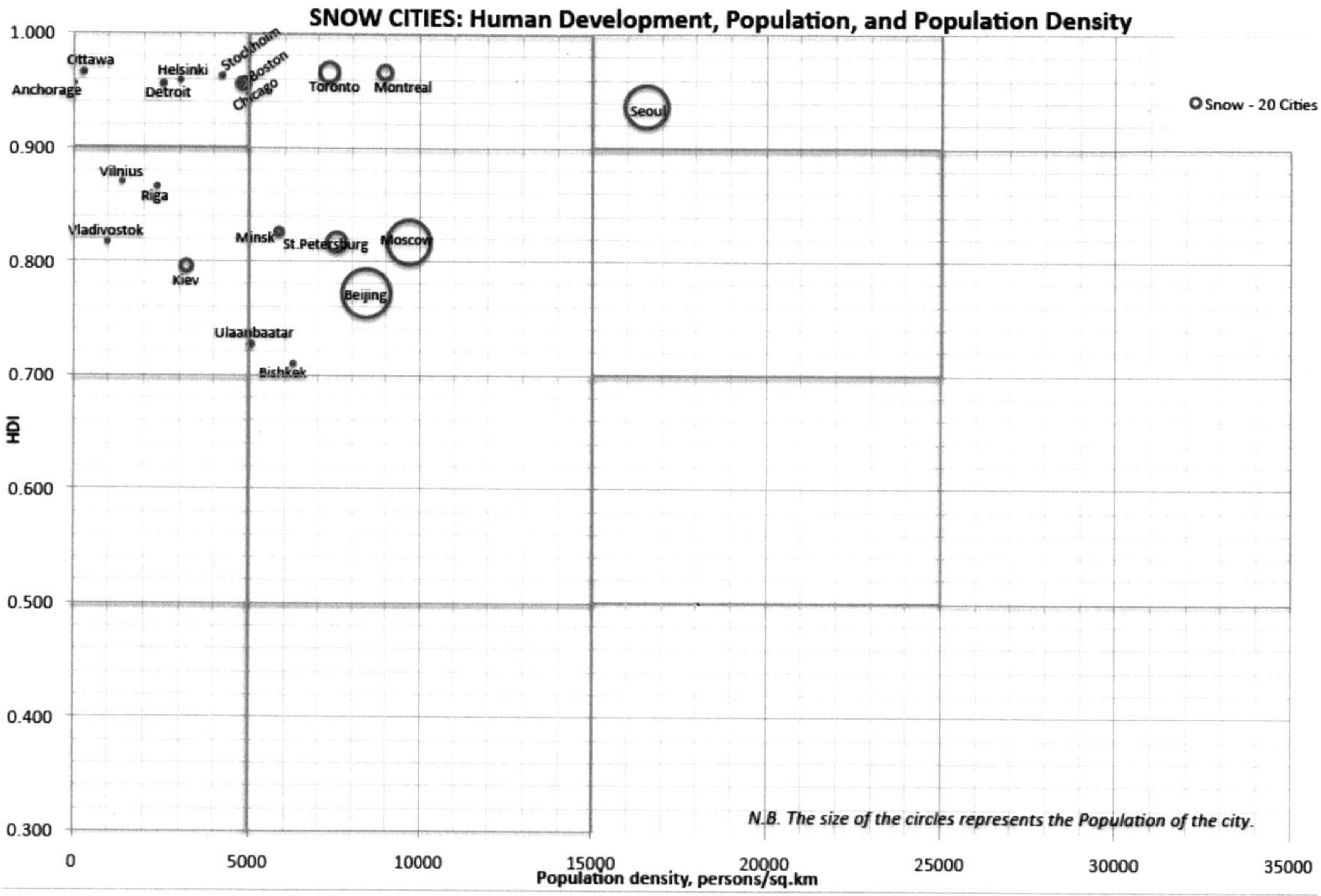


Figure 4.1.1d Snow climate cities on the Human Development Index – Population – Population Density space

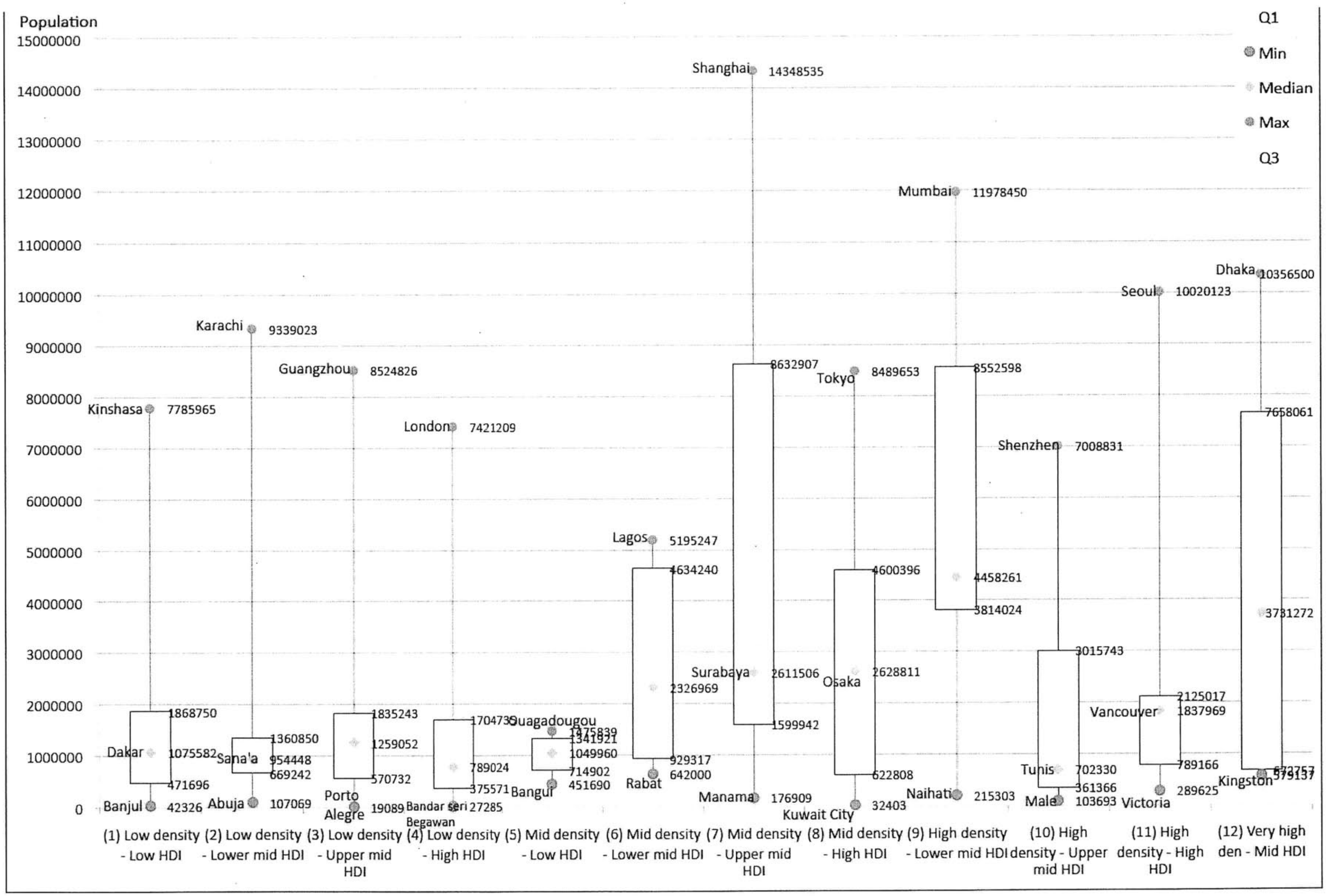


Figure 4.1.2. Population size distribution within city groups

Figure 4.1.2 shows the population size distribution of cities within each of the 12 Population Density – HDI groups. The box plots show the interquartile population range of cities across the different combinations of Population density and HDI, as well the maximum and minimum city populations for each group. A box plot is a convenient way of graphically depicting the populations of the cities in each group through their five-number summaries: the smallest observation (minimum population), lower quartile (Q1), median, upper quartile (Q3), and largest observation (maximum population). A box plot may also indicate which cities, if any, might be considered outliers. The interquartile range (difference between Q1 population and Q3 population) shows the population range into which the middle 50% of the cities fall. This is a robust statistic that helps indicate the degree of dispersion in the group.

The Middle density – Low HDI, Middle density – Lower Middle HDI, and High density – Lower Middle HDI groups have interquartile ranges that are approximately equal distances away from the minimum and the maximum populations in the group. This suggests minimal skewness in the populations of the cities in these groups. The Middle density – Low HDI group's cities have populations that are tightly clustered between 700,000 and 1.4 million people.

The rest of the groups' interquartile ranges (the middle 50% of the cities) are significantly skewed toward the smallest city population in the group, suggesting that the largest 25% of the cities are significantly larger than all the rest of the cities. All of the groups in the Low density band, regardless of HDI, have interquartile ranges less than 2 million, and their largest cities have populations between 7 million and 10 million. Furthermore, over 75% of the cities in the Groups 1 through 5 in Figure 7 have population under 2 million people. The High Density – High HDI group also has 75% of its cities with population and interquartile range under 2 million but its largest city, Seoul, has population of 10.02 million.

Groups 6, 8, and 10 have interquartile ranges between 2 million and 4 million, implying a larger spread in city population in these groups. Seventy five percent of the cities in these three groups have population under 5 million. Groups 7, 9, and 12 have the widest interquartile ranges and also the largest cities, with 75% having population under 9 million, and largest cities all with population greater than 10 million. Furthermore, Group 7 (Middle Density – Upper Middle HDI) contains the majority of cities with population of 10 million or greater.

4.2 Classification trees and decision rules for the 9 resources

Figures 4.2.1 through 4.2.9 present the results of the classification tree analyses that were conducted on the 155 Cities, for each of the 8 resources and 1 output (carbon dioxide) under consideration, as well as the decision rules that can be used to classify cities that were not included in the training and validation data sets.

Recall that the objective is to classify each city as a Low, Medium, or High per capita consumer of each of the resources in question and a Low, Medium, or High per capita emitter of carbon dioxide. Taking the Total energy consumption tree as an example (Figure 4.2.1), we consider the top node: the label above it indicates the variable represented at this node (i.e. the variable selected for the first split). In this case, that variable is GDP per capita. The value indicates the split threshold -- the value that splits the records entering that node, or US$13,480 in this case. Any city where GDP per capita < 13,480 goes to the left. Any city where GDP per capita ≥ the split threshold goes to the right. The cities going to the left (the ones with lower GDP per capita) then get split up further according to climate (where a = Tropical, b = Arid, c = Temperate, d = Snow). When the condition a, b, or c holds true, the city goes to the left. Otherwise, if it is a Snow city (with GDP per capita < 13,480), it is classified as having Medium total energy consumption per capita. The rest of the tree is read in a similar manner, with cities being classified to the left of a node if the condition at that node is satisfied, or to the right if the city does not satisfy the condition.

4.2.1 Total Energy consumption

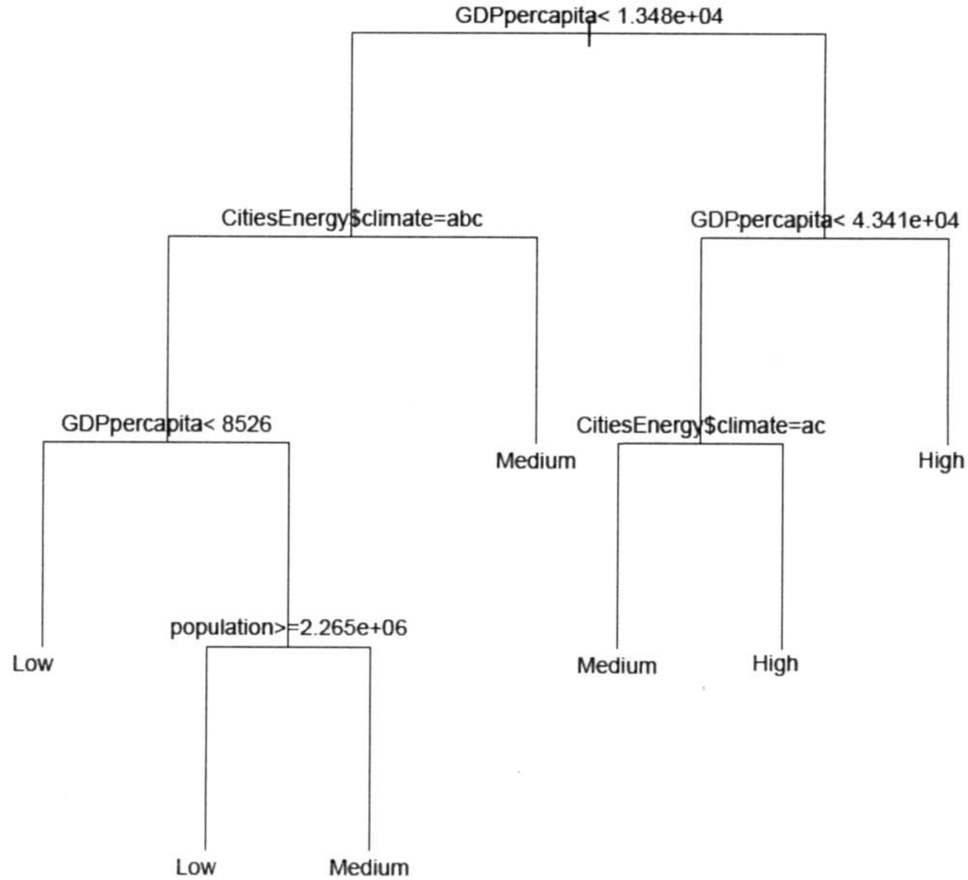


Figure 4.2.1 Total Energy consumption classification tree

The decision rule for the Total Energy consumption classification tree will be described as follows. I will describe the rule that results in classification to the leftmost node first, and proceed from left to right.

- IF GDP per capita is less than 13,480 (2000US$), climate classification is Tropical, Arid, or Temperate, *and* GDP per capita of the cities satisfying the *second* condition is less than 8,526 (2000US$), THEN Total Energy consumption is LOW.
- IF GDP per capita is less than 13,480 (2000US$), climate classification is Tropical, Arid, or Temperate, GDP per capita of the cities satisfying the *second* condition is greater than 8,526 (2000US$), *and* population is greater than or equal to 2.265 million, THEN Total Energy consumption is LOW.
- IF GDP per capita is less than 13,480 (2000US$), climate classification is Tropical, Arid, or Temperate, GDP per capita of the cities satisfying the *second* condition is greater than or equal to 8,526 (2000US$), *and* population is less than 2.265 million, THEN Total Energy consumption is MEDIUM.
- IF GDP per capita is less than 13,480 (2000US$), *and* climate classification is Snow, THEN Total Energy consumption is MEDIUM.
- IF 13,480 ≤ GDP per capita < 43,410 (2000US$), *and* climate classification is either Tropical or Temperate, THEN Total Energy consumption is MEDIUM.
- IF 13,480 ≤ GDP per capita < 43,410 (2000US$), *and* climate classification is either Arid or Snow, THEN Total Energy consumption is HIGH.
- IF GDP per capita ≥ 43,410 (2000US$), THEN Total Energy consumption is HIGH.

4.2.2 Electricity consumption

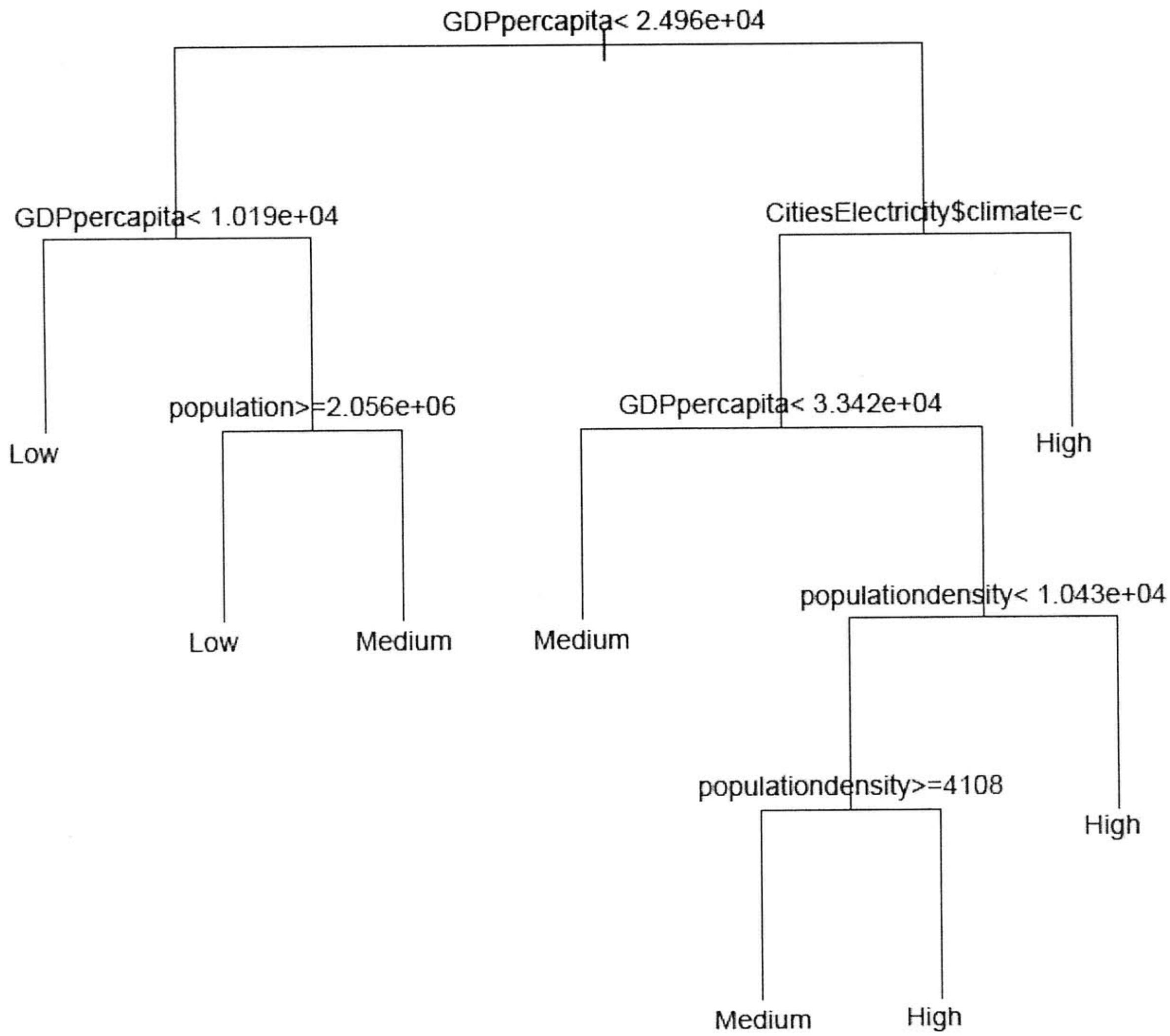


Figure 4.2.2 Electricity consumption classification tree

The decision rule for the Electricity consumption classification tree is as follows:

- IF GDP per capita is less than 10,190 (2000US$), THEN Electricity consumption is LOW.
- IF 10,190 ≤ GDP per capita 24,960 (2000US$), *and* population is greater than or equal to 2.056 million, THEN Electricity consumption is LOW.
- IF 10,190 ≤ GDP per capita 24,960 (2000US$), *and* population is less than 2.056 million, THEN Electricity consumption is MEDIUM.
- IF 24,960 ≤ GDP per capita < 33,420 (2000US$), *and* climate is temperate, THEN Electricity consumption is MEDIUM.
- IF GDP per capita ≥ 33,420 (2000US$), climate is temperate, *and* 4108 ≤ population density < 10,430 per sq.km, THEN Electricity consumption is MEDIUM.
- IF GDP per capita ≥ 33,420 (2000US$), climate is temperate, *and* population density < 4108 per sq.km, THEN Electricity consumption is HIGH.
- IF GDP per capita ≥ 33,420 (2000US$), climate is temperate, *and* population density ≥ 10,430 per sq.km, THEN Electricity consumption is HIGH.
- IF 24,960 ≤ GDP per capita, *and* climate is tropical, arid, or snow, THEN Electricity consumption is HIGH.

4.2.3 Fossil fuel consumption

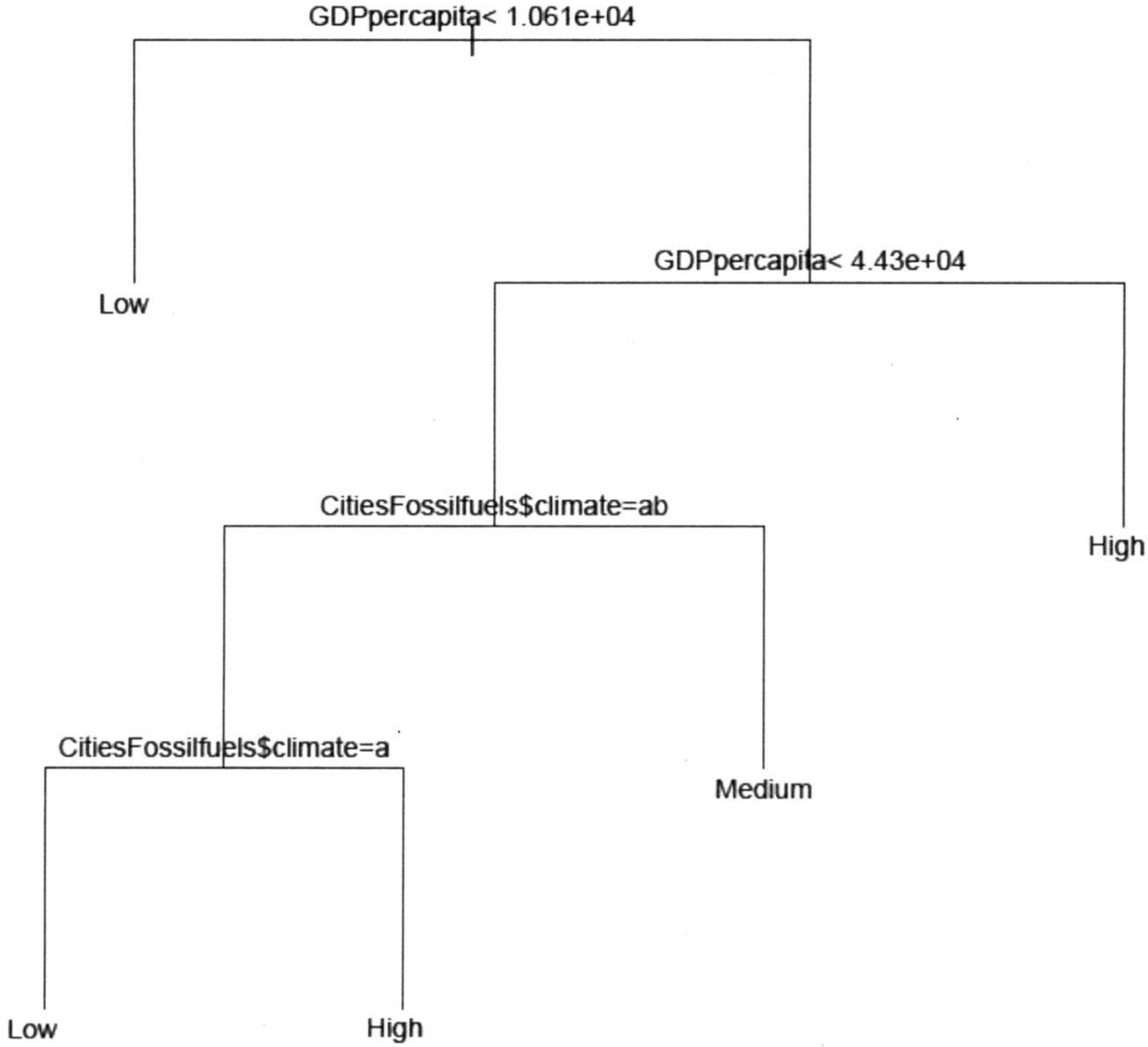


Figure 4.2.3 Fossil fuel consumption classification tree

The decision rule for the Fossil fuel consumption classification tree is as follows:

- IF GDP per capita is less than 10,610 (2000US$), THEN Fossil fuel consumption is LOW.
- IF 10,610 ≤ GDP per capita < 44,300 (2000US$), *and* climate is tropical, THEN Fossil fuel consumption is LOW.
- IF 10,610 ≤ GDP per capita < 44,300 (2000US$), *and* climate is arid, THEN Fossil fuel consumption is HIGH.
- IF 10,610 ≤ GDP per capita < 44,300 (2000US$), *and* climate is either temperate or snow, THEN Fossil fuel consumption is MEDIUM.
- IF 44,300 (2000US$) ≤ GDP per capita, THEN Fossil fuel consumption is HIGH.

4.2.4 Industrial minerals & ores consumption

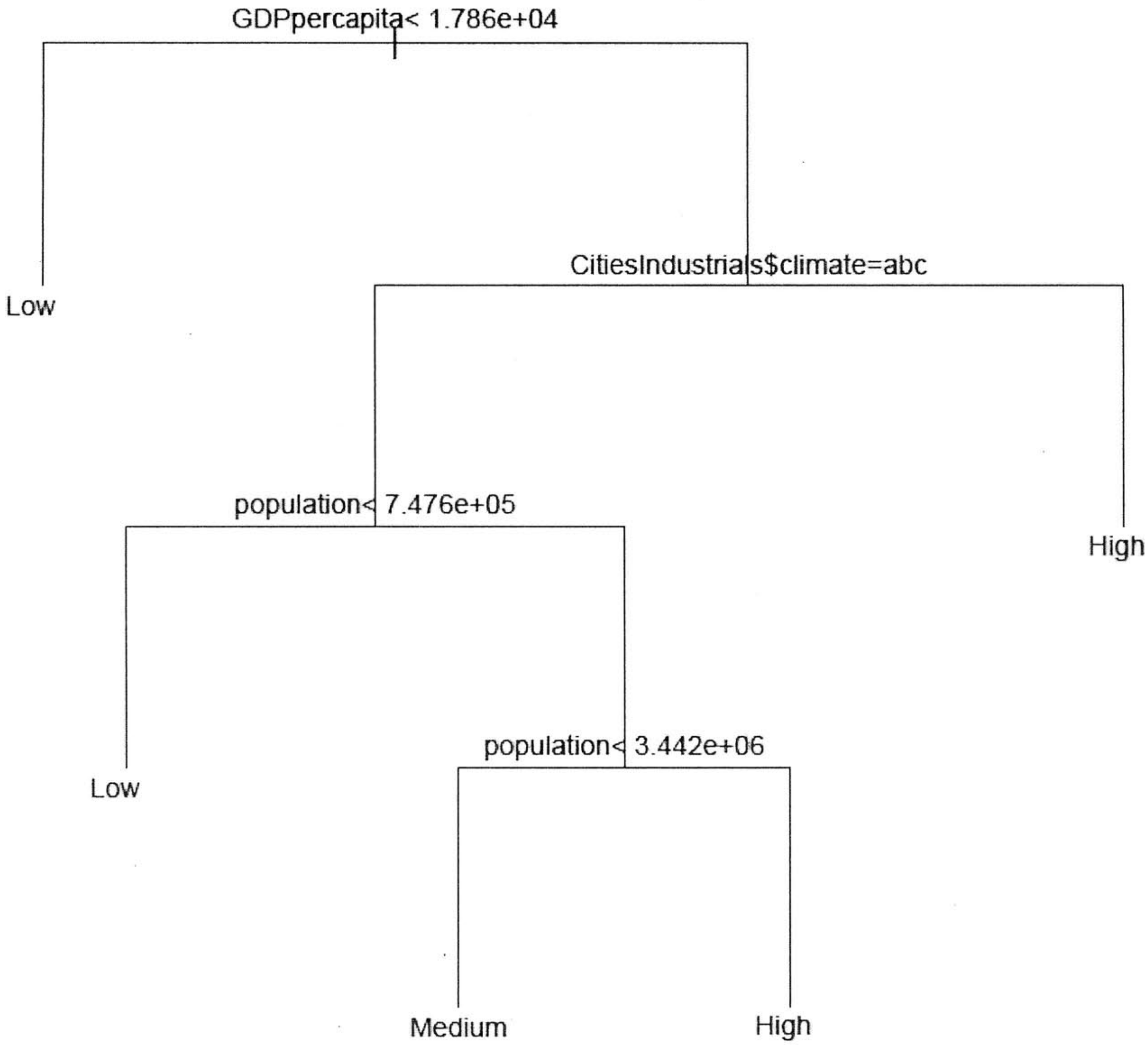


Figure 4.2.4 Industrial minerals & ores consumption classification tree

The decision rule for the Industrial minerals & ores consumption classification tree is as follows:

- IF GDP per capita is less than 17,860 (2000US$), THEN Industrial minerals & ores consumption is LOW.
- IF GDP per capita ≥ 17,860 (2000US$), climate is either tropical, arid, or temperate, *and* population is less than 747,600, THEN Industrial minerals & ores consumption is LOW.
- IF GDP per capita ≥ 17,860 (2000US$), climate is either tropical, arid, or temperate, *and* 747,600 ≤ population < 3.442 million, THEN Industrial mineral & ore consumption is MEDIUM.
- IF GDP per capita ≥ 17,860 (2000US$), climate is either tropical, arid, or temperate, *and* population ≥ 3.442 million, THEN Industrial minerals & ores consumption is HIGH.
- IF GDP per capita ≥ 17,860 (2000US$), *and* climate is snow, THEN Industrial minerals & ores consumption is HIGH.

4.2.5 Construction minerals consumption

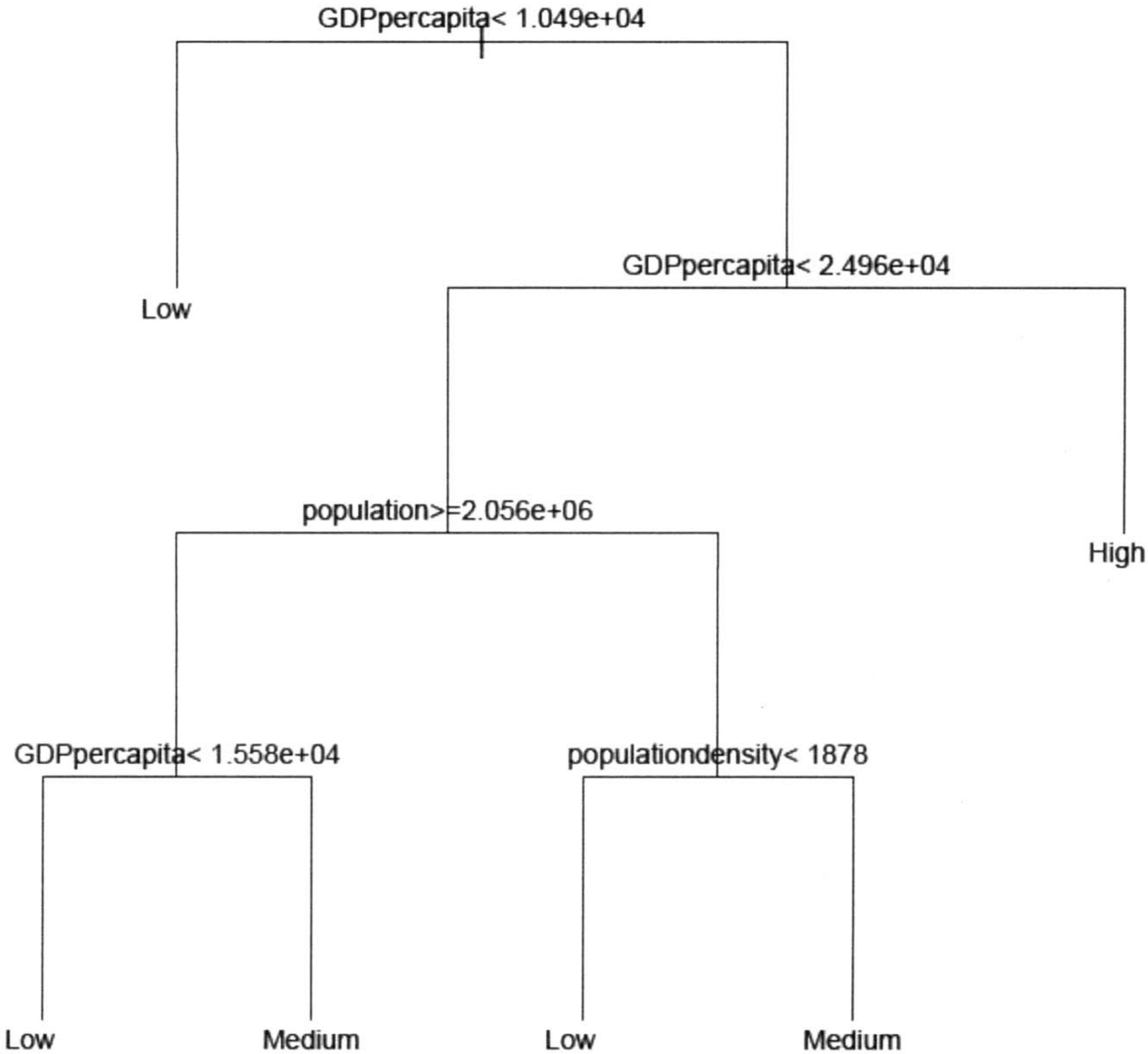


Figure 4.2.5 Construction minerals consumption classification tree

The decision rule for the Construction mineral consumption tree is as follows:

- IF GDP per capita < 10,490 (2000US$), THEN Construction mineral consumption is LOW.
- IF 10,490 ≤ GDP per capita < 24,960 (2000US$), population ≥ 2.056 million, *and* GDP per capita is less than 15,580, THEN Construction mineral consumption is LOW.
- IF 10,490 ≤ GDP per capita < 24,960 (2000US$), population ≥ 2.056 million, *and* GDP per capita is greater than or equal to 15,580, THEN Construction mineral consumption is MEDIUM.
- IF 10,490 ≤ GDP per capita < 24,960 (2000US$), population < 2.056 million, *and* population density < 1,878 per sq.km, THEN Construction mineral consumption is LOW.
- IF 10,490 ≤ GDP per capita < 24,960 (2000US$), population is less than 2.056 million, *and* population density ≥ 1,878 per sq.km, THEN Construction mineral consumption is MEDIUM.
- IF GDP per capita ≥ 24,960 (2000US$), THEN Construction mineral consumption is HIGH.

4.2.6 Biomass consumption

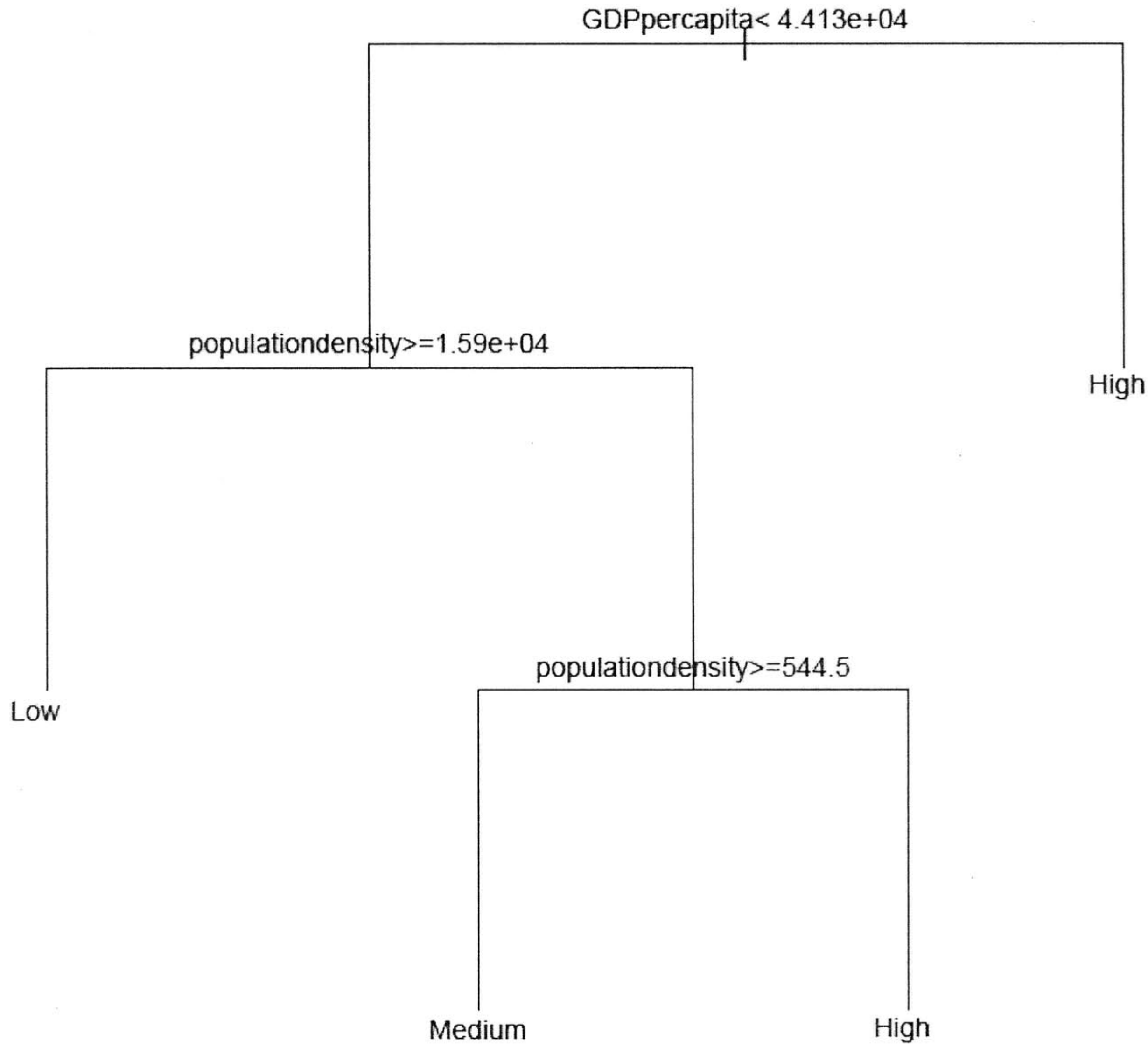


Figure 4.2.6 Biomass consumption classification tree

The decision rule for the Biomass consumption classification tree is as follows:

- IF GDP per capita is less than 44,130 (2000US$), *and* population density is greater than or equal to 15,900 per sq.km, THEN Biomass consumption is LOW.
- IF GDP per capita is less than 44,130 (2000US$), *and* 544.5 ≤ population density < 15,900 per sq.km, THEN Biomass consumption is MEDIUM.
- IF GDP per capita is less than 44,130 (2000US$), *and* population density < 544.5 per sq.km, THEN Biomass consumption is HIGH.
- IF GDP per capita is greater than or equal to 44,130 (2000US$), THEN Biomass consumption is HIGH.

4.2.7 Water consumption

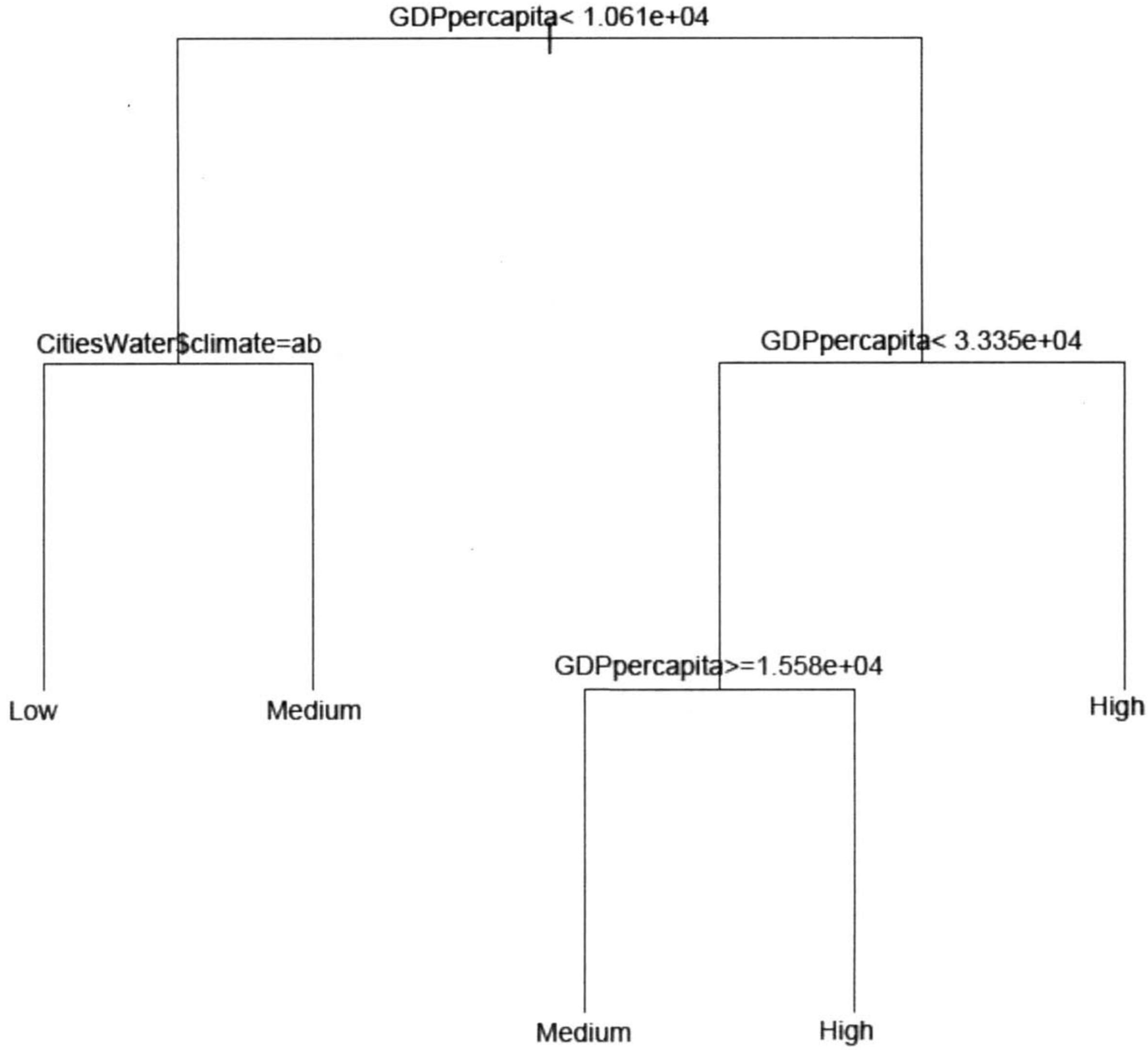


Figure 4.2.7 Water consumption classification tree

The decision rule for the Water consumption classification tree is as follows:

- IF GDP per capita is less than 10,610 (2000US$), *and* climate is either tropical or arid, THEN Water consumption is LOW.
- IF GDP per capita is less than 10,610 (2000US$), *and* climate is either temperate or snow, THEN Water consumption is MEDIUM.
- IF 15,580 ≤ GDP per capita < 33,350 (2000US$), THEN Water consumption is MEDIUM.
- IF 10,610 ≤ GDP per capita < 15,580 (2000US$), THEN Water consumption is HIGH.
- IF GDP per capita is greater than or equal to 33,350 (2000US$), THEN Water consumption is HIGH.

4.2.8 Total Domestic Material consumption

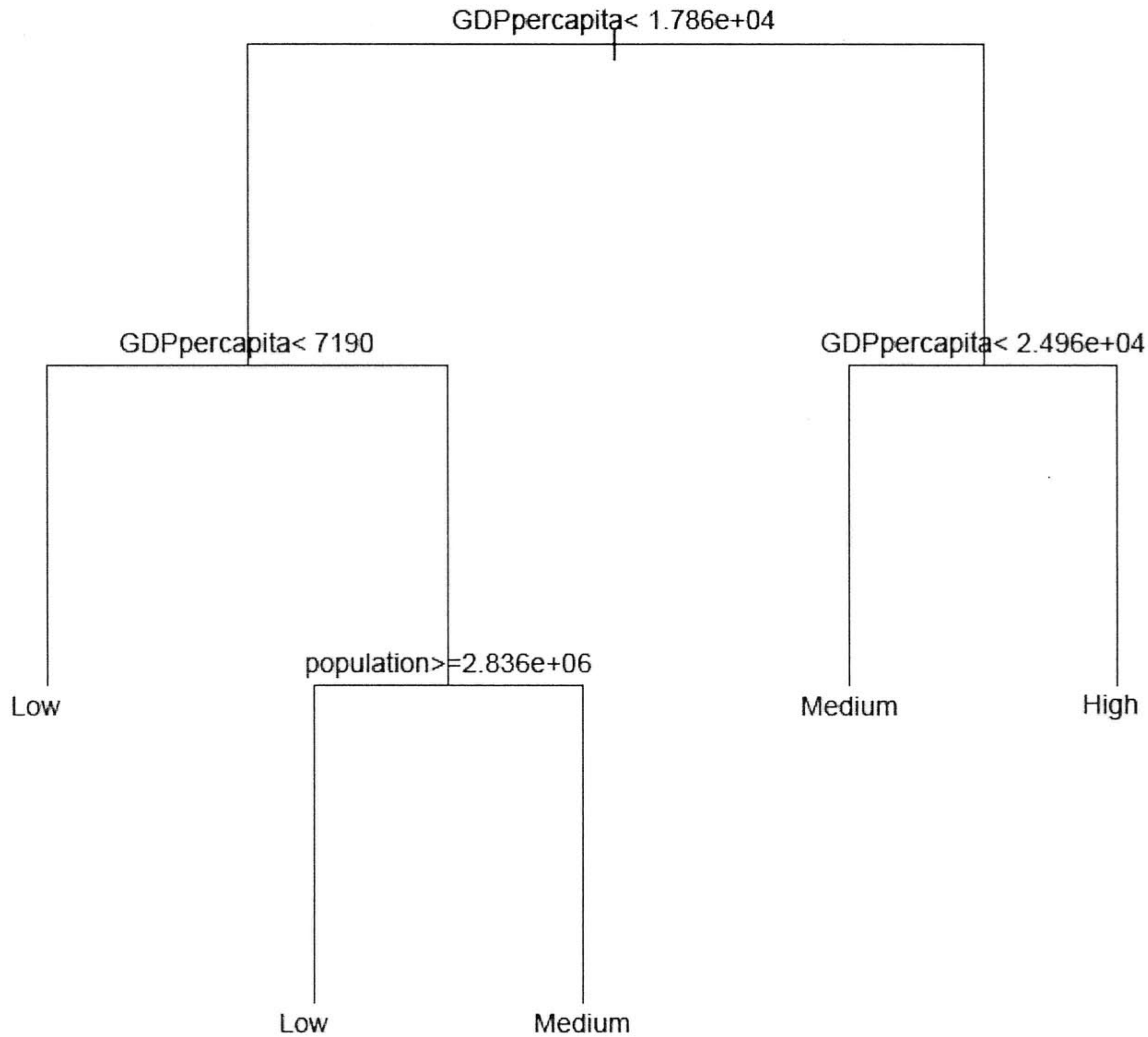


Figure 4.2.8 Total Domestic Material Consumption classification tree

The decision rule for the Total Domestic Material consumption classification tree is as follows:

- IF GDP per capita is less than 7,190 (2000US$), THEN Total Domestic Material Consumption is LOW.
- IF 7,190 ≤ GDP per capita < 17,860 (2000US$), *and* population is greater than or equal to 2.836 million, THEN Water consumption is LOW.
- IF 7,190 ≤ GDP per capita < 17,860 (2000US$), *and* population is less than 2.836 million, THEN Water consumption is MEDIUM.
- IF 17,860 ≤ GDP per capita < 24,960 (2000US$), THEN Water consumption is MEDIUM.
- IF GDP per capita is greater than or equal to 24,960 (2000US$), THEN Water consumption is HIGH.

4.2.9 Carbon dioxide emissions

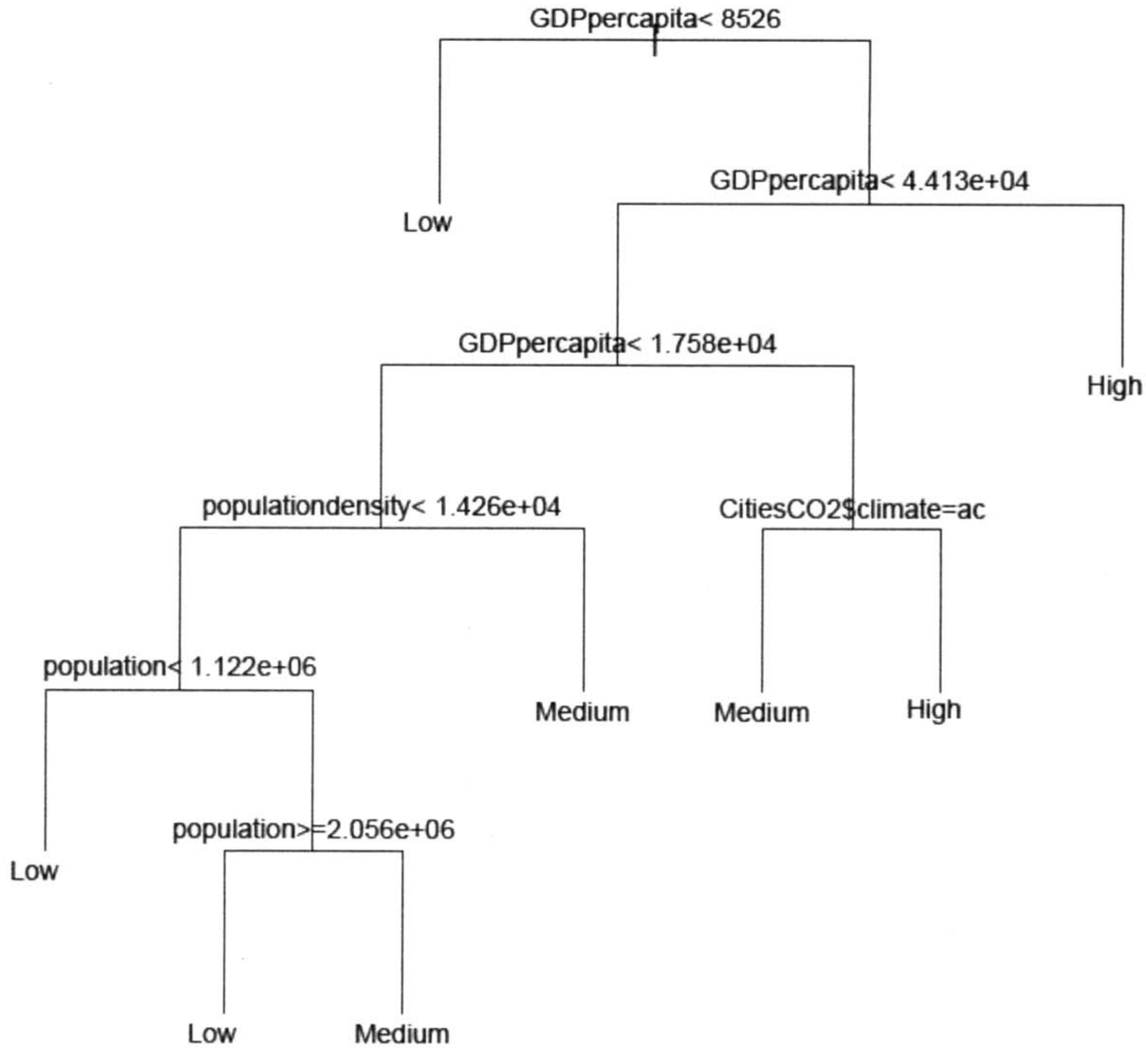


Figure 4.2.9 Carbon dioxide emissions classification tree

The decision rule for the Carbon dioxide emissions classification tree is as follows:

- IF GDP per capita < 8,526 (2000US$), THEN Carbon dioxide emissions are LOW.
- IF 8,526 ≤ GDP per capita < 17,580 (2000US$), population density < 14,260 per sq.km, *and* population is less than 1.122 million, THEN CO_2 emissions are LOW.
- IF 8,526 ≤ GDP per capita < 17,580 (2000US$), population density < 14,260 per sq.km, *and* population ≥ 2.056 million, THEN CO_2 emissions are LOW.
- IF 8,526 ≤ GDP per capita < 17,580 (2000US$), population density < 14,260 per sq.km, *and* 1.122 million ≤ population < 2.056 million, THEN CO_2 emissions are MEDIUM.
- IF 8,526 ≤ GDP per capita < 17,580 (2000US$), population density is greater than or equal to 14,260 per sq.km, THEN CO_2 emissions are MEDIUM.
- IF 17,580 ≤ GDP per capita < 44,130 (2000US$), *and* climate is either tropical or temperate, THEN carbon dioxide emissions are MEDIUM.
- IF 17,580 ≤ GDP per capita < 44,130 (2000US$), *and* climate is either arid or snow, THEN carbon dioxide emissions are HIGH.
- IF GDP per capita is greater than or equal to 44,130 (2000US$), THEN carbon dioxide emissions are HIGH.

4.3 *Municipal Solid Waste*

Fischer-Kowalski and Huttler (1999) stated that estimates of wastes, emissions, and other outputs from a society are difficult to estimate. This is because the residues of metabolic processes are both physically and chemically complex. Furthermore, there are relatively few countries in the world with municipal solid waste collection services. More often that not, there is either no solid waste collection service, or collection is contracted out to private companies that are not mandated to record the quantities that they collect. In The Weight of Nations (Matthews et al, 2000) the dearth of available primary data for compilation of output indicators was noted, especially in comparison to input indicators. Because of this lack of cross-sectional output or waste data across the range of world cities, I discuss municipal solid waste generation separately, and present figures from cities with available data.

Local governments and agencies, in both developing and developed countries, can influence the city's solid waste generation, reuse, and recycling rates by providing material recovery and recycling facilities at strategic locations. Other output reduction measures could include offering incentives to neighborhoods with low quantities of collected solid waste or high quantities of recovered materials. Businesses that reuse recycled or recovered materials could also be given incentives for contributing to a circular economy. All of these initiatives would require basic data on the quantities and types of collected solid waste, as well as the locations of households that generated the waste.

Solid waste also indirectly contributes to greenhouse gas emissions, in the form of methane gas released by landfills. Accurate measurement and prediction of landfilling rates can enhance the design of methane capture interventions, thereby facilitating emissions reductions. Another way in which the measurement and reuse of wastes can contribute to reductions in greenhouse gas emissions is through initiatives to use biomass waste as fuel.

As part of their climate action plans, some cities explicitly state strategies to reduce waste generation. For example, the City of Chicago Climate Action Plan (2008) has, as one of five primary goals, the reduction of the amount of waste sent to landfills. Proposed strategies for achieving the city's 90 percent landfill waste reduction goal (by 2020) include encouraging consumers to recycle packaging material and carry out home composting. This would involve awareness and education programs for residents. In addition, Chicago developed a

“Waste to Profit Network”, which diverted waste from landfills by encouraging companies to develop new products that use recovered materials as inputs.

Much can be done with information regarding solid waste generation, as well as other types of residues and emissions. In this section, I present the findings of a survey of available data on cities’ solid waste collection (Figure 4.3.1). Cities are placed on a chart that compares per capita solid waste generation with population density, population, and climate.

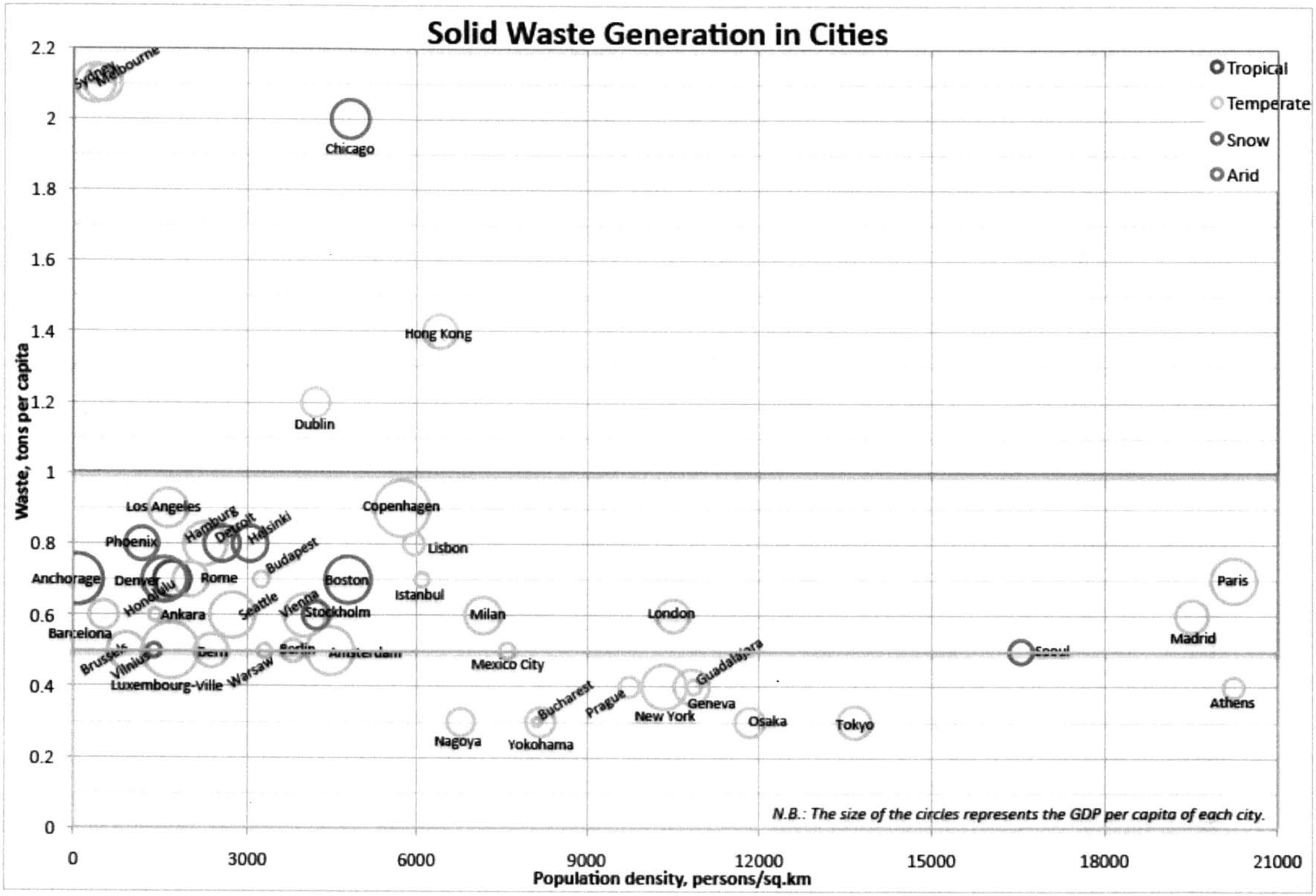


Figure 4.3.1 Solid waste generation, population density, and GDP per capita

Although data is not available for enough cities to carry out a classification tree analysis of waste per capita in relation to the predictor variables, by situating the cities on this chart, some interesting relationships can be gleaned.

First, it is difficult to comment on solid waste generation in tropical cities, since Honolulu is the only available sample city in that climate group. Most of the cities in temperate climates fall in the 0.5 – 1.0 tons per capita band, along with all but one of the snow climate cities, regardless of population density. Both of the arid cities also have between 0.7 – 0.8 tons of waste generation per capita. Falling below the 0.5 tons per capita level are ten temperate cities. The highest levels are observed in snow city Chicago, and temperate cities Sydney, Melbourne, Hong Kong, and Dublin.

Tables 4.3.1a through 4.3.1f show the characteristics of the cities falling into each level per capita solid waste generation. Although these are not numerous enough to be considered representative samples, it is useful to make observations about this particular set of cities.

Table 4.3.1a Characteristics of cities with per capita solid waste generation < 0.5 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density, per sq.km.	Koppen Climate Classification
Bucharest	0.3	11,500	1,931,838	8,121	Temperate
Nagoya	0.3	34,811	2,215,062	6,785	Temperate
Osaka	0.3	36,922	2,628,811	11,836	Temperate
Yokohama	0.3	37,054	3,579,628	8,184	Temperate
Tokyo	0.3	41,456	8,489,653	13,663	Temperate
Guadalajara	0.4	18,837	1,640,589	10,865	Temperate
Prague	0.4	25,500	1,188,126	9,741	Temperate
Athens	0.4	26,042	789,166	20,235	Temperate
Geneva	0.4	44,017	178,574	10,829	Temperate
New York, NY	0.4	56,149	8,274,527	10,350	Temperate
	Minimum	11,500	178,574	6,785	
	Median	35,867	2,073,450	10,590	
	Maximum	56,149	8,489,653	20,235	
	Std deviation	13,042	2,945,486	3,787	

The cities shown in Table 4.3.1a have a number of notable characteristics. Although we cannot establish a correlation due to the small sample size, we note that the median GDP per capita is the second lowest of all the groups, with a standard deviation on the order of the minimum GDP value in the group. The range and variance of city sizes, on the other hand, is very large. This suggests that population level may not directly influence the amount of per capita waste generation. However, these cities also have the highest median population *density*, with a standard deviation lower than the minimum value. This implies that there may be gains to be derived from higher density, in terms of reducing solid waste generation. This could be a result of smaller living spaces, which could lead to lower rates of both disposable and durable material consumption, and thus less solid waste. Construction and demolition (C&D) debris, in particular, represents a significant portion of the waste stream in many urban areas. Smaller living spaces, brought about by increased population density, therefore have a great impact on overall solid waste reduction. Interestingly, if C&D waste generation is tracked, it may be possible to develop new and profitable markets for it (e.g., sheetrock).

Table 4.3.1b Characteristics of cities with per capita solid waste generation of 0.5 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density,per sq.km.	Koppen Climate Classification
Vilnius	0.5	17,400	543,494	1,379	Snow
Warsaw	0.5	17,977	1,704,717	3,297	Temperate
Mexico City	0.5	20,496	11,285,654	7,600	Temperate
Berlin	0.5	28,529	3,386,667	3,801	Temperate
Seoul	0.5	29,706	10,020,123	16,553	Snow
Bern	0.5	41,900	122,256	2,368	Temperate
Brussels	0.5	45,355	144,784	899	Temperate
Amsterdam	0.5	60,514	742,884	4,467	Temperate
Luxembourg-Ville	0.5	70,597	84,644	1,660	Temperate
	Minimum	17,400	84,644	899	
	Median	29,706	742,884	3,297	
	Maximum	70,597	11,285,654	16,553	
	Std deviation	19,101	4,411,694	4,897	

Table 4.3.1c Characteristics of cities with per capita solid waste generation of 0.6 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density,per sq.km.	Koppen Climate Classification
Ankara	0.6	15,608	3,517,182	1,398	Temperate
Stockholm	0.6	34,668	789,024	4,219	Snow
Barcelona	0.6	35,976	1,605,602	516	Temperate
London	0.6	41,271	7,421,209	10,505	Temperate
Madrid	0.6	41,315	3,128,600	19,509	Temperate
Milan	0.6	46,180	1,306,086	7,174	Temperate
Vienna	0.6	53,776	1,664,146	4,013	Temperate
Seattle, WA	0.6	56,788	594,210	2,733	Temperate
	Minimum	15,608	594,210	516	
	Median	41,293	1,634,874	4,116	
	Maximum	56,788	7,421,209	19,509	
	Std deviation	12,811	2,240,265	6,241	

Table 4.3.1d Characteristics of cities with per capita solid waste generation of 0.7 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density,per sq.km.	Koppen Climate Classification
Istanbul	0.7	18,090	11,174,257	6,103	Temperate
Budapest	0.7	19,876	1,699,213	3,237	Temperate
Rome	0.7	43,127	2,626,640	2,009	Temperate
Honolulu, HI	0.7	45,444	375,571	1,692	Tropical
Denver, CO	0.7	55,700	588,349	1,558	Arid
Paris	0.7	57,027	2,125,017	20,238	Temperate
Boston, MA	0.7	58,686	599,351	4,783	Snow
Anchorage, AK	0.7	63,549	279,671	64	Snow
	Minimum	18,090	279,671	64	
	Median	50,572	1,149,282	2,623	
	Maximum	63,549	11,174,257	20,238	
	Std deviation	17,523	3,639,372	6,466	

Table 4.3.1e Characteristics of cities with per capita solid waste generation between 0.8 – 0.9 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density,per sq.km.	Koppen Climate Classification
Lisbon	0.8	27,292	504,726	5,954	Temperate
Phoenix, AZ	0.8	41,260	1,552,259	1,168	Arid
Helsinki	0.8	44,249	566,526	3,040	Snow
Detroit, MI	0.8	44,344	916,952	2,552	Snow
Hamburg	0.8	54,103	1,704,735	2,258	Temperate
Los Angeles, CA	0.9	48,896	3,834,340	1,616	Temperate
Copenhagen	0.9	71,164	505,141	5,740	Temperate
	Minimum	27,292	504,726	1,168	
	Median	44,344	916,952	2,552	
	Maximum	71,164	3,834,340	5,954	
	Std deviation	13,374	1,194,832	1,915	

Table 4.3.1f Characteristics of cities with per capita solid waste generation > 1.0 tons

CITIES	Waste per capita,tons	GDP per capita	Population	Population density,per sq.km.	Koppen Climate Classification
Dublin	1.2	36,721	495,781	4,202	Temperate
Hong Kong	1.4	42,700	6,925,900	6,421	Temperate
Chicago, IL	2.0	48,840	2,836,658	4,819	Snow
Melbourne	2.1	46,137	3,806,092	495	Temperate
Sydney	2.1	49,226	4,336,374	357	Temperate
	Minimum	36,721	495,781	357	
	Median	46,137	3,806,092	4,202	
	Maximum	49,226	6,925,900	6,421	
	Std deviation	5,181	2,336,293	2,710	

The summary of solid waste generation and median values of GDP per capita, population, and population density are shown in Table 4.3.2 below:

	MEDIAN				
Solid waste per capita, tons	GDP per capita	Population	Population density, per sq.km	Number of cities	Percentage of Total
<0.5	35867	2073450	10590	10	21%
0.5	29706	742884	3297	9	19%
0.6	41293	1634874	4116	8	17%
0.7	50572	1149282	2623	8	17%
0.8 - 0.9	44344	916952	2552	7	15%
>1.0	46137	3806092	4202	5	11%

Table 4.3.2 Summary of solid waste generation and city characteristics

It is clear that useful relationships between the predictor variables and per capita solid waste generation cannot be derived from the small sample size of cities with available data. However, from Figure 4.3.1 and Table 4.3.2, we can see that approximately 20% of the sample cities have solid waste generation below 0.5 tons per capita. A mere 11% have waste generation rates above 1.0 tons per capita, while approximately 2/3 of the sample cities have solid waste output between 0.5 – 1.0 tons per capita. Seventy-five percent of the 0.5 – 1.0 ton per capita waste generating cities have a population density 8,000 persons per square meter. The cities with the lowest per capita solid waste are clustered around 10,000 per sq. m population density. The two cities with two of the lowest population densities in the sample (Sydney and Melbourne) also have the highest waste generation rates (greater than 2.0 tons per capita).

The observations that were mentioned above suggest relationships that would be interesting to investigate further. In order to carry out the classification in a more rigorous manner (e.g. using classification trees), data regarding solid waste generation needs to be made available for more cities spanning different geographical locations, climates, levels of affluence, population size, and population density. Most notably, there is a degree of bias in the solid waste data that is currently available, since a minimum level of affluence is necessary for cities to have widespread municipal solid waste collection and data gathering. For the poorest cities in developing countries, it is likely that a very small percentage of households and neighborhoods are actually served by local government-run garbage collection.

Once such data is available, actions can be taken to reduce the environmental impact of solid waste outputs, including their impact on greenhouse gas emissions. Recycling programs, for example, would reduce CO_2 emissions by avoiding the use of energy during the extraction and processing of virgin raw materials to manufacture new products. Also, reducing the quantities of solid waste that are diverted to landfills reduces the amount of methane released into the atmosphere. Finally, if extensive data on biomass waste generation and collection is available, biomass energy initiatives could be supported and the city level.

Municipal programs could include expanding recycling and composting programs to more sectors of the city; encouraging recycling of construction and demolition debris; and increasing recycling in city departments. Supporting data regarding the amount of collected recyclable and compostable solid waste, for example, could assist in demonstrating the cost effectiveness of such programs. In particular, if reductions in solid waste generation or diversion to landfills can be expressed in terms of reduction in greenhouse gas generation attributable to an urban area, these suggested actions could be packaged as carbon offset programs, further increasing the desirability of the initiatives.

On the other hand, source reduction, reuse and other waste prevention programs could be strengthened by the availability of status quo generation rates. Incentives could be put in place to encourage producers to be responsible for the waste associated with the products they manufacture and distribute – during production, packaging and at the end of the product's life. Increasing the recyclability or compostability of selected product types and securing producer participation and/or funding to collect and divert wastes from landfills could also be encouraged. Waste audits are the first step to increasing waste prevention.

4.4 Typology of urban metabolic profiles

Figures 4.4.1 and 4.4.2 show the results of the resource consumption typology analysis. Types I and II contain cities for which all elements of the metabolic profile are low, with the exception of water in Type I (low to medium) and biomass in Type II (medium).

Types III and V represent categories of cities whose metabolic profiles show two similar consumption types. For type III, the first 5 components of the profile (carbon dioxide emissions, total energy, electricity, fossil fuels, and industrial minerals & ores) are all low, and then we see an increase to low-medium beginning at construction minerals, medium for biomass, peaking at water, and finally a medium level for total domestic material consumption. Type V is similar in that biomass dominates the metabolic profile. However, instead of construction minerals leading the first five components (as in type III), total energy, electricity, fossil fuels, industrial minerals & ores and construction minerals are all at the low-medium level, with only carbon dioxide emissions at low.

Type IV has medium to high consumption of industrial minerals and ores, followed by medium consumption of biomass and water, and low to medium consumption of construction minerals. Carbon dioxide, total energy, electricity, and fossil fuel consumption for these cities are all low.

Cities that belong to type VI have a biomass material component that is higher than both construction minerals and industrial minerals & ores, which are at low consumption levels. Total domestic material consumption is low, as is total energy, electricity, and fossil fuel consumption. On the other hand, carbon dioxide emissions are at the medium level.

Japanese cities comprise type VII, most notable for its high industrial mineral & ore, construction mineral, and total domestic material consumption. Biomass consumption is low. Carbon dioxide emissions and fossil fuel consumption are at the medium level, while total energy consumption is low. On the other hand, electricity consumption is high.

Type VIII consists of cities for which all metabolic components are at the medium level, with the exception of electricity consumption, which is low.

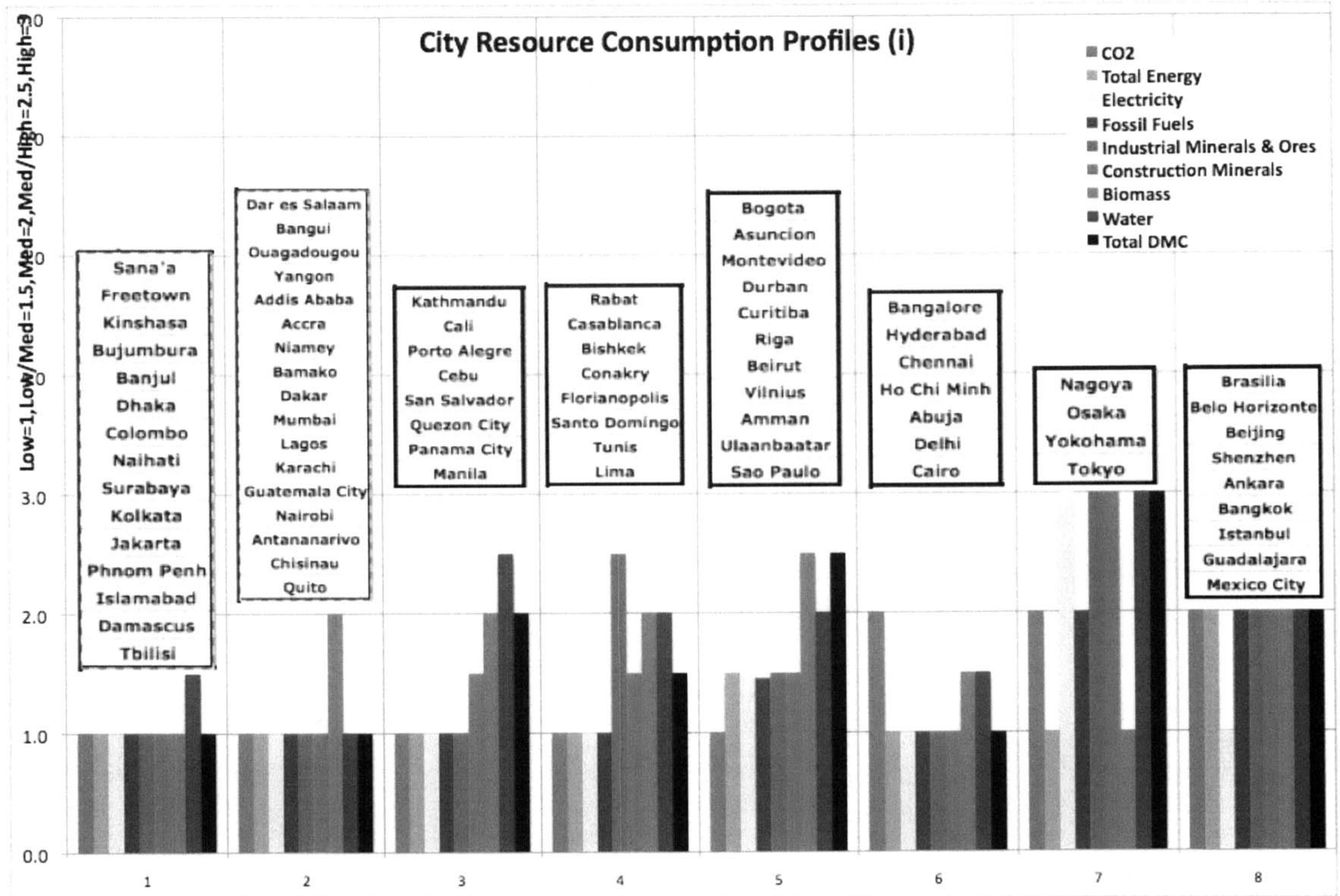


Figure 4.4.1 Typology of urban metabolic profiles (a)

Figure 4.4.2 shows metabolic types IX through XV. Type IX has medium to high levels of biomass consumption. Construction minerals and ores are at the medium level, while consumption of industrial minerals and ores lags at the low level. Carbon dioxide emissions, total energy, electricity, and fossil fuels are all at the medium level.

For type X, all components of the resource consumption profile are at the medium level, except for industrial minerals and ores, water, and total domestic material consumption, which are at the medium to high level.

Type XI cities have medium levels of carbon dioxide emissions, medium to high levels of total energy and fossil fuel consumption, but high electricity consumption. Medium to high biomass consumption can also be observed. Consumption of industrial metals and ores is at the medium level.

For Type XII, carbon emission levels are high. Industrial minerals and ores are consumed at higher levels than either construction minerals, or biomass. Electricity consumption, on the other hand, is only at the low to medium level; total energy consumption is at the medium level.

The biomass and construction minerals consumption in Type XIII is higher than that of industrial minerals and ores; carbon dioxide emissions per capita are High.

Type XIV consists of cities in which per capita consumption of industrial minerals & ores is negative to very low. Biomass consumption in these cities is also very low, domestic use of construction materials is at the medium to high level. Water and Total Domestic Material Consumption are also medium to high. Most notably, the three energy-related components are all high (fossil fuels, total energy and electricity). Finally, carbon dioxide emissions per capita are also high.

Cities in the High Consumption type (XV) type exhibit high consumption levels for all of the eight resources, as well as carbon dioxide, which are under consideration.

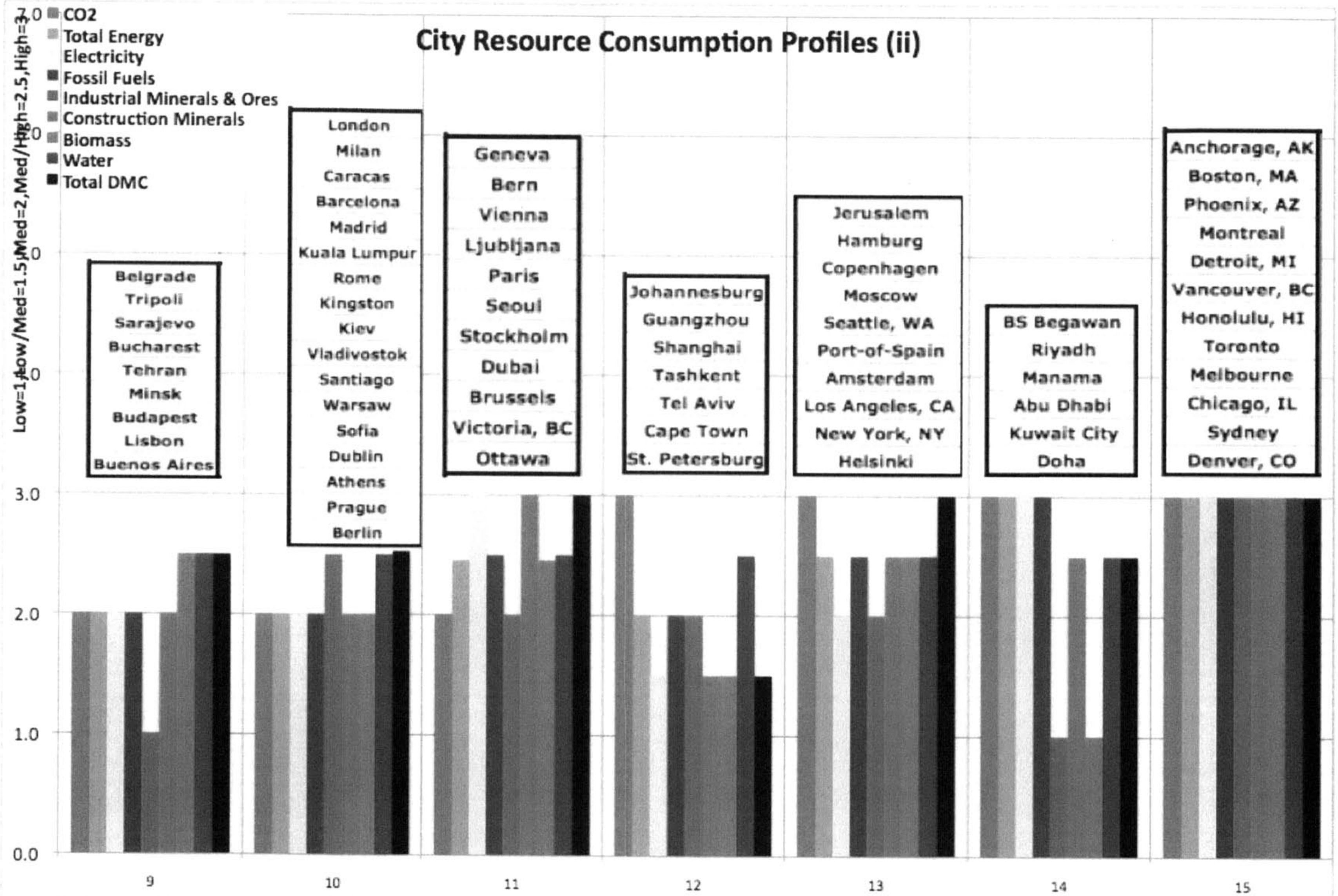


Figure 4.4.2 Typology of urban metabolic profiles (b)

Chapter 5. Discussion of Results

5.1 Map of the 155 representative cities

The map of the 155 cities was created in order to examine the way cities are clustered with respect only to the predictor, or independent, variables of affluence (represented on the Map by the Human Development Index, or HDI), population density, population size, and climate. The discussion in Chapter 4 showed some patterns and general characteristics of the cities under consideration. In this section, I will discuss one possible application of the 155 representative cities map that considers the relationship of the predictor variables to one dependent variable, greenhouse gas emissions.

In their recent urban greenhouse gas inventory research, Kennedy et al [11,12] illustrate how and why urban greenhouse gas emissions differ, and these distinctions are potentially useful in relation to the 155 Representative Cities Map. Comparing the ten global cities studied in the greenhouse gas inventory in light of the city types proposed in the Representative Cities Map can add a layer of information to the types. Table 5.1 shows the ten cities that were included in the greenhouse gas inventory study. Climate, population, population density, and HDI are the predictor variables that were used for classifying cities in the 155 Cities representative map.

Table 5.1.1 Cities used by Kennedy et al [11,12] for greenhouse gas inventorying

CITIES	Climate	Population	Urban density, persons/sq.km	HDI
Bangkok	Tropical	5658953	8084	0.783
Barcelona	Temperate	1605602	19509	0.955
Cape Town	Temperate	3497097	12059	0.683
Denver	Arid	579744	1558	0.956
Geneva	Temperate	432,058	10829	0.960
London	Temperate	7364100	10505	0.947
Los Angeles	Temperate	9519338	1616	0.956
New York	Temperate	8170000	10350	0.956
Prague	Temperate	1181610	9741	0.903
Toronto	Snow	5555912	3677	0.966

Table 5.1.2 shows the total greenhouse gas emissions of the ten cities, in tons of carbon dioxide equivalent per capita. The components of the emissions contributed by the end-

uses electricity, heating and industrial fuels, ground transportation, and waste (methane emissions from landfills) are also shown in Table 5.2.

CITIES	Total, tons CO2e/cap	Electricity	Heating/ Industrial	Ground transport	Waste
Bangkok	10.70	2.77	2.49	2.27	1.23
Barcelona	4.20	0.67	0.85	0.77	0.24
Cape Town	11.60	3.38	1.15	1.44	1.78
Denver	21.50	9.10	4.12	6.31	0.59
Geneva	7.80	0.35	3.45	1.85	0.38
London	9.60	2.50	2.58	1.22	0.21
Los Angeles	13.00	2.46	1.37	4.92	0.49
New York	10.50	3.01	3.13	1.53	0.35
Prague	9.40	3.31	3.2	1.44	0.11
Toronto	11.60	2.47	3.3	4.05	0.33

Table 5.1.2 Total GHG emissions and emissions by sector, tons CO_2 equiv. per capita

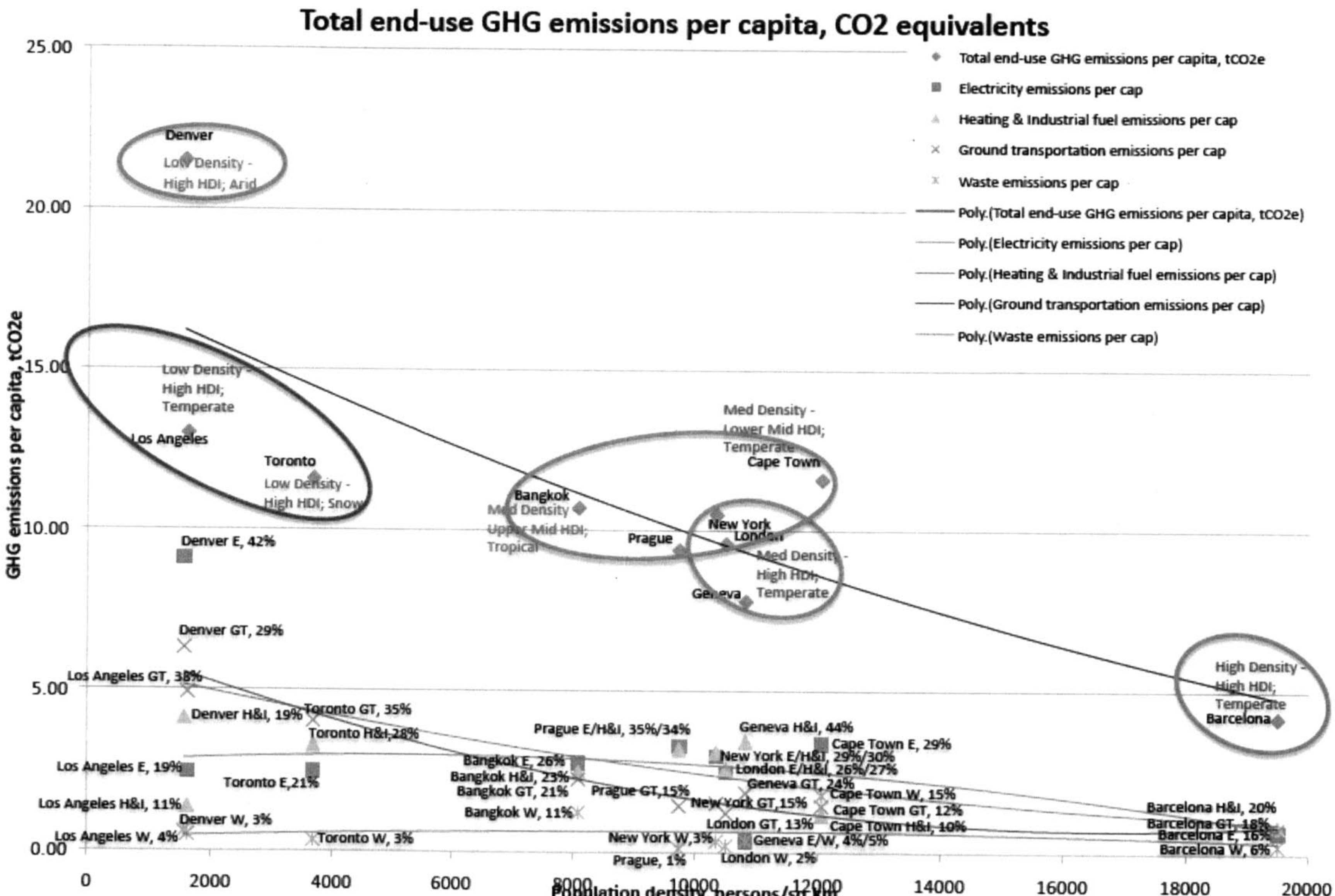


Figure 5.1.1 Greenhouse gas emissions per capita, with breakdown by sector (after Kennedy et al [12])

Figure 5.1.1 shows the total end-use greenhouse gas emissions for the ten cities studied by Kennedy et al [12], versus population density. In general, the total GHG emissions per capita are inversely proportional to urban population density. However, examining the breakdown of urban emissions by sector provides additional illumination and further information for grouping the cities together.

We note from Table 5.1.2 that Denver, Bangkok, Prague, and Cape Town's total emissions are dominated by electricity use. However, Denver's total emissions are over 60% larger than the next city, Los Angeles. Denver's emissions due to electricity are also nearly three times that of Cape Town, the city with the next highest magnitude of electricity-related GHG emissions. Ground transportation follows electricity as Denver's second-largest source of emissions, which may be a result of the fact that Denver has the lowest urban density among the ten cities. I thus separate Denver, but group Bangkok, Prague and Cape Town together. The latter three cities are within the Medium density range.

Los Angeles and Toronto, the cities with the lowest urban population densities after Denver, have their end-use emissions primarily composed of greenhouse gases related to ground transportation. Los Angeles, having a temperate climate, has the second-largest percentage of its emissions as a result of electricity use. On the other hand, the highest fraction of Toronto's emissions after ground transportation is due to heating fuels, presumably because of its snow climate. It is important to note that the greenhouse gas intensity of electricity use is highly dependent on the fuel mix used for generation, and the level of emissions would be related to this mix as well as to demand.

The next group is Medium density – High HDI with emissions dominated by heating and industrial fuels (New York, London, and Geneva). However, the emissions due to electricity for both New York and London are only one percentage point lower than those due to heating and industry. Geneva's electricity generation is almost entirely from hydropower (Kennedy et al [12]), resulting in emissions from electricity that are a mere 4% of total, due to the extremely low greenhouse gas intensity of hydropower generation. The grouping of these three cities is based on their similarities in population density, level of development, climate, and major emissions source.

Finally the High density – High HDI city of Barcelona, with the lowest total greenhouse gas emissions out of the ten cities (a mere 20% of Denver's total emissions), owes most of its emissions to heating and industrial fuels (20%). These are followed closely by ground transportation (18%) and electricity (16%). The smallest component of Barcelona's emissions is waste-related emissions, at 6% of total.

Cape Town is unique among the ten cities in that it is the only city at the Lower HDI level. Heating and industrial fuels make up the smallest component of Cape Town's total emissions, making it one of only two cities for which waste-related emissions are not the smallest fraction. (The other city is Geneva, whose low GHG-intensity hydropower electricity generation makes that the smallest component of its total emissions.) In fact, the second-largest component of greenhouse gas emissions for Cape Town is from waste, suggesting that land-filling of waste is still extremely common in this city.

Figure 5.1.1 also shows the difference in trends across cities for the four end-use sectors. The electricity (red) and ground transportation (violet) trend lines follow the total emissions (black) trend line in that all three generally decrease with increasing population density. On the other hand, the trends for emissions due to heating & industrial fuels as well as waste are relatively constant across all cities and levels of population density. These observations are consistent with the hypotheses that efficiencies in electricity distribution and consumption arise in more densely populated areas, and that less driving (with the associated motor gasoline emissions arising from private, low-occupancy transport) occurs in less sprawling cities. Furthermore, the level of industrial activity and land-filling of waste are not usually correlated to residential population density, but rather to the level of development of a city. Thus, the flat trend lines for heating & industrial emissions and waste emissions across population densities are consistent with theory about the drivers of greenhouse gas generation.

Superimposing the greenhouse gas emissions groups from Figure 5.1.1 onto the 155 Representative Cities Map gives us Figure 5.1.2, shown below.

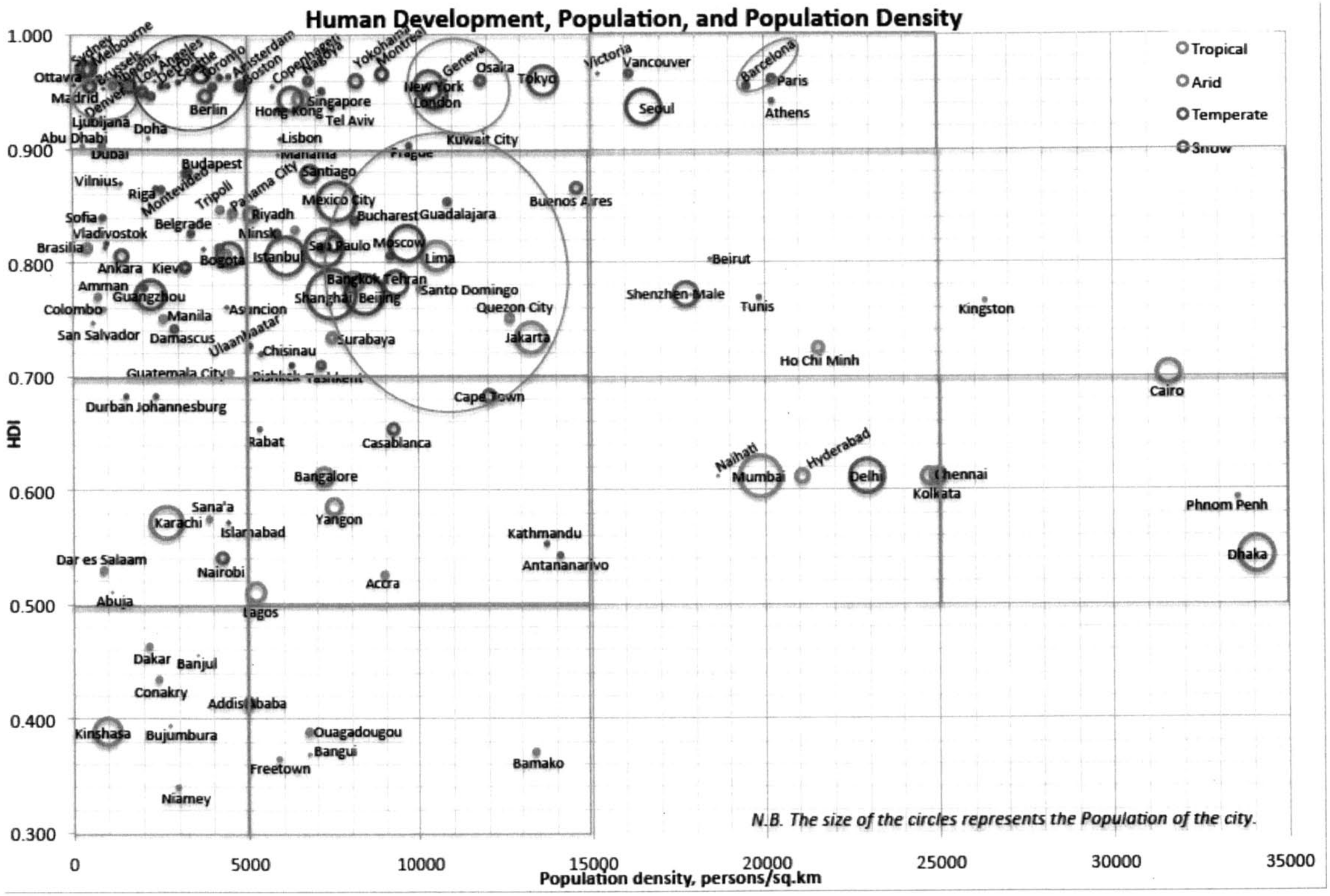


Figure 5.1.2 Total greenhouse gas emissions groups and the representative cities groupings

The combination of the greenhouse gas emissions grouping of the ten global cities from Kennedy et al [11,12] are relatively consistent with the groupings that are proposed in the 155 Representative Cities Map. In the High HDI (horizontal) band, the differences in dominant emissions component follow differing climate and population density. On the other hand, in the Medium density (vertical) band, the difference in the dominant emissions component appears to be related to differing climate and level of development.

5.2 Analysis of the drivers of metabolic profiles

Growing cities in industrializing countries (for example, in Asia) are experiencing a "building up" of a modern infrastructure that is necessary to support the growth of industrial production. This infrastructure includes both residential and commercial buildings; roads and transportation systems; utility networks; water supply and sewerage systems. Developing country cities are also where the most rapid and widespread urbanization is predicted to occur in the foreseeable future. An understanding of the character of metabolism in this type of city as well as other types is, therefore, essential to good urban resource management and policy.

The main goals of urban metabolism research include the observation of available natural and anthropogenic resources and, importantly, levels of human consumption with respect to this availability. These observations fall under the broader objectives of sustainable urban development. Brunner (2007) cautions against "seeking uniform solutions" to problems of inefficient urban resource consumption, since the resource context varies across cities. Urban resource management priorities therefore differ, and the satisfaction of these needs must be based on reasonable observations of the most pressing metabolic issues.

Furthermore, it is productive to examine the metabolic profiles of various types of cities in the industrialized world. If a high level of economic development (and the associated increase in human welfare) is the major goal of urban policy, then the type of cities that have less resource-intensive metabolism for a given level of affluence should be the benchmark. Teasing out these typologies is therefore a useful exercise. The contrast between Types X and XV (Fig. 5.2.1b) illustrate this idea.

Krausman et al (2008) hypothesize that the transition from agrarian to industrialized society is a process that is accompanied by distinct biophysical characteristics. Since the different countries of the world began this process at different periods in history, they are at different points along the transformation, with some economies still in the early or agrarian phase. Furthermore, because the technological mechanisms and processes underlying industrialization vary, countries that are at the same levels of economic or industrial development may have different associated metabolic profiles.

In the analysis of the various metabolic profiles associated with each city type, we focus less on particular components or resources, but on the 'shape' of the overall resource consumption. We assume that the transformation from an agrarian to industrial to service economy is ongoing for the cities that we examined, and that they can be categorized based on the metabolic profiles associated with each of these stages. Furthermore, although cities in the same type may differ significantly in their culture and social structure, this does not preclude them from having similar resource consumption profiles.

Krausman et al (2008) enumerate key factors that determine the metabolic patterns that are typically associated with industrialized economies, namely: material- and energy-intensive production systems (including agriculture); the construction, operation, and maintenance of infrastructure; the mobility of goods due to improvements in transportation infrastructure; and a high material standard of living with the associated increases in energy and electricity consumption (e.g. for heating and cooling). In the following sections, I describe the fifteen Urban Resource Consumption Profiles shown in Fig. 5.2.1a and Fig. 5.2.1b.

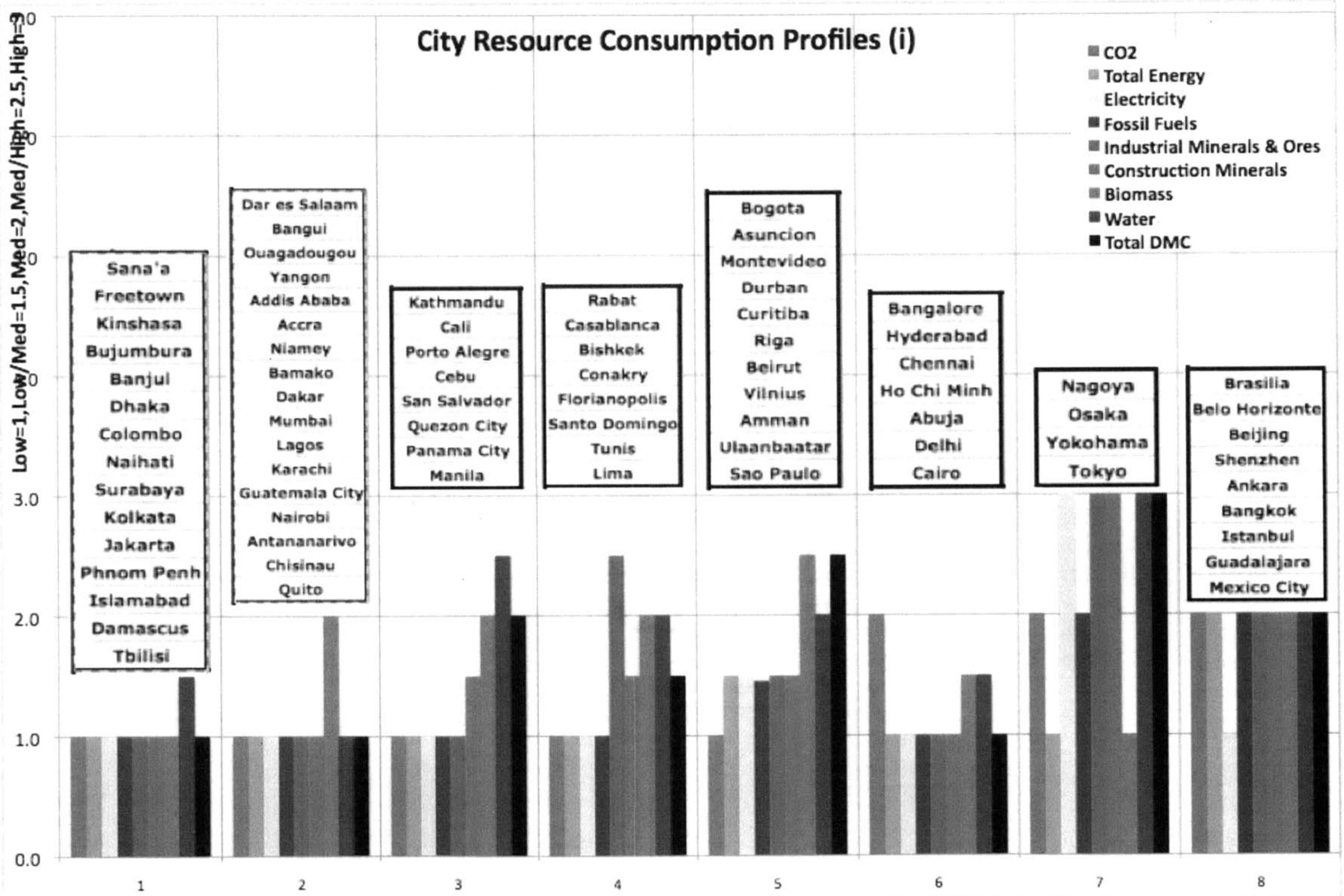


Figure 5.2.1a Typology of urban metabolic profiles (a)

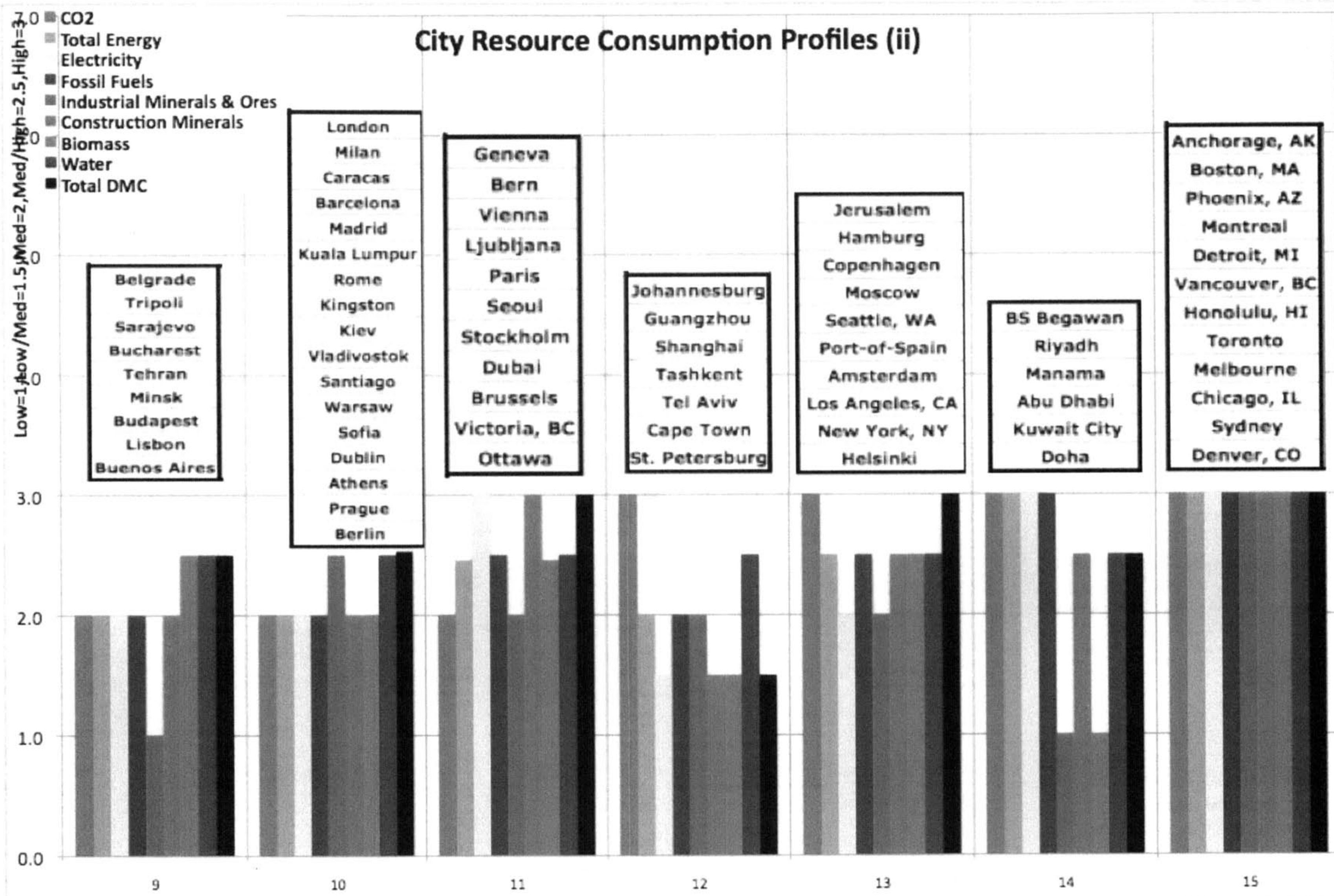


Figure 5.2.1b Typology of urban metabolic profiles (b)

Types I and II contain cities in very low to lower-middle income developing countries. All elements of the metabolic profile are low, with the exception of water in Type I (low to medium) and biomass in Type II (medium). A low standard of living is associated with these 2 metabolic profiles, with type II economies being heavily agricultural.

It is useful to discuss Types III and V together, as they represent categories of cities whose metabolic profiles shows two similar consumption types that can be associated with areas in the process of industrialization. For type III, the first 5 components of the profile (carbon dioxide emissions, total energy, electricity, fossil fuels, and industrial minerals & ores) are all low, and then we see an increase to low-medium beginning at construction minerals, medium for biomass, peaking at water, and finally a medium level for total domestic material consumption. This shape is reflective of largely agricultural economies whose infrastructure is growing to accommodate industrial development, which lags construction. Major industries are biomass- and water-intensive: food processing, beverages, textiles, rice, jute, sugar, wood, and fishing. Type V is similar in that biomass dominates the metabolic profile. This is due to the major industries of food and beverages, processing of animal products, natural fibers, textiles, wood and furniture products, and sugar. However, instead of construction leading the first five components (as in type III), total energy, electricity, fossil fuels, industrial minerals & ores and construction minerals are all at the low-medium level, with only carbon dioxide emissions at low. Carbon dioxide is at a lower level compared to energy, electricity, and fossil fuels because hydroelectric power and oil are the major sources of energy for most of the cities in type V.

Type IV has medium to high consumption of industrial minerals and ores, followed by medium consumption of biomass and water, and low to medium consumption of construction minerals. Carbon dioxide, total energy, electricity, and fossil fuel consumption for these cities are all low. Mining and refining of minerals, steel, metal fabrication, and light manufacturing are major industries for type IV, and construction supports this industrial activity. A profile like this accompanies this set of developing countries due to the abundance of minerals and other natural resources, allowing for the growth of the mining industry, as well as light manufacturing based on the availability of industrial minerals and ores. However, biomass-based industries are still a major part of the economy (textiles, agribusiness, beverages, fishing and fish processing, textiles, clothing, food processing, sugar processing, wood, agricultural processing, and leather goods).

Cities that belong to type VI are all in countries at the early stages of industrialization, with a still relatively low standard of living. The biomass material component (linked to textiles, food, wood, and paper industries) is higher than both construction minerals and industrial minerals & ores, which are at low consumption levels. Total domestic material consumption is low, as is total energy, electricity, and fossil fuel consumption. On the other hand, carbon dioxide emissions are at the medium level, brought about by the mix of coal and oil as main energy sources in these cities.

Japanese cities comprise type VII, most notable for its high industrial mineral & ore, construction mineral, and total domestic material consumption. Japan is one of the world's largest and most technologically advanced producers of motor vehicles, electronic equipment, machine tools, steel and nonferrous metals, ships, and chemicals. Biomass consumption is low, reflecting an absence of major agro-industries. Despite this extremely high level of industrialization, carbon dioxide emissions and fossil fuel consumption are at the medium level, while total energy consumption is low; this indicates a relatively low energy intensity of industry. Main energy sources consist of natural gas, oil, and hydropower. Electricity consumption is high, associated with affluence and a high standard of living, but the relatively clean energy mix keeps carbon dioxide emissions at the medium level.

Type VIII consists of industrializing cities for which all metabolic components are at the medium level, with the exception of electricity consumption, which is low. Low electricity consumption is an indicator of lower standards of living associated with personal income or affluence. Major industries for this group include textiles, agricultural processing, beverages, and tobacco, which account for the medium levels of biomass consumption. Light manufacturing, metals, electronics, and mining are reflected in medium levels of industrial mineral and ore consumption. The construction and cement industries result in medium levels of construction mineral consumption. Oil and natural gas are the dominant energy sources, as reflected in the medium levels of carbon dioxide emissions.

Type IX is composed exclusively of cities in transition/industrializing countries. Although the term "transition economies" usually covers the countries of Central and Eastern Europe and the Former Soviet Union, this term may have a wider context. There are countries emerging from a socialist-type command economy; moreover, in a wider sense the definition of transition economy refers to all countries that attempt to change their basic constitutional elements towards market-style fundamentals. Their origin could also be an economically underdeveloped country in Africa, such as Libya. In addition, in 2002 the World Bank defined Bosnia and Herzegovina, as well as Serbia and Montenegro as transition economies. Iran is also a current example, demonstrating early stages of a transition economy (Iranian Economic Reform Plan, 2010). Food processing, textiles, wood and cork, paper, dairy products, and timber, tobacco products are major industries in Type IX, and explain the medium to high levels of biomass consumption. Construction minerals and ores are at the medium level, reflecting the growth of infrastructure that leads full industrialization, while consumption of industrial minerals and ores lags at the low level. Carbon dioxide emissions, total energy, electricity, and fossil fuels are all at the medium level. Oil and natural gas are the main energy sources for this group.

For type X, all components of the resource consumption profile are at the medium level, except for industrial minerals and ores, water, and total domestic material consumption, which are at the medium to high level. These cities are located in highly developed countries with a mix of diverse services and industry, as well as transition/industrializing economies with some metal and machinery industries. Despite the high affluence, total domestic material consumption, and strong industrial base of these cities, their carbon dioxide emissions, total energy, electricity, and fossil fuel emissions are only at the medium level. The relatively low carbon dioxide intensity can be explained by the dominance of natural gas, hydroelectric power, and oil in the energy supply. It is, however, useful to contrast the relative lower intensity of the other components with the intensity of the High Consumption type XV.

Type XI cities have medium levels of carbon dioxide emissions, medium to high levels of total energy and fossil fuel consumption, but high electricity consumption. Wood and paper products, food, and the textile industries result in medium to high biomass consumption. Consumption of industrial metals and ores is at the medium level, due to the significance of metal, equipment, and machinery industries. Oil, hydroelectric, and nuclear are the main sources of energy in this type, resulting in medium levels of carbon dioxide emissions despite the medium to high total energy and fossil fuel components, and the high electricity consumption. High electricity consumption is associated with high levels of personal affluence, leading to high residential and commercial energy consumption.

Type XII cities are found in South Africa, China, Uzbekistan, Israel, and the Russian Federation. For this group, the energy sector is critical to the economy, as the countries rely heavily on their energy-intensive mining industries. Coal is used for most of their energy needs; as a result, carbon emission levels are high. Russia's primary energy supply consists mainly of natural gas, followed by coal and oil. The broad range of mining and extractive industries in these countries results in industrial minerals and ores being consumed at higher levels than either construction minerals, or biomass. Electricity consumption, on the other hand, is only at the low to medium level, reflecting lower levels of personal affluence; total energy consumption is higher due to the energy intensity of industry.

Cities in Type XIII are found in countries that are among the world's largest and most technologically advanced producers of coal, cement, food and beverages, and textiles. Agro-industries, wood and paper, and construction are also major components of the economy in these countries. Accordingly, the biomass and construction minerals consumption in this group is higher than that of industrial minerals and ores. Coal and oil are major sources of energy, as reflected in the high carbon dioxide emissions per capita.

Type XIV consists exclusively of cities found in some of the world's major petroleum-producing countries (Saudi Arabia, United Arab Emirates, Kuwait, Bahrain, Qatar, and Brunei). Per capita consumption of industrial minerals & ores is negative to very low, indicating that exports from industries such as aluminum, iron, and steel are much greater than domestic use. Furthermore, economic activity is concentrated in the petroleum industry rather than in manufacturing or processing of other goods. Biomass consumption in these cities is also very low, an effect of the arid climates that make irrigation difficult. The levels of affluence in these cities also contribute, in particular, to massive construction projects, resulting in medium to high domestic use of construction minerals. Water and Total Domestic Material Consumption are also medium to high, reflecting the standard of living in these cities, including the importation of water for personal consumption. Most notably, the three energy-related components are all high (fossil fuels, total energy and electricity), an effect of the abundance of petroleum as a resource. Finally, carbon dioxide emissions per capita are also high. This is a reflection both of the oil-based energy supply and high levels of personal consumption (as opposed to industrial- or manufacturing-related emissions).

Cities in the High Consumption type (XV) can be found in the leading industrial powers of the world. These countries (the United States, Canada, and Australia) are highly diversified and technologically advanced; major industries that comprise the bulk of these national economies include petroleum, steel, motor vehicles, telecommunications, chemicals, electronics, food processing, consumer goods, lumber, mining, transportation equipment, steel, processed and unprocessed minerals, as well as wood and paper products. These industries are both material- and energy-intensive, and manufacturing and processing operations are usually concentrated in the urban areas that are found in group XV. High levels of affluence elevate the standard of living, which leads to high residential material and energy consumption as well.

Chapter 6. Conclusions

6.1 Relation of findings to the study objectives

A major challenge to urban sustainability researchers today is to understand and predict how cities with differing socio-economic, demographic, and geographic characteristics will interact with the natural environment in which they exist. The increasing concentration of people in cities presents both opportunities and challenges with regard to optimizing resource consumption while providing urban dwellers with the quality of life that they seek in cities. On the one hand, cities are the loci of industry, commerce, and employment, and certain economies of scale are gained with respect to infrastructure and delivery of social services. On the other hand, the sophistication of urban living has led to changes in consumption and human behavior, which tend to increase rather than decrease the metabolism of contemporary cities.

These complex urban socio-economic phenomena make it necessary to gain a quantitative understanding of the different forms of resource consumption and intensity in cities. This understanding of the typology of urban metabolic profiles is a significant step toward creating policies that reduce excesses of consumption where these excesses exist, and could help prevent the development of blanket initiatives that do not address where the true problems lie in each particular type of city.

At the beginning of this thesis, we stated the goal of contributing to current research efforts to develop a comprehensive and holistic approach to the characterization of urban resource consumption. The practical implications of such an approach would include better-informed urban development strategies based on a framework of urban metabolism. The optimization of resource consumption in cities, however, is not the end goal in itself. Instead, resource efficiency should ultimately lead to the improvement of the urban quality of life and efficiency of growth. An important result was to differentiate between more- and less-resource intensive urban metabolic profiles for cities that are at similarly high levels of economic development and affluence. The lower-intensity metabolic profile that simultaneously delivers the desired quality of life is a useful benchmark for cities in developing countries.

The major motivation of this work is the lack of understanding regarding typological differences among cities in terms of energy and material fluxes. Most studies of material and energy use refer to the country level, whereas most relevant policy decisions are made and implemented at the local level. The methods discussed here could potentially bridge the gap between the scale at which information is available, and the level at which urban development and planning is conducted. The urban scale, being the level at which economic activity is concentrated, has great potential for more resource-efficient industry as well as household and personal consumption.

Targeted policy making is perhaps one of the best ways to address the myriad environmental and sustainability concerns of cities, and a typology of cities will become increasingly important for effective urban data collection and indicator evaluation. The classification of cities' resource consumption provides support for sound policies, allowing for more efficient performance evaluation. The most relevant city 'sustainability indicators' can be determined based on particular urban metabolic types, and initiatives can be put in place to collect this data, leading to fact-based urban resource management and allocation.

Indicators of both consumption and outputs need to be measured, standardized, targeted, and compared across cities and over time. Because municipalities' resources for collecting indicator data may be limited, a lack of focus on the most pressing resource inefficiencies limits the ability of cities to observe trends, share best practices and address their most significant consumption issues.

This work is a first step toward providing cities with a standardized system for the estimation and prediction of their resource consumption typology. The intention is that this will allow cities to identify what data should be collected on a regular basis, and focus policy-making on the resources that the city uses most intensively. Improved data collection at the urban scale will create a positive feedback loop, in that better data can be used to improve the next generation of classification tree analysis and city typology refinement.

This thesis specifies and characterizes the different types of urban metabolic profiles to which the cities of the world belong. It describes the resource consumption and carbon dioxide emissions of 155 globally representative cities and attempts to formulate a typology of cities based on their metabolic character. The different types can be interpreted as representing cities in various stages of industrialization and development, and gives valuable insight into the associated resource utilization of different modes of economic production.

In addition to providing a rational typology of urban metabolic profiles, this research also developed classification trees that can serve as predictive models to assist the urban metabolism research community when resource consumption data gaps exist at the city level. Any city that was not included in the model training set used in this study can be described by "dropping" it through each of the resource classification trees. Based on a city's GDP per capita, population, population density, and climate, predictions can be made of its levels of consumption of the resources for which trees were built in this study. The municipality can then verify whether its resource intensity is, in fact, weighted toward the particular resources suggested by the classification trees, and act accordingly.

In this work, I measured the materials used/mobilized for sustaining economic activity as well as household consumption in cities. A major finding was that the urban metabolic profiles of different types of cities appear to be intimately related to the dominant industries in the country. This is reasonable, given that industries and centers of commerce and production are often located in the major cities of each country. Consumption indicators are also sensitive to specific factors, for example, whether a country is a major source of natural resources such as oil, gas, or particular minerals and metal ores.

Output indicators, such as municipal solid waste generation per capita, are important components of a city's metabolic profile. However, available data are usually significantly less complete than for other indicators such as material or energy consumption. In the next iteration of this work, it is essential that outputs be explicitly included in the urban metabolic profiles. In fact, the absence of data regarding output generation rates suggests that waste management is lagging in all but a few cities in the representative set.

This assessment of the resource consumption profile of 155 cities throughout the world is a rough estimate of the actual per capita quantities that are consumed. The analysis was based on a narrow set of local data and many admittedly crude assumptions. However, the work already provides us with an insight into the typological differences among different groups of cities.

The typology of cities addresses the need to evaluate current situations and future trends for certain critical resources and to take policy measures to prevent their inefficient usage. Because municipalities are often overwhelmed by the complexity and difficulty of the urban environmental issues they face, problems are often not dealt with in a focused manner. The typology of cities can help municipalities identify their most important resource consumption issues and their current metabolic type, and take countermeasures as appropriate. For example, a Type XII city must make more effort to promote a cleaner energy mix, and decouple the link between economic development and the consumption of fossil fuels and industrial minerals & ores.

The city typology can also help predict urban environmental issues from the experiences of cities at more affluent stages of economic development, and allow developing cities to take preventative measures or institute policies that will lead to a less intensive metabolic profile, even in the face of high levels of industrialization. With strong leadership and planning, a city can take an alternative evolutionary path by identifying relative strengths and constraints, and avoiding unfavorable types of metabolism. In this context, the global typology of cities provides a useful tool for municipalities, because it can help identify challenges to long-term urban resource planning with a view towards economic development.

6.2 Recommendations for future research

The present assessment could be improved in various steps: first, the city-level assessment could be reworked using a more complete set of urban statistics, rather than depending on the more general country-level data. Second, local data on solid waste and wastewater generation would allow the inclusion of outputs in the urban metabolic profiles. Third, if standardized consumption and output data are collected by local governments on a regular basis, the change in urban metabolic profiles and groupings over time could provide insight into the transitions of different cities toward or away from resource efficiency as they proceed along the trajectory of industrialization and economic growth. Historical developments or the effects of policy changes could be traced and associated with metabolic trends.

This work illustrates a method to document and classify cities' use of resources. This first assessment is still quite simple because of a limited amount of local data that we were able to gather for this project. However, the usefulness of this method lies in the fact that, using a richer data set, the typology could serve as a base-line analysis for planners and the public to identify potential means of optimizing resource consumption, measuring progress toward sustainability and comparing trends and scenarios for the future.

The typology has the potential to show to what extent a given level of quality of life will require higher or lower resource consumption in cities, and what determines the differences in different categories of cities. In addition, the typology can point out what opportunities intelligent urbanization offers to reduce and balance out the resource profiles associated with the urban lifestyle. In this way, the city typology identifies core sustainability challenges and helps find ways to secure people's quality of life while simultaneously taking advantage of opportunities to de-materialize urban development.

Future research topics should include rigorous data-based analyses, such as quantitative cross-city analyses and chronological analyses of more cities; and the presentation of policy recommendations based on these analyses.

Finally, perhaps the most important question for researchers to answer is: how can city-dwellers in different types of cities be persuaded and motivated to reduce their environmental impacts and move toward more responsible consumption? The need to make consumption more efficient applies even more to the long-established industries in urban areas, as personal and household decisions cannot have their desired impact until modes of production and energy provision have themselves become less resource-intensive. The urban metabolism research community is faced with the task of establishing *what* sustainable consumption is, and assisting in making it a norm. This will involve not only quantitative reductions in cities' use of materials and energy; it will also require urban development practitioners to develop practical, implementable ways by which an acceptable quality of life may be achieved for city dwellers.

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APPENDIX A

APPENDIX A.1 Total Energy Consumption data set

CITIES	energy per cap, kgoe	energy class	population	GDP per cap, 2000US$	population density/sq.km	climate
Kinshasa	289	1	7785965	300	955	1
Addis Ababa	290	1	2646000	800	4992	3
Kathmandu	339	1	671846	1100	13711	3
Yangon	298	1	4477638	1200	7488	1
Dar es Salaam	492	1	1360850	1300	856	1
Accra	406	1	1658937	1400	8967	1
Durban	905	1	669242	1483	1513	3
Dakar	270	1	1075582	1700	2151	1
Nairobi	483	1	2948109	1700	4236	3
Phnom Penh	344	1	703963	1900	33522	1
Chisinau	944	1	660726	2400	5372	3
Sana'a	328	1	954448	2500	3864	2
Mumbai	492	1	11978450	3598	19865	1
Lagos	743	1	5195247	3697	5200	1
Colombo	462	1	615000	4200	880	1
Asuncion	674	1	513399	4200	4388	3
Tbilisi	714	1	1108600	4600	2038	3
Damascus	961	1	1658000	4700	2894	3
Guatemala City	638	1	1022001	5300	4482	1
Naihati	371	1	215303	6046	18641	1
Dhaka	158	1	10356500	6095	34067	1
Karachi	489	1	9339023	6430	2648	2
Surabaya	733	1	2611506	6811	7440	1
Kolkata	460	1	4572876	7033	24718	1
Islamabad	400	1	529180	7181	4410	3
San Salvador	764	1	507665	7300	573	1
Quito	789	1	1559295	7300	9172	3
Tunis	843	1	702330	7700	19847	3
Santo Domingo	825	1	913540	8000	10030	1
Rabat	401	1	642000	8175	5321	3
Florianopolis	924	1	406564	8253	924	3
Amman	1,294	2	1204110	5100	717	2
Sarajevo	1,334	2	527049	6300	3738	3
Bujumbura			235440	300	2738	1
Bangui			451690	700	6742	1

Niamey			707951	700	2962	2
Freetown			802639	900	5859	1
Antananarivo			1015140	1000	14099	3
Conakry			1091500	1100	2426	1
Bamako			1297281	1100	13374	1
Ouagadougou			1475839	1200	6739	2
Banjul			42326	1300	3527	1
Male			103693	4500	17884	1
Panama City	800	1	484261	11100	4526	1
Cebu	472	1	718821	11371	2558	1
Montevideo	875	1	1345010	11600	2538	3
Manila	499	1	1581082	13423	2575	1
Beirut	1,390	2	361366	10700	18437	3
Kingston	1,448	2	579137	8800	26324	1
Sofia	2,593	2	1155403	12300	859	3
Belgrade	2,161	2	1313994	10300	3379	3
Bucharest	1,775	2	1931838	11500	8121	3
Caracas	2,274	2	1975294	10915	4562	1
Tashkent	1,796	2	2137218	11600	7124	3
Dubai	11,133	3	1089000	11400	846	2
Cali	618	1	2392877	12741	4372	1
Casablanca	447	1	2995000	10374	9244	3
Ho Chi Minh City	617	1	3015743	13200	21541	1
Hyderabad	453	1	3637483	9538	21065	1
Chennai	458	1	4343645	8902	24963	2
Bangalore	463	1	5104047	10514	7199	1
Cairo	794	1	6758581	12192	31582	2
Bogota	667	1	7102602	11960	4467	3
Lima	498	1	8445211	12864	10557	2
Jakarta	798	1	8820603	10082	13284	1
Delhi	485	1	9879172	10486	22922	3
Shenzhen	1254	2	7008831	11047	17744	3
Bishkek	542	1	798300	2100	6271	4
Ulaanbaatar	1,024	2	1012733	3000	5038	4
Kiev	3,041	2	2676789	7200	3210	4
Riga	1,946	2	719928	10499	2376	4
Minsk	2,746	2	1789098	10800	5847	4
Vladivostok	3745	2	579811	12207	966	4
Beijing	1299	2	11509595	13325	8413	4
Quezon City	510	1	2173831	14080	12661	1
Abuja	566	1	107069	24411	1091	1
Porto Alegre	746	1	19089	16667	45	3
Johannesburg	912	1	752349	32023	2364	3

Nagoya	537	1	2215062	34811	6785	3
Osaka	544	1	2628811	36922	11836	3
Yokohama	555	1	3579628	37054	8184	3
Tokyo	590	1	8489653	41456	13663	3
Kuala Lumpur	2,570	2	1551306	15000	6384	1
Bangkok	1,526	2	5658953	17751	8084	1
Brasilia	1046	2	2383784	30564	411	1
Guangzhou	1272	2	8524826	14044	2218	3
Shanghai	1,319	2	14348535	15547	7442	3
Ankara	1,108	2	3517182	15608	1398	3
Tehran	2,288	2	7088287	16131	9327	3
Warsaw	2,429	2	1704717	17977	3297	3
Istanbul	1,201	2	11174257	18090	6103	3
Guadalajara	1497	2	1640589	18837	10865	3
Budapest	2,757	2	1699212.5	19876	3237	3
Mexico City	1,713	2	11285654	20496	7600	3
Sao Paulo	1,164	2	11016703	20589	7234	3
Santiago	1,813	2	4960815	20979	6823	3
Curitiba	1025	2	1788559	23268	4189	3
Belo Horizonte	1046	2	2399920	24317	7164	3
Prague	4,418	2	1188126	25500	9741	3
Athens	2,794	2	789166	26042	20235	3
Lisbon	2,574	2	504725.5	27292	5954	3
Buenos Aires	1639	2	2965403	28292	51	3
Berlin	4,187	2	3386667	28529	3801	3
Ljubljana	3,629	2	250953	28900	1530	3
Cape Town	1016	2	3497097	32037	12059	3
Barcelona	1227	2	1605602	35976	516	3
Dublin	3,647	2	495781	36721	4202	3
Tel Aviv	2923	2	387233.5	39003	7476	3
London	3,894	2	7421209	41271	10505	3
Madrid	1286	2	3128600	41315	19509	3
Bern	3535	2	122256	41900	2368	3
Jerusalem	3,059	2	740475	42432	5914	3
Hong Kong	2,653	2	6925900	42700	6421	3
Rome	3,169	2	2626640	43127	2009	3
Port-of-Spain	9,624	3	43396	23100	3616	1
Victoria, BC	6977	3	289625	13539	15243	3
Tripoli	2,999	2	1500000	13900	4205	2
Vilnius	2,543	2	543494	17400	1379	4
St. Petersburg	4328	2	4569616	19987	7541	4
Seoul	4,415	2	10020123	29706	16553	4
Moscow	4,586	2	10456490	30712	9673	4

Riyadh	6,077	3	4087152	23964	5109	2
Manama	11,232	3	176909	36100	5897	2
Phoenix, AZ	6262	3	1552259	41260	1168	2
Ottawa	7500	3	812129	19402	292	4
St. John's	6473	3	99182	27646	222	4
Stockholm	5,784	3	789024	34668	4219	4
Montreal	8267	3	3268513	40709	8955	4
Geneva	3,630	2	178574	44017	10829	3
Milan	3018	2	1306086	46180	7174	3
Vienna	4,135	2	1664146	53776	4013	3
Hamburg	3991	2	1704735	54103	2258	3
Seattle, WA	3556	2	594210	56788	2733	3
Paris	4,537	2	2125017	57027	20238	3
Copenhagen	1042	2	505141	71164	5740	3
Abu Dhabi	10581	3	527000	43700	293	2
Helsinki	6,554	3	566526	44249	3040	4
Detroit, MI	7596	3	916952	44344	2552	4
Vancouver, BC	7941	3	1837969	44884	16123	3
Brussels	5,889	3	144784	45355	899	3
Honolulu, HI	6786	3	375571	45444	1692	1
Toronto	8,469	3	4612191	45537	3677	4
Melbourne	5866	3	3806092	46137	495	3
Chicago, IL	7949	3	2836658	48840	4819	4
Los Angeles, CA	5886	3	3834340	48896	1616	3
Sydney	5920	3	4336374	49226	357	3
Singapore	7,260	3	4588600	51656	6582	1
Bandar seri begawan	7,014	3	27285	53900	272	1
Kuwait City	11,102	3	32403	55600	11900	2
Denver, CO	7704	3	588349	55700	1558	2
New York, NY	5276	3	8274527	56149	10350	3
Boston, MA	5906	3	599351	58686	4783	4
Amsterdam	5,048	3	742884	60514	4467	3
Anchorage, AK	26790	3	279671	63549	64	4
Luxembourg-Ville	10,134	3	84644	70597	1660	3
Doha	18,123	3	344939	100300	2174	2

APPENDIX A.2 Electricity Consumption data set

CITIES	Electricity per cap, kWh	electricity class	GDP per cap, 2000US$	population	climate	Pop.density /sq.km
Kinshasa	91	1	300	7785965	1	955
Addis Ababa	34	1	800	2646000	3	4992
Kathmandu	79	1	1100	671846	3	13711
Yangon	82	1	1200	4477638	1	7488
Dar es Salaam	65	1	1300	1360850	1	856
Accra	261	1	1400	1658937	1	8967
Nairobi	138	1	1700	2948109	3	4236
Dakar	158	1	1700	1075582	1	2151
Phnom Penh	55	1	1900	703963	1	33522
Bishkek	1842	1	2100	798300	4	6271
Chisinau	1472	1	2400	660726	3	5372
Sana'a	175	1	2500	954448	2	3864
Ulaanbaatar	1272	1	3000	1012733	4	5038
Mumbai	476	1	3598	11978450	1	19865
Lagos	127	1	3697	5195247	1	5200
Colombo	378	1	4200	615000	1	880
Asuncion	849	1	4200	513399	3	4388
Tbilisi	1672	1	4600	1108600	3	2038
Damascus	1394	1	4700	1658000	3	2894
Guatemala City	522	1	5300	1022001	1	4482
Naihati	359	1	6046	215303	1	18641
Dhaka	136	1	6095	10356500	1	34067
Karachi	455	1	6430	9339023	2	2648
Surabaya	467	1	6811	2611506	1	7440
Kolkata	445	1	7033	4572876	1	24718
Islamabad	372	1	7181	529180	3	4410
Quito	714	1	7300	1559295	3	9172
San Salvador	733	1	7300	507665	1	573
Tunis	1205	1	7700	702330	3	19847
Santo Domingo	1277	1	8000	913540	1	10030
Rabat	573	1	8175	642000	3	5321
Florianopolis	1600	1	8253	406564	3	924
Chennai	443	1	8902	4343645	2	24963
Hyderabad	438	1	9538	3637483	1	21065
Jakarta	509	1	10082	8820603	1	13284
Durban	4327	2	1483	669242	3	1513
Amman	2160	2	5100	1204110	2	717
Sarajevo	2387	2	6300	527049	3	3738
Kiev	3246	2	7200	2676789	4	3210

Kingston	2478	2	8800	579137	1	26324
St. John's	13233	3	6374	99182	4	222
Bujumbura			300	235440	1	2738
Bangui			700	451690	1	6742
Niamey			700	707951	2	2962
Freetown			900	802639	1	5859
Antananarivo			1000	1015140	3	14099
Conakry			1100	1091500	1	2426
Bamako			1100	1297281	1	13374
Ouagadougou			1200	1475839	2	6739
Banjul			1300	42326	1	3527
Male			4500	103693	1	17884
Abuja	97	1	24411	107069	1	1091
Panama City	1500	1	11100	484261	1	4526
Cebu	539	1	11371	718821	1	2558
Manila	569	1	13423	1581082	1	2575
Port-of-Spain	5038	2	23100	43396	1	3616
Kuala Lumpur	3174	2	15000	1551306	1	6384
Caracas	2928	2	10915	1975294	1	4562
Porto Alegre	1292	1	16667	19089	3	45
Guadalajara	1719	1	18837	1640589	3	10865
Curitiba	1775	1	23268	1788559	3	4189
Tripoli	3327	2	13900	1500000	2	4205
Beirut	2242	2	10700	361366	3	18437
Sofia	4122	2	12300	1155403	3	859
Belgrade	3922	2	10300	1313994	3	3379
Montevideo	2007	2	11600	1345010	3	2538
Budapest	3771	2	19876	1699213	3	3237
Warsaw	3437	2	17977	1704717	3	3297
Bucharest	2331	2	11500	1931838	3	8121
Vilnius	3104	2	17400	543494	4	1379
Vladivostok	4725	2	12207	579811	4	966
Riga	2702	2	10499	719928	4	2376
Minsk	3208	2	10800	1789098	4	5847
Dubai	13708	3	11400	1089000	2	846
Victoria, BC	14264	3	13539	289625	3	15243
Ottawa	15332	3	19402	812129	4	292
Casablanca	638	1	10374	2995000	3	9244
Delhi	470	1	10486	9879172	3	22922
Bangalore	448	1	10514	5104047	1	7199
Shenzhen	1696	1	11047	7008831	3	17744
Tashkent	1659	1	11600	2137218	3	7124
Cairo	1235	1	12192	6758581	2	31582
Cali	475	1	12741	2392877	1	4372

Lima	831	1	12864	8445211	2	10557
Ho Chi Minh City	573	1	13200	3015743	1	21541
Beijing	1756	1	13325	11509595	4	8413
Guangzhou	1719	1	14044	8524826	3	2218
Quezon City	582	1	14080	2173831	1	12661
Shanghai	1783	1	15547	14348535	3	7442
Ankara	1772	1	15608	3517182	3	1398
Bogota	2053	2	11960	7102602	3	4467
Bangkok	1899	1	17751	5658953	1	8084
Istanbul	1921	1	18090	11174257	3	6103
Mexico City	1968	1	20496	11285654	3	7600
Belo Horizonte	1812	1	24317	2399920	3	7164
Tehran	2117	2	16131	7088287	3	9327
St. Petersburg	5459	2	19987	4569616	4	7541
Sao Paulo	2016	2	20589	11016703	3	7234
Santiago	3074	2	20979	4960815	3	6823
Riyadh	6813	2	23964	4087152	2	5109
Prague	6342	2	25500	1188126	3	9741
Athens	5242	2	26042	789166	3	20235
Lisbon	4663	2	27292	504726	3	5954
Buenos Aires	2418	2	28292	2965403	3	51
Ljubljana	6918	2	28900	250953	3	1530
Johannesburg	4363	2	32023	752349	3	2364
Cape Town	4858	2	32037	3497097	3	12059
Berlin	7113	3	28529	3386667	3	3801
Barcelona	5867	2	35976	1605602	3	516
Los Angeles, CA	6905	2	48896	3834340	3	1616
Rome	5852	2	43127	2626640	3	2009
Hamburg	6779	2	54103	1704735	3	2258
Sydney	11265	3	49226	4336374	3	357
Melbourne	11163	3	46137	3806092	3	495
Brussels	8510	3	45355	144784	3	899
Luxembourg-Ville	15681	3	70597	84644	3	1660
Bern	8088	3	41900	122256	3	2368
Seattle, WA	11268	3	56788	594210	3	2733
Vienna	7886	3	53776	1664146	3	4013
Dublin	6234	2	36721	495781	3	4202
Amsterdam	6988	2	60514	742884	3	4467
Copenhagen	6665	2	71164	505141	3	5740
Jerusalem	6750	2	42432	740475	3	5914
Hong Kong	5878	2	42700	6925900	3	6421

Milan	5572	2	46180	1306086	3	7174
Tel Aviv	6451	2	39003	387234	3	7476
New York, NY	6680	2	56149	8274527	3	10350
Nagoya	7465	3	34811	2215062	3	6785
Yokohama	7720	3	37054	3579628	3	8184
London	6233	2	41271	7421209	3	10505
Madrid	6147	2	41315	3128600	3	19509
Geneva	8305	3	44017	178574	3	10829
Osaka	7555	3	36922	2628811	3	11836
Tokyo	8201	3	41456	8489653	3	13663
Vancouver, BC	16234	3	44884	1837969	3	16123
Paris	7945	3	57027	2125017	3	20238
Brasilia	1811	1	30564	2383784	1	411
Stockholm	399	1	34668	789024	4	4219
Moscow	5785	2	30712	10456490	4	9673
Honolulu, HI	10912	3	45444	375571	1	1692
Singapore	8507	3	51656	4588600	1	6582
Bandar seri begawan	8424	3	53900	27285	1	272
Manama	11401	3	36100	176909	2	5897
Phoenix, AZ	12051	3	41260	1552259	2	1168
Abu Dhabi	13029	3	43700	527000	2	293
Kuwait City	15345	3	55600	32403	2	11900
Denver, CO	11260	3	55700	588349	2	1558
Doha	15108	3	100300	344939	2	2174
Seoul	7804	3	29706	10020123	4	16553
Montreal	16902	3	40709	3268513	4	8955
Helsinki	16120	3	44249	566526	4	3040
Detroit, MI	11615	3	44344	916952	4	2552
Toronto	17314	3	45537	4612191	4	3677
Chicago, IL	12571	3	48840	2836658	4	4819
Boston, MA	11275	3	58686	599351	4	4783
Anchorage, AK	10689	3	63549	279671	4	64

APPENDIX A.3 Fossil Fuels Consumption data set

CITIES	fossil fuels per cap, tons	fossil class	population	GDP per cap, 2000US$	population density/sq.km	climate
Kinshasa	0.01	1	7785965	300	955	1
Bujumbura	0.01	1	235440	300	2738	1
Phnom Penh	0.02	1	703963	1900	33522	1
Addis Ababa	0.02	1	2646000	800	4992	3
Bamako	0.02	1	1297281	1100	13374	1
Dar es Salaam	0.03	1	1360850	1300	856	1
Bangui	0.03	1	451690	700	6742	1
Ouagadougou	0.03	1	1475839	1200	6739	2
Niamey	0.04	1	707951	700	2962	2
Antananarivo	0.05	1	1015140	1000	14099	3
Kathmandu	0.05	1	671846	1100	13711	3
Conakry	0.05	1	1091500	1100	2426	1
Yangon	0.07	1	4477638	1200	7488	1
Freetown	0.07	1	802639	900	5859	1
Banjul	0.08	1	42326	1300	3527	1
Dhaka	0.08	1	10356500	6095	34067	1
Accra	0.1	1	1658937	1400	8967	1
Nairobi	0.11	1	2948109	1700	4236	3
Abuja	0.12	1	107069	24411	1091	1
Dakar	0.16	1	1075582	1700	2151	1
Lagos	0.16	1	5195247	3697	5200	1
Colombo	0.19	1	615000	4200	880	1
Sana'a	0.2	1	954448	2500	3864	2
Asuncion	0.21	1	513399	4200	4388	3
Islamabad	0.23	1	529180	7181	4410	3
Ho Chi Minh City	0.23	1	3015743	13200	21541	1
Karachi	0.28	1	9339023	6430	2648	2
Guatemala City	0.29	1	1022001	5300	4482	1
San Salvador	0.3	1	507665	7300	573	1
Tbilisi	0.31	1	1108600	4600	2038	3
Cebu	0.33	1	718821	11371	2558	1
Rabat	0.34	1	642000	8175	5321	3
Manila	0.35	1	1581082	13423	2575	1
Quezon City	0.36	1	2173831	14080	12661	1
Naihati	0.36	1	215303	6046	18641	1
Lima	0.37	1	8445211	12864	10557	2
Casablanca	0.38	1	2995000	10374	9244	3

Bishkek	0.43	1	798300	2100	6271	4
Hyderabad	0.44	1	3637483	9538	21065	1
Surabaya	0.44	1	2611506	6811	7440	1
Chennai	0.45	1	4343645	8902	24963	2
Kolkata	0.45	1	4572876	7033	24718	1
Bangalore	0.45	1	5104047	10514	7199	1
Porto Alegre	0.45	1	19089	16667	45	3
Cali	0.45	1	2392877	12741	4372	1
Delhi	0.47	1	9879172	10486	22922	3
Mumbai	0.48	1	11978450	3598	19865	1
Jakarta	0.48	1	8820603	10082	13284	1
Bogota	0.49	1	7102602	11960	4467	3
Florianopolis	0.56	1	406564	8253	924	3
Chisinau	0.6	1	660726	2400	5372	3
Quito	0.62	1	1559295	7300	9172	3
Montevideo	0.62	1	1345010	11600	2538	3
Curitiba	0.62	1	1788559	23268	4189	3
Brasilia	0.63	1	2383784	30564	411	1
Belo Horizonte	0.64	1	2399920	24317	7164	3
Panama City	0.64	1	484261	11100	4526	1
Cairo	0.67	1	6758581	12192	31582	2
Tunis	0.69	1	702330	7700	19847	3
Sao Paulo	0.71	1	11016703	20589	7234	3
Santo Domingo	0.74	1	913540	8000	10030	1
Damascus	0.99	1	1658000	4700	2894	3
Riga	0.99	1	719928	10499	2376	4
Amman	1.04	2	1204110	5100	717	2
Santiago	1.04	2	4960815	20979	6823	3
Shenzhen	1.08	2	7008831	11047	17744	3
Guangzhou	1.09	2	8524826	14044	2218	3
Beijing	1.11	2	11509595	13325	8413	4
Shanghai	1.13	2	14348535	15547	7442	3
Bangkok	1.15	2	5658953	17751	8084	1
Vilnius	1.32	2	543494	17400	1379	4
Beirut	1.39	2	361366	10700	18437	3
Kingston	1.45	2	579137	8800	26324	1
Buenos Aires	1.47	2	2965403	28292	51	3
Tehran	1.63	2	7088287	16131	9327	3
Caracas	1.67	2	1975294	10915	4562	1
Ankara	1.71	2	3517182	15608	1398	3
Guadalajara	1.85	2	1640589	18837	10865	3
Istanbul	1.85	2	11174257	18090	6103	3
Tashkent	1.93	2	2137218	11600	7124	3

Kuala Lumpur	2.04	2	1551306	15000	6384	1
Mexico City	2.11	2	11285654	20496	7600	3
Minsk	2.15	2	1789098	10800	5847	4
Ulaanbaatar	2.17	2	1012733	3000	5038	4
Bern	2.23	2	122256	41900	2368	3
Geneva	2.29	2	178574	44017	10829	3
Stockholm	2.31	2	789024	34668	4219	4
Bucharest	2.44	2	1931838	11500	8121	3
Lisbon	2.45	2	504725.5	27292	5954	3
Sarajevo	2.52	2	527049	6300	3738	3
Paris	2.55	2	2125017	57027	20238	3
Kiev	2.74	2	2676789	7200	3210	4
Milan	2.9	2	1306086	46180	7174	3
Rome	3.05	2	2626640	43127	2009	3
Vienna	3.14	2	1664146	53776	4013	3
Barcelona	3.16	2	1605602	35976	516	3
Budapest	3.2	2	1699212.5	19876	3237	3
Nagoya	3.31	2	2215062	34811	6785	3
Madrid	3.31	2	3128600	41315	19509	3
Osaka	3.35	2	2628811	36922	11836	3
Tripoli	3.37	2	1500000	13900	4205	2
Yokohama	3.43	2	3579628	37054	8184	3
Durban	3.49	2	669242	1483	1513	3
Johannesburg	3.52	2	752349	32023	2364	3
Tel Aviv	3.55	2	387233.5	39003	7476	3
Tokyo	3.64	2	8489653	41456	13663	3
London	3.66	2	7421209	41271	10505	3
Vladivostok	3.68	2	579811	12207	966	4
Jerusalem	3.71	2	740475	42432	5914	3
Belgrade	3.73	2	1313994	10300	3379	3
Dublin	3.8	2	495781	36721	4202	3
Seoul	3.91	2	10020123	29706	16553	4
Cape Town	3.92	2	3497097	32037	12059	3
Helsinki	3.93	2	566526	44249	3040	4
Copenhagen	4.03	2	505141	71164	5740	3
Ljubljana	4.15	2	250953	28900	1530	3
Port-of-Spain	4.25	2	43396	23100	3616	1
St. Petersburg	4.25	2	4569616	19987	7541	4
Warsaw	4.35	2	1704717	17977	3297	3
Moscow	4.5	2	10456490	30712	9673	4
Sofia	4.59	2	1155403	12300	859	3
St. John's	4.77	2	99182	27646	222	4
Hamburg	4.95	2	1704735	54103	2258	3

Brussels	5.09	3	144784	45355	899	3
Victoria, BC	5.14	3	289625	13539	15243	3
Riyadh	5.14	3	4087152	23964	5109	2
Berlin	5.2	3	3386667	28529	3801	3
Amsterdam	5.32	3	742884	60514	4467	3
Bandar seri begawan	5.4	3	27285	53900	272	1
Ottawa	5.53	3	812129	19402	292	4
Vancouver, BC	5.85	3	1837969	44884	16123	3
Montreal	6.09	3	3268513	40709	8955	4
Toronto	6.24	3	4612191	45537	3677	4
Anchorage, AK	6.38	3	279671	63549	64	4
Honolulu, HI	6.52	3	375571	45444	1692	1
Denver, CO	6.72	3	588349	55700	1558	2
Seattle, WA	6.73	3	594210	56788	2733	3
Boston, MA	6.73	3	599351	58686	4783	4
Detroit, MI	6.94	3	916952	44344	2552	4
Prague	7	3	1188126	25500	9741	3
Phoenix, AZ	7.2	3	1552259	41260	1168	2
Chicago, IL	7.51	3	2836658	48840	4819	4
Los Angeles, CA	7.67	3	3834340	48896	1616	3
New York, NY	8.09	3	8274527	56149	10350	3
Athens	8.2	3	789166	26042	20235	3
Manama	8.63	3	176909	36100	5897	2
Melbourne	9.58	3	3806092	46137	495	3
Sydney	9.66	3	4336374	49226	357	3
Kuwait City	10.99	3	32403	55600	11900	2
Abu Dhabi	15	3	527000	43700	293	2
Dubai	15.78	3	1089000	11400	846	2
Doha	21.41	3	344939	100300	2174	2

APPENDIX A.4 Industrial Minerals & Ores Consumption data set

CITIES	industrial minerals per cap, tons	industrial class	population	GDP per cap, 2000US$	population density/sq.km	climate
Port-of-Spain	-3.18	1	43396	23100	3616	1
Doha	-2.42	1	344939	100300	2174	2
Manama	-0.69	1	176909	36100	5897	2
Kuwait City	-0.35	1	32403	55600	11900	2
Tbilisi	-0.1	1	1108600	4600	2038	3
Vilnius	0	1	543494	17400	1379	4
Dhaka	0	1	10356500	6095	34067	1
Bandar seri begawan	0	1	27285	53900	272	1
Tripoli	0	1	1500000	13900	4205	2
Sana'a	0	1	954448	2500	3864	2
Kathmandu	0	1	671846	1100	13711	3
Freetown	0	1	802639	900	5859	1
Yangon	0.01	1	4477638	1200	7488	1
Bangui	0.01	1	451690	700	6742	1
Antananarivo	0.01	1	1015140	1000	14099	3
Colombo	0.01	1	615000	4200	880	1
Addis Ababa	0.01	1	2646000	800	4992	3
Banjul	0.01	1	42326	1300	3527	1
Nairobi	0.01	1	2948109	1700	4236	3
Dar es Salaam	0.01	1	1360850	1300	856	1
Abuja	0.02	1	107069	24411	1091	1
Lagos	0.02	1	5195247	3697	5200	1
Ouagadougou	0.02	1	1475839	1200	6739	2
Phnom Penh	0.03	1	703963	1900	33522	1
Bujumbura	0.03	1	235440	300	2738	1
Islamabad	0.03	1	529180	7181	4410	3
Abu Dhabi	0.03	1	527000	43700	293	2
Dubai	0.03	1	1089000	11400	846	2
Kinshasa	0.04	1	7785965	300	955	1
Karachi	0.04	1	9339023	6430	2648	2
Minsk	0.04	1	1789098	10800	5847	4
Sarajevo	0.05	1	527049	6300	3738	3
Chisinau	0.05	1	660726	2400	5372	3
Ho Chi Minh City	0.05	1	3015743	13200	21541	1
Naihati	0.06	1	215303	6046	18641	1
Asuncion	0.07	1	513399	4200	4388	3
Hyderabad	0.08	1	3637483	9538	21065	1

Guatemala City	0.08	1	1022001	5300	4482	1
Chennai	0.08	1	4343645	8902	24963	2
Kolkata	0.08	1	4572876	7033	24718	1
Bangalore	0.08	1	5104047	10514	7199	1
Delhi	0.08	1	9879172	10486	22922	3
Mumbai	0.08	1	11978450	3598	19865	1
Cairo	0.1	1	6758581	12192	31582	2
San Salvador	0.12	1	507665	7300	573	1
Niamey	0.13	1	707951	700	2962	2
Cebu	0.14	1	718821	11371	2558	1
Riga	0.14	1	719928	10499	2376	4
Manila	0.15	1	1581082	13423	2575	1
Quito	0.15	1	1559295	7300	9172	3
Quezon City	0.15	1	2173831	14080	12661	1
Riyadh	0.16	1	4087152	23964	5109	2
Panama City	0.17	1	484261	11100	4526	1
Surabaya	0.18	1	2611506	6811	7440	1
Bangkok	0.18	1	5658953	17751	8084	1
Jakarta	0.19	1	8820603	10082	13284	1
Belgrade	0.19	1	1313994	10300	3379	3
Cali	0.19	1	2392877	12741	4372	1
Dakar	0.2	1	1075582	1700	2151	1
Bogota	0.21	1	7102602	11960	4467	3
Damascus	0.21	1	1658000	4700	2894	3
Montevideo	0.23	1	1345010	11600	2538	3
Bamako	0.23	1	1297281	1100	13374	1
Vienna	0.26	1	1664146	53776	4013	3
Budapest	0.34	1	1699212.5	19876	3237	3
Amsterdam	0.36	1	742884	60514	4467	3
Shenzhen	0.36	1	7008831	11047	17744	3
Guangzhou	0.37	1	8524826	14044	2218	3
Beijing	0.37	1	11509595	13325	8413	4
Shanghai	0.38	1	14348535	15547	7442	3
Accra	0.39	1	1658937	1400	8967	1
Bucharest	0.4	1	1931838	11500	8121	3
Buenos Aires	0.4	1	2965403	28292	51	3
Tehran	0.41	1	7088287	16131	9327	3
Beirut	0.42	1	361366	10700	18437	3
Porto Alegre	0.44	1	19089	16667	45	3
Tel Aviv	0.44	1	387233.5	39003	7476	3
Jerusalem	0.46	1	740475	42432	5914	3
Bern	0.46	1	122256	41900	2368	3
Ankara	0.47	1	3517182	15608	1398	3
Geneva	0.48	1	178574	44017	10829	3
Lisbon	0.49	1	504725.5	27292	5954	3

Santo Domingo	0.5	2	913540	8000	10030	1
Istanbul	0.51	2	11174257	18090	6103	3
Florianopolis	0.54	2	406564	8253	924	3
Prague	0.54	2	1188126	25500	9741	3
London	0.58	2	7421209	41271	10505	3
Curitiba	0.6	2	1788559	23268	4189	3
Kuala Lumpur	0.61	2	1551306	15000	6384	1
Brasilia	0.61	2	2383784	30564	411	1
Belo Horizonte	0.61	2	2399920	24317	7164	3
Hamburg	0.64	2	1704735	54103	2258	3
Rabat	0.66	2	642000	8175	5321	3
Caracas	0.67	2	1975294	10915	4562	1
Berlin	0.68	2	3386667	28529	3801	3
Copenhagen	0.68	2	505141	71164	5740	3
Sao Paulo	0.68	2	11016703	20589	7234	3
Casablanca	0.73	2	2995000	10374	9244	3
Paris	0.75	2	2125017	57027	20238	3
Bishkek	0.81	2	798300	2100	6271	4
Brussels	0.83	2	144784	45355	899	3
Ljubljana	0.83	2	250953	28900	1530	3
Milan	0.86	2	1306086	46180	7174	3
Barcelona	0.89	2	1605602	35976	516	3
Athens	0.89	2	789166	26042	20235	3
Rome	0.9	2	2626640	43127	2009	3
Madrid	0.93	2	3128600	41315	19509	3
Tunis	1	3	702330	7700	19847	3
Nagoya	1	3	2215062	34811	6785	3
Osaka	1.01	3	2628811	36922	11836	3
Yokohama	1.04	3	3579628	37054	8184	3
Vladivostok	1.07	3	579811	12207	966	4
Tokyo	1.1	3	8489653	41456	13663	3
Warsaw	1.2	3	1704717	17977	3297	3
Conakry	1.22	3	1091500	1100	2426	1
St. Petersburg	1.23	3	4569616	19987	7541	4
Moscow	1.31	3	10456490	30712	9673	4
Guadalajara	1.52	3	1640589	18837	10865	3
Mexico City	1.74	3	11285654	20496	7600	3
Stockholm	1.77	3	789024	34668	4219	4
Seoul	1.77	3	10020123	29706	16553	4
Kiev	1.86	3	2676789	7200	3210	4
Durban	1.94	3	669242	1483	1513	3
Tashkent	1.95	3	2137218	11600	7124	3

Johannesburg	1.95	3	752349	32023	2364	3
Ulaanbaatar	2.06	3	1012733	3000	5038	4
Amman	2.12	3	1204110	5100	717	2
Cape Town	2.18	3	3497097	32037	12059	3
Lima	2.34	3	8445211	12864	10557	2
Helsinki	2.42	3	566526	44249	3040	4
Dublin	2.49	3	495781	36721	4202	3
St. John's	2.64	3	99182	27646	222	4
Sofia	2.72	3	1155403	12300	859	3
Victoria, BC	2.84	3	289625	13539	15243	3
Anchorage, AK	2.96	3	279671	63549	64	4
Honolulu, HI	3.02	3	375571	45444	1692	1
Ottawa	3.06	3	812129	19402	292	4
Denver, CO	3.12	3	588349	55700	1558	2
Seattle, WA	3.12	3	594210	56788	2733	3
Boston, MA	3.12	3	599351	58686	4783	4
Detroit, MI	3.22	3	916952	44344	2552	4
Vancouver, BC	3.24	3	1837969	44884	16123	3
Phoenix, AZ	3.34	3	1552259	41260	1168	2
Montreal	3.37	3	3268513	40709	8955	4
Toronto	3.45	3	4612191	45537	3677	4
Chicago, IL	3.48	3	2836658	48840	4819	4
Los Angeles, CA	3.55	3	3834340	48896	1616	3
Kingston	3.61	3	579137	8800	26324	1
New York, NY	3.75	3	8274527	56149	10350	3
Melbourne	7.44	3	3806092	46137	495	3
Sydney	7.51	3	4336374	49226	357	3
Santiago	7.67	3	4960815	20979	6823	3

APPENDIX A.5 Construction Minerals consumption data set

CITIES	const. minerals per cap, tons	construction class	population	GDP per cap, 2000US$	pop. density /sq.km	climate
Abuja	0.76	1	107069	24411	1091	1
Ouagadougou	1	1	1475839	1200	6739	2
Bujumbura	1	1	235440	300	2738	1
Phnom Penh	1	1	703963	1900	33522	1
Bangui	1	1	451690	700	6742	1
Kinshasa	1	1	7785965	300	955	1
Addis Ababa	1	1	2646000	800	4992	3
Banjul	1	1	42326	1300	3527	1
Nairobi	1	1	2948109	1700	4236	3
Antananarivo	1	1	1015140	1000	14099	3
Bamako	1	1	1297281	1100	13374	1
Ulaanbaatar	1	1	1012733	3000	5038	4
Niamey	1	1	707951	700	2962	2
Lagos	1	1	5195247	3697	5200	1
Freetown	1	1	802639	900	5859	1
Dar es Salaam	1	1	1360850	1300	856	1
Sana'a	1	1	954448	2500	3864	2
Cairo	1.12	1	6758581	12192	31582	2
Durban	1.15	1	669242	1483	1513	3
Johannesburg	1.16	1	752349	32023	2364	3
Cape Town	1.29	1	3497097	32037	12059	3
Islamabad	1.64	1	529180	7181	4410	3
Dhaka	2	1	10356500	6095	34067	1
Tbilisi	2	1	1108600	4600	2038	3
Accra	2	1	1658937	1400	8967	1
Conakry	2	1	1091500	1100	2426	1
Bishkek	2	1	798300	2100	6271	4
Kathmandu	2	1	671846	1100	13711	3
Karachi	2	1	9339023	6430	2648	2
Chisinau	2	1	660726	2400	5372	3
Dakar	2	1	1075582	1700	2151	1
Tashkent	2	1	2137218	11600	7124	3
Ho Chi Minh City	2	1	3015743	13200	21541	1
Naihati	2.22	1	215303	6046	18641	1
Hyderabad	2.71	1	3637483	9538	21065	1
Chennai	2.74	1	4343645	8902	24963	2
Kolkata	2.75	1	4572876	7033	24718	1
Surabaya	2.75	1	2611506	6811	7440	1

Bangalore	2.77	1	5104047	10514	7199	1
Delhi	2.9	1	9879172	10486	22922	3
Mumbai	2.94	1	11978450	3598	19865	1
Quito	3	1	1559295	7300	9172	3
Jakarta	3	1	8820603	10082	13284	1
Damascus	3	1	1658000	4700	2894	3
Rabat	3.59	1	642000	8175	5321	3
Shenzhen	3.8	1	7008831	11047	17744	3
Porto Alegre	3.84	1	19089	16667	45	3
Guangzhou	3.86	1	8524826	14044	2218	3
Beijing	3.94	1	11509595	13325	8413	4
Shanghai	4	1	14348535	15547	7442	3
Guatemala City	4	1	1022001	5300	4482	1
Kingston	4	1	579137	8800	26324	1
Amman	4	1	1204110	5100	717	2
Casablanca	4	1	2995000	10374	9244	3
Yangon	4	1	4477638	1200	7488	1
Belgrade	4	1	1313994	10300	3379	3
Colombo	4	1	615000	4200	880	1
Kiev	4	1	2676789	7200	3210	4
Riyadh	4.24	1	4087152	23964	5109	2
London	4.26	1	7421209	41271	10505	3
Cali	4.63	1	2392877	12741	4372	1
Florianopolis	4.76	1	406564	8253	924	3
Milan	4.79	1	1306086	46180	7174	3
Amsterdam	4.8	1	742884	60514	4467	3
Vladivostok	4.9	1	579811	12207	966	4
Minsk	5	2	1789098	10800	5847	4
Sarajevo	5	2	527049	6300	3738	3
Sofia	5	2	1155403	12300	859	3
Bogota	5	2	7102602	11960	4467	3
Santo Domingo	5	2	913540	8000	10030	1
San Salvador	5	2	507665	7300	573	1
Tehran	5	2	7088287	16131	9327	3
Beirut	5	2	361366	10700	18437	3
Tripoli	5	2	1500000	13900	4205	2
Panama City	5	2	484261	11100	4526	1
Asuncion	5	2	513399	4200	4388	3
Lima	5	2	8445211	12864	10557	2
Bucharest	5	2	1931838	11500	8121	3
Tunis	5	2	702330	7700	19847	3
Caracas	5	2	1975294	10915	4562	1
Rome	5.03	2	2626640	43127	2009	3
Cebu	5.11	2	718821	11371	2558	1

Curitiba	5.28	2	1788559	23268	4189	3
Brasilia	5.39	2	2383784	30564	411	1
Belo Horizonte	5.39	2	2399920	24317	7164	3
Manila	5.4	2	1581082	13423	2575	1
Quezon City	5.52	2	2173831	14080	12661	1
Ankara	5.53	2	3517182	15608	1398	3
St. Petersburg	5.66	2	4569616	19987	7541	4
Sao Paulo	6	2	11016703	20589	7234	3
Riga	6	2	719928	10499	2376	4
Vilnius	6	2	543494	17400	1379	4
Moscow	6	2	10456490	30712	9673	4
Istanbul	6	2	11174257	18090	6103	3
Guadalajara	6.12	2	1640589	18837	10865	3
Athens	6.63	2	789166	26042	20235	3
Paris	6.81	2	2125017	57027	20238	3
Santiago	7	2	4960815	20979	6823	3
Kuala Lumpur	7	2	1551306	15000	6384	1
Mexico City	7	2	11285654	20496	7600	3
Warsaw	7	2	1704717	17977	3297	3
Port-of-Spain	7	2	43396	23100	3616	1
Montevideo	7	2	1345010	11600	2538	3
Dublin	7.1	2	495781	36721	4202	3
Barcelona	7.32	2	1605602	35976	516	3
Brussels	7.41	2	144784	45355	899	3
Madrid	7.67	2	3128600	41315	19509	3
Bangkok	7.91	2	5658953	17751	8084	1
Anchorage, AK	7.96	2	279671	63549	64	4
Buenos Aires	8	3	2965403	28292	51	3
Manama	8	3	176909	36100	5897	2
Bandar seri begawan	8	3	27285	53900	272	1
Prague	8	3	1188126	25500	9741	3
Budapest	8	3	1699212.5	19876	3237	3
Seoul	8	3	10020123	29706	16553	4
Honolulu, HI	8.12	3	375571	45444	1692	1
Lisbon	8.18	3	504725.5	27292	5954	3
Denver, CO	8.38	3	588349	55700	1558	2
Seattle, WA	8.39	3	594210	56788	2733	3
Boston, MA	8.39	3	599351	58686	4783	4
Hamburg	8.45	3	1704735	54103	2258	3
Tel Aviv	8.6	3	387233.5	39003	7476	3
Detroit, MI	8.65	3	916952	44344	2552	4
Berlin	8.86	3	3386667	28529	3801	3

Phoenix, AZ	8.97	3	1552259	41260	1168	2
Jerusalem	9	3	740475	42432	5914	3
Kuwait City	9	3	32403	55600	11900	2
Ljubljana	9	3	250953	28900	1530	3
Nagoya	9.3	3	2215062	34811	6785	3
St. John's	9.34	3	99182	27646	222	4
Chicago, IL	9.36	3	2836658	48840	4819	4
Osaka	9.41	3	2628811	36922	11836	3
Vienna	9.46	3	1664146	53776	4013	3
Abu Dhabi	9.5	3	527000	43700	293	2
Los Angeles, CA	9.56	3	3834340	48896	1616	3
Yokohama	9.61	3	3579628	37054	8184	3
Bern	9.74	3	122256	41900	2368	3
Melbourne	9.91	3	3806092	46137	495	3
Stockholm	9.94	3	789024	34668	4219	4
Sydney	10	3	4336374	49226	357	3
Doha	10	3	344939	100300	2174	2
Geneva	10	3	178574	44017	10829	3
Dubai	10	3	1089000	11400	846	2
Victoria, BC	10.07	3	289625	13539	15243	3
New York, NY	10.09	3	8274527	56149	10350	3
Tokyo	10.21	3	8489653	41456	13663	3
Ottawa	10.82	3	812129	19402	292	4
Vancouver, BC	11.46	3	1837969	44884	16123	3
Montreal	11.93	3	3268513	40709	8955	4
Copenhagen	12.17	3	505141	71164	5740	3
Toronto	12.22	3	4612191	45537	3677	4
Helsinki	18.44	3	566526	44249	3040	4

Appendix A.6 Biomass Consumption data set

CITIES	biomass per cap, tons	biomass class	population	GDP per cap, 2000US$	Pop. density /sq.km	climate
Sana'a	0.89	1	954448	2500	3864	2
Manama	0.95	1	176909	36100	5897	2
Amman	0.97	1	1204110	5100	717	2
Bandar seri begawan	1.16	1	27285	53900	272	1
Kuwait City	1.22	1	32403	55600	11900	2
Dhaka	1.25	1	10356500	6095	34067	1
Riyadh	1.26	1	4087152	23964	5109	2
Nagoya	1.35	1	2215062	34811	6785	3
Colombo	1.35	1	615000	4200	880	1
Osaka	1.36	1	2628811	36922	11836	3
Yokohama	1.39	1	3579628	37054	8184	3
Tokyo	1.48	1	8489653	41456	13663	3
Beirut	1.51	1	361366	10700	18437	3
Naihati	1.54	1	215303	6046	18641	1
Tbilisi	1.57	1	1108600	4600	2038	3
Freetown	1.61	1	802639	900	5859	1
Seoul	1.64	1	10020123	29706	16553	4
Rabat	1.66	1	642000	8175	5321	3
Port-of-Spain	1.67	1	43396	23100	3616	1
Damascus	1.68	1	1658000	4700	2894	3
Tashkent	1.69	1	2137218	11600	7124	3
Kinshasa	1.76	1	7785965	300	955	1
Surabaya	1.77	1	2611506	6811	7440	1
Islamabad	1.79	1	529180	7181	4410	3
Doha	1.82	1	344939	100300	2174	2
Ho Chi Minh City	1.84	1	3015743	13200	21541	1
Bujumbura	1.84	1	235440	300	2738	1
Casablanca	1.85	1	2995000	10374	9244	3
Phnom Penh	1.86	1	703963	1900	33522	1
Hyderabad	1.88	1	3637483	9538	21065	1
Shenzhen	1.88	1	7008831	11047	17744	3
Banjul	1.88	1	42326	1300	3527	1
Chennai	1.9	1	4343645	8902	24963	2
Guangzhou	1.9	1	8524826	14044	2218	3
Kolkata	1.91	1	4572876	7033	24718	1
Bangalore	1.92	1	5104047	10514	7199	1
Jakarta	1.93	1	8820603	10082	13284	1
Beijing	1.94	1	11509595	13325	8413	4
Tunis	1.94	1	702330	7700	19847	3
Tripoli	1.95	1	1500000	13900	4205	2

Shanghai	1.97	1	14348535	15547	7442	3
Tel Aviv	1.99	1	387233.5	39003	7476	3
Delhi	2.01	2	9879172	10486	22922	3
Cairo	2.04	2	6758581	12192	31582	2
Mumbai	2.04	2	11978450	3598	19865	1
Cebu	2.05	2	718821	11371	2558	1
Jerusalem	2.09	2	740475	42432	5914	3
Tehran	2.09	2	7088287	16131	9327	3
Abuja	2.13	2	107069	24411	1091	1
Manila	2.17	2	1581082	13423	2575	1
Karachi	2.19	2	9339023	6430	2648	2
Quezon City	2.22	2	2173831	14080	12661	1
Yangon	2.23	2	4477638	1200	7488	1
Sarajevo	2.3	2	527049	6300	3738	3
Chisinau	2.37	2	660726	2400	5372	3
Nairobi	2.47	2	2948109	1700	4236	3
Kathmandu	2.5	2	671846	1100	13711	3
Dar es Salaam	2.53	2	1360850	1300	856	1
Santo Domingo	2.54	2	913540	8000	10030	1
Belgrade	2.57	2	1313994	10300	3379	3
Accra	2.63	2	1658937	1400	8967	1
Dakar	2.63	2	1075582	1700	2151	1
Niamey	2.65	2	707951	700	2962	2
Ankara	2.66	2	3517182	15608	1398	3
Vladivostok	2.69	2	579811	12207	966	4
San Salvador	2.71	2	507665	7300	573	1
Kingston	2.76	2	579137	8800	26324	1
Lagos	2.79	2	5195247	3697	5200	1
Istanbul	2.89	2	11174257	18090	6103	3
Conakry	2.89	2	1091500	1100	2426	1
Abu Dhabi	2.97	2	527000	43700	293	2
Ouagadougou	3.01	2	1475839	1200	6739	2
Bern	3.04	2	122256	41900	2368	3
Sofia	3.05	2	1155403	12300	859	3
Riga	3.05	2	719928	10499	2376	4
Antananarivo	3.06	2	1015140	1000	14099	3
Bangkok	3.08	2	5658953	17751	8084	1
Bucharest	3.1	2	1931838	11500	8121	3
St. Petersburg	3.11	2	4569616	19987	7541	4
Dubai	3.12	2	1089000	11400	846	2
Geneva	3.12	2	178574	44017	10829	3
London	3.16	2	7421209	41271	10505	3
Addis Ababa	3.16	2	2646000	800	4992	3

Lima	3.18	2	8445211	12864	10557	2
Guadalajara	3.3	2	1640589	18837	10865	3
Moscow	3.3	2	10456490	30712	9673	4
Milan	3.34	2	1306086	46180	7174	3
Bishkek	3.38	2	798300	2100	6271	4
Durban	3.49	2	669242	1483	1513	3
Rome	3.5	2	2626640	43127	2009	3
Johannesburg	3.51	2	752349	32023	2364	3
Bamako	3.54	2	1297281	1100	13374	1
Quito	3.54	2	1559295	7300	9172	3
Barcelona	3.64	2	1605602	35976	516	3
Guatemala City	3.67	2	1022001	5300	4482	1
Athens	3.73	2	789166	26042	20235	3
Caracas	3.75	2	1975294	10915	4562	1
Panama City	3.75	2	484261	11100	4526	1
Mexico City	3.77	2	11285654	20496	7600	3
Madrid	3.81	2	3128600	41315	19509	3
Santiago	3.81	2	4960815	20979	6823	3
Cape Town	3.91	2	3497097	32037	12059	3
Cali	4.01	2	2392877	12741	4372	1
Warsaw	4.1	2	1704717	17977	3297	3
Kiev	4.12	2	2676789	7200	3210	4
Bogota	4.33	2	7102602	11960	4467	3
Ljubljana	4.46	2	250953	28900	1530	3
Bangui	4.47	2	451690	700	6742	1
Prague	4.62	2	1188126	25500	9741	3
Kuala Lumpur	4.72	2	1551306	15000	6384	1
Vilnius	4.9	2	543494	17400	1379	4
Hamburg	4.91	2	1704735	54103	2258	3
Berlin	5.15	3	3386667	28529	3801	3
Anchorage, AK	5.15	3	279671	63549	64	4
Honolulu, HI	5.26	3	375571	45444	1692	1
Stockholm	5.36	3	789024	34668	4219	4
Vienna	5.37	3	1664146	53776	4013	3
Denver, CO	5.43	3	588349	55700	1558	2
Seattle, WA	5.43	3	594210	56788	2733	3
Boston, MA	5.44	3	599351	58686	4783	4
Amsterdam	5.47	3	742884	60514	4467	3
Budapest	5.47	3	1699212.5	19876	3237	3
Porto Alegre	5.47	3	19089	16667	45	3
Lisbon	5.54	3	504725.5	27292	5954	3
Detroit, MI	5.6	3	916952	44344	2552	4
Minsk	5.61	3	1789098	10800	5847	4

St. John's	5.63	3	99182	27646	222	4
Phoenix, AZ	5.81	3	1552259	41260	1168	2
Chicago, IL	6.06	3	2836658	48840	4819	4
Victoria, BC	6.06	3	289625	13539	15243	3
Los Angeles, CA	6.19	3	3834340	48896	1616	3
Brussels	6.35	3	144784	45355	899	3
Helsinki	6.51	3	566526	44249	3040	4
Ottawa	6.52	3	812129	19402	292	4
New York, NY	6.53	3	8274527	56149	10350	3
Paris	6.71	3	2125017	57027	20238	3
Florianopolis	6.78	3	406564	8253	924	3
Vancouver, BC	6.9	3	1837969	44884	16123	3
Montreal	7.18	3	3268513	40709	8955	4
Toronto	7.36	3	4612191	45537	3677	4
Curitiba	7.52	3	1788559	23268	4189	3
Brasilia	7.67	3	2383784	30564	411	1
Belo Horizonte	7.67	3	2399920	24317	7164	3
Sao Paulo	8.54	3	11016703	20589	7234	3
Copenhagen	10.99	3	505141	71164	5740	3
Buenos Aires	12.02	3	2965403	28292	51	3
Dublin	13.02	3	495781	36721	4202	3
Ulaanbaatar	14	3	1012733	3000	5038	4
Melbourne	15.9	3	3806092	46137	495	3
Sydney	16.05	3	4336374	49226	357	3
Montevideo	18.26	3	1345010	11600	2538	3
Asuncion	21.56	3	513399	4200	4388	3

APPENDIX A.7 Water Consumption data set

CITIES	water per cap, m3	water class	population	GDP per cap, 2000US$	pop. density /sq.km	climate
Freetown	7	1	802639	900	5859	1
Bangui	7	1	451690	700	6742	1
Conakry	8	1	1091500	1100	2426	1
Ouagadougou	11	1	1475839	1200	6739	2
Yangon	14	1	4477638	1200	7488	1
Male	18	1	103693	4500	17884	1
Sana'a	19	1	954448	2500	3864	2
Addis Ababa	19	1	2646000	800	4992	3
Accra	19	1	1658937	1400	8967	1
Banjul	21	1	42326	1300	3527	1
Niamey	21	1	707951	700	2962	2
Colombo	21	1	615000	4200	880	1
Dakar	23	1	1075582	1700	2151	1
Dar es Salaam	23	1	1360850	1300	856	1
Kinshasa	25	1	7785965	300	955	1
Naihati	27	1	215303	6046	18641	1
Bujumbura	28	1	235440	300	2738	1
Bamako	28	1	1297281	1100	13374	1
Tunis	32	1	702330	7700	19847	3
Kolkata	34	1	4572876	7033	24718	1
Dhaka	34	1	10356500	6095	34067	1
Bangalore	34	1	5104047	10514	7199	1
Chennai	35	1	4343645	8902	24963	2
Delhi	36	1	9879172	10486	22922	3
Guatemala City	36	1	1022001	5300	4482	1
Mumbai	36	1	11978450	3598	19865	1
Bogota	37	1	7102602	11960	4467	3
Hyderabad	37	1	3637483	9538	21065	1
Abuja	37	1	107069	24411	1091	1
Tripoli	38	1	1500000	13900	4205	2
Surabaya	41	1	2611506	6811	7440	1
Jakarta	45	1	8820603	10082	13284	1
Montevideo	48	1	1345010	11600	2538	3
Lagos	49	1	5195247	3697	5200	1
Ho Chi Minh City	49	1	3015743	10915	21541	1
Durban	50	2	669242	1483	1513	3
Rabat	50	2	642000	8175	5321	3
Quezon City	53	2	2173831	14080	12661	1

Curitiba	54	2	1788559	23268	4189	3
Lima	54	2	8445211	12864	10557	2
Belo Horizonte	55	2	2399920	24317	7164	3
Islamabad	55	2	529180	7181	4410	3
Casablanca	56	2	2995000	10374	9244	3
Hamburg	57	2	1704735	54103	2258	3
San Salvador	58	2	507665	7300	573	1
Athens	58	2	789166	26042	20235	3
Damascus	59	2	1658000	4700	2894	3
Berlin	60	2	3386667	28529	3801	3
Brussels	61	2	144784	45355	899	3
Vilnius	61	2	543494	17400	1379	4
Florianopolis	64	2	406564	8253	924	3
Copenhagen	64	2	505141	71164	5740	3
Brasilia	65	2	2383784	30564	411	1
Quito	65	2	1559295	7300	9172	3
Cebu	65	2	718821	11371	2558	1
Porto Alegre	66	2	19089	16667	45	3
Nairobi	66	2	2948109	1700	4236	3
Karachi	67	2	9339023	6430	2648	2
Phnom Penh	68	2	703963	1900	33522	1
Antananarivo	68	2	1015140	1000	14099	3
Warsaw	70	2	1704717	17977	3297	3
Bangkok	71	2	5658953	17751	8084	1
Caracas	71	2	1975294	13200	4562	1
Guadalajara	72	2	1640589	18837	10865	3
Cape Town	72	2	3497097	32037	12059	3
Barcelona	72	2	1605602	35976	19509	3
Santo Domingo	74	2	913540	8000	10030	1
Sarajevo	76	2	527049	6300	3738	3
Helsinki	76	2	566526	44249	3040	4
Chisinau	76	2	660726	2400	5372	3
Sao Paulo	78	2	11016703	20589	7234	3
Vienna	79	2	1664146	53776	4013	3
Santiago	80	2	4960815	20979	6823	3
Bucharest	80	2	1931838	11500	8121	3
Madrid	80	2	3128600	41315	516	3
Kingston	81	2	579137	8800	26324	1
Mexico City	82	2	11285654	20496	7600	3
Ulaanbaatar	84	2	1012733	3000	5038	4
Seoul	85	2	10020123	29706	16553	4
Istanbul	85	2	11174257	18090	6103	3
Prague	86	2	1188126	25500	9741	3
Ljubljana	87	2	250953	28900	1530	3

Ankara	88	2	3517182	15608	1398	3
Riyadh	89	2	4087152	23964	5109	2
Johannesburg	89	2	752349	32023	2364	3
Asuncion	90	2	513399	4200	4388	3
Budapest	91	2	1699213	19876	3237	3
Kuwait City	95	2	32403	55600	11900	2
Amman	95	2	1204110	5100	717	2
Bishkek	96	2	798300	2100	6271	4
London	96	2	7421209	41271	10505	3
Paris	98	2	2125017	57027	20238	3
Tehran	99	2	7088287	16131	9327	3
Singapore	99	2	4588600	51656	6582	1
Riga	100	3	719928	10499	2376	4
Luxembourg-Ville	102	3	84644	70597	1660	3
Boston, MA	115	3	599351	58686	4783	4
Detroit, MI	118	3	916952	44344	2552	4
Minsk	118	3	1789098	10800	5847	4
Seattle, WA	118	3	594210	56788	2733	3
Bandar seri begawan	119	3	27285	53900	272	1
Sofia	119	3	1155403	12300	859	3
Rome	120	3	2626640	43127	2009	3
Tel Aviv	122	3	387234	39003	7476	3
Melbourne	123	3	3806092	46137	495	3
Manila	123	3	1581082	13423	2575	1
Lisbon	123	3	504726	27292	5954	3
Sydney	124	3	4336374	49226	357	3
Chicago, IL	124	3	2836658	48840	4819	4
Amsterdam	126	3	742884	60514	4467	3
Jerusalem	128	3	740475	42432	5914	3
Bern	130	3	122256	41900	2368	3
Beirut	134	3	361366	10700	18437	3
Doha	134	3	344939	100300	2174	2
Kuala Lumpur	138	3	1551306	15000	6384	1
Buenos Aires	140	3	2965403	28292	14608	3
Panama City	142	3	484261	11100	4526	1
Anchorage, AK	147	3	279671	63549	64	4
New York, NY	149	3	8274527	56149	10350	3
Geneva	149	3	178574	44017	10829	3
Shenzhen	151	3	7008831	11047	17744	3
Guangzhou	153	3	8524826	14044	2218	3
Kiev	153	3	2676789	7200	3210	4
Beijing	156	3	11509595	13325	8413	4

Los Angeles, CA	157	3	3834340	48896	1616	3
Cali	158	3	2392877	12741	4372	1
Shanghai	158	3	14348535	15547	7442	3
Tashkent	165	3	2137218	11600	7124	3
Milan	167	3	1306086	46180	7174	3
St. Petersburg	171	3	4569616	19987	7541	4
Moscow	188	3	10456490	30712	9673	4
Manama	192	3	176909	36100	5897	2
Phoenix, AZ	209	3	1552259	41260	1168	2
Abu Dhabi	215	3	527000	43700	293	2
St. John's	218	3	99182	6374	222	4
Port-of-Spain	227	3	43396	23100	3616	1
Dubai	227	3	1089000	11400	846	2
Honolulu, HI	228	3	375571	45444	1692	1
Denver, CO	232	3	588349	55700	1558	2
Vladivostok	233	3	579811	12207	966	4
Victoria, BC	234	3	289625	13539	15243	3
Nagoya	241	3	2215062	34811	6785	3
Osaka	244	3	2628811	36922	11836	3
Yokohama	249	3	3579628	37054	8184	3
Ottawa	252	3	812129	19402	292	4
Tokyo	264	3	8489653	41456	13663	3
Vancouver, BC	267	3	1837969	44884	16123	3
Montreal	278	3	3268513	40709	8955	4
Toronto	285	3	4612191	45537	3677	4
Dublin	297	3	495781	36721	4202	3
Stockholm	303	3	789024	34668	4219	4
Tbilisi	304	3	1108600	4600	2038	3
Kathmandu	319	3	671846	1100	13711	3
Cairo	355	3	6758581	12192	31582	2
Belgrade			1313994	10300	3379	3

APPENDIX A.8 Total Domestic Material Consumption data set

CITIES	Tot. DMC per cap, tons	Tot. DMC class	population	GDP per cap, 2000US$	pop. density /sq.km	climate
Sana'a	2.09	1	954448	2500	3864	2
Freetown	2.68	1	802639	900	5859	1
Kinshasa	2.81	1	7785965	300	955	1
Bujumbura	2.89	1	235440	300	2738	1
Phnom Penh	2.9	1	703963	1900	33522	1
Banjul	2.97	1	42326	1300	3527	1
Abuja	3.02	1	107069	24411	1091	1
Dhaka	3.33	1	10356500	6095	34067	1
Dar es Salaam	3.57	1	1360850	1300	856	1
Nairobi	3.6	1	2948109	1700	4236	3
Islamabad	3.69	1	529180	7181	4410	3
Tbilisi	3.78	1	1108600	4600	2038	3
Niamey	3.82	1	707951	700	2962	2
Cairo	3.93	1	6758581	12192	31582	2
Lagos	3.97	1	5195247	3697	5200	1
Ouagadougou	4.06	1	1475839	1200	6739	2
Antananarivo	4.12	1	1015140	1000	14099	3
Ho Chi Minh City	4.13	1	3015743	13200	21541	1
Naihati	4.18	1	215303	6046	18641	1
Addis Ababa	4.19	1	2646000	800	4992	3
Karachi	4.51	1	9339023	6430	2648	2
Kathmandu	4.55	1	671846	1100	13711	3
Bamako	4.79	1	1297281	1100	13374	1
Dakar	4.98	1	1075582	1700	2151	1
Chisinau	5.02	1	660726	2400	5372	3
Hyderabad	5.1	1	3637483	9538	21065	1
Accra	5.12	1	1658937	1400	8967	1
Surabaya	5.15	1	2611506	6811	7440	1
Chennai	5.16	1	4343645	8902	24963	2
Kolkata	5.18	1	4572876	7033	24718	1
Bangalore	5.22	1	5104047	10514	7199	1
Delhi	5.47	1	9879172	10486	22922	3
Bangui	5.51	1	451690	700	6742	1
Mumbai	5.54	1	11978450	3598	19865	1
Colombo	5.55	1	615000	4200	880	1
Jakarta	5.6	1	8820603	10082	13284	1
Damascus	5.88	1	1658000	4700	2894	3
Conakry	6.16	1	1091500	1100	2426	1
Rabat	6.25	1	642000	8175	5321	3

Yangon	6.3	1	4477638	1200	7488	1
Bishkek	6.62	1	798300	2100	6271	4
Casablanca	6.96	1	2995000	10374	9244	3
Shenzhen	7.12	1	7008831	11047	17744	3
Guangzhou	7.22	1	8524826	14044	2218	3
Quito	7.31	1	1559295	7300	9172	3
Beijing	7.37	1	11509595	13325	8413	4
Shanghai	7.48	1	14348535	15547	7442	3
Tashkent	7.58	1	2137218	11600	7124	3
Cebu	7.63	1	718821	11371	2558	1
Guatemala City	8.04	2	1022001	5300	4482	1
Manila	8.06	2	1581082	13423	2575	1
Amman	8.12	2	1204110	5100	717	2
San Salvador	8.13	2	507665	7300	573	1
Quezon City	8.24	2	2173831	14080	12661	1
Beirut	8.31	2	361366	10700	18437	3
Tunis	8.64	2	702330	7700	19847	3
Santo Domingo	8.79	2	913540	8000	10030	1
Tehran	9.13	2	7088287	16131	9327	3
Cali	9.29	2	2392877	12741	4372	1
Panama City	9.56	2	484261	11100	4526	1
Port-of-Spain	9.73	2	43396	23100	3616	1
Sarajevo	9.86	2	527049	6300	3738	3
Bogota	10.02	2	7102602	11960	4467	3
Durban	10.06	2	669242	1483	1513	3
Johannesburg	10.14	2	752349	32023	2364	3
Riga	10.18	2	719928	10499	2376	4
Porto Alegre	10.21	2	19089	16667	45	3
Tripoli	10.32	2	1500000	13900	4205	2
Ankara	10.38	2	3517182	15608	1398	3
Belgrade	10.49	2	1313994	10300	3379	3
Riyadh	10.81	2	4087152	23964	5109	2
Lima	10.89	2	8445211	12864	10557	2
Bucharest	10.94	2	1931838	11500	8121	3
Caracas	11.09	2	1975294	10915	4562	1
Istanbul	11.25	2	11174257	18090	6103	3
Cape Town	11.3	2	3497097	32037	12059	3
London	11.66	2	7421209	41271	10505	3
Kingston	11.82	2	579137	8800	26324	1
Milan	11.88	2	1306086	46180	7174	3
Vilnius	12.22	2	543494	17400	1379	4
Bangkok	12.32	2	5658953	17751	8084	1
Vladivostok	12.34	2	579811	12207	966	4

Rome	12.48	2	2626640	43127	2009	3
Florianopolis	12.64	2	406564	8253	924	3
Kiev	12.73	2	2676789	7200	3210	4
Guadalajara	12.78	2	1640589	18837	10865	3
Minsk	12.8	2	1789098	10800	5847	4
Curitiba	14.02	2	1788559	23268	4189	3
St. Petersburg	14.26	2	4569616	19987	7541	4
Brasilia	14.31	2	2383784	30564	411	1
Belo Horizonte	14.32	2	2399920	24317	7164	3
Kuala Lumpur	14.37	2	1551306	15000	6384	1
Bandar seri begawan	14.56	2	27285	53900	272	1
Tel Aviv	14.58	2	387233.5	39003	7476	3
Mexico City	14.62	2	11285654	20496	7600	3
Nagoya	14.96	2	2215062	34811	6785	3
Barcelona	15	3	1605602	35976	516	3
Moscow	15.11	3	10456490	30712	9673	4
Osaka	15.14	3	2628811	36922	11836	3
Jerusalem	15.26	3	740475	42432	5914	3
Seoul	15.33	3	10020123	29706	16553	4
Sofia	15.36	3	1155403	12300	859	3
Yokohama	15.47	3	3579628	37054	8184	3
Bern	15.47	3	122256	41900	2368	3
Madrid	15.72	3	3128600	41315	19509	3
Geneva	15.89	3	178574	44017	10829	3
Sao Paulo	15.93	3	11016703	20589	7234	3
Amsterdam	15.93	3	742884	60514	4467	3
Tokyo	16.43	3	8489653	41456	13663	3
Warsaw	16.64	3	1704717	17977	3297	3
Lisbon	16.66	3	504725.5	27292	5954	3
Paris	16.82	3	2125017	57027	20238	3
Manama	16.89	3	176909	36100	5897	2
Budapest	17.01	3	1699212.5	19876	3237	3
Vienna	18.23	3	1664146	53776	4013	3
Ljubljana	18.44	3	250953	28900	1530	3
Hamburg	18.95	3	1704735	54103	2258	3
Ulaanbaatar	19.23	3	1012733	3000	5038	4
Stockholm	19.38	3	789024	34668	4219	4
Athens	19.45	3	789166	26042	20235	3
Santiago	19.53	3	4960815	20979	6823	3
Brussels	19.68	3	144784	45355	899	3
Berlin	19.88	3	3386667	28529	3801	3
Prague	20.16	3	1188126	25500	9741	3
Kuwait City	20.86	3	32403	55600	11900	2

Buenos Aires	21.88	3	2965403	28292	51	3
St. John's	22.38	3	99182	27646	222	4
Anchorage, AK	22.45	3	279671	63549	64	4
Honolulu, HI	22.92	3	375571	45444	1692	1
Denver, CO	23.65	3	588349	55700	1558	2
Seattle, WA	23.67	3	594210	56788	2733	3
Boston, MA	23.68	3	599351	58686	4783	4
Victoria, BC	24.12	3	289625	13539	15243	3
Detroit, MI	24.4	3	916952	44344	2552	4
Phoenix, AZ	25.31	3	1552259	41260	1168	2
Ottawa	25.93	3	812129	19402	292	4
Montevideo	26.11	3	1345010	11600	2538	3
Chicago, IL	26.4	3	2836658	48840	4819	4
Dublin	26.41	3	495781	36721	4202	3
Asuncion	26.85	3	513399	4200	4388	3
Los Angeles, CA	26.97	3	3834340	48896	1616	3
Vancouver, BC	27.45	3	1837969	44884	16123	3
Abu Dhabi	27.5	3	527000	43700	293	2
Copenhagen	27.87	3	505141	71164	5740	3
New York, NY	28.46	3	8274527	56149	10350	3
Montreal	28.58	3	3268513	40709	8955	4
Dubai	28.93	3	1089000	11400	846	2
Toronto	29.28	3	4612191	45537	3677	4
Doha	30.81	3	344939	100300	2174	2
Helsinki	31.29	3	566526	44249	3040	4
Melbourne	42.83	3	3806092	46137	495	3
Sydney	43.22	3	4336374	49226	357	3

APPENDIX A.9 Carbon dioxide emissions data set

CITIES	CO_2 per cap, tons	CO_2 class	population	GDP per cap, 2000US$	pop. density /sq.km	climate
Bujumbura	0.02	1	235440	300	2738	1
Kinshasa	0.04	1	7785965	300	955	1
Bamako	0.05	1	1297281	1100	13374	1
Bangui	0.06	1	451690	700	6742	1
Ouagadougou	0.06	1	1475839	1200	6739	2
Niamey	0.08	1	707951	700	2962	2
Addis Ababa	0.09	1	2646000	800	4992	3
Kathmandu	0.13	1	671846	1100	13711	3
Conakry	0.15	1	1091500	1100	2426	1
Dar es Salaam	0.16	1	1360850	1300	856	1
Antananarivo	0.17	1	1015140	1000	14099	3
Yangon	0.2	1	4477638	1200	7488	1
Banjul	0.23	1	42326	1300	3527	1
Freetown	0.26	1	802639	900	5859	1
Phnom Penh	0.35	1	703963	1900	33522	1
Dakar	0.39	1	1075582	1700	2151	1
Nairobi	0.4	1	2948109	1700	4236	3
Accra	0.47	1	1658937	1400	8967	1
Colombo	0.66	1	615000	4200	880	1
Asuncion	0.7	1	513399	4200	4388	3
Sana'a	1.11	1	954448	2500	3864	2
Guatemala City	1.15	1	1022001	5300	4482	1
Bishkek	1.28	1	798300	2100	6271	4
San Salvador	1.32	1	507665	7300	573	1
Lagos	1.39	1	5195247	3697	5200	1
Dhaka	1.45	1	10356500	6095	34067	1
Durban	1.47	1	669242	1483	1513	3
Tbilisi	1.47	1	1108600	4600	2038	3
Florianopolis	1.77	1	406564	8253	924	3
Mumbai	2.03	1	11978450	3598	19865	1
Chisinau	2.11	1	660726	2400	5372	3
Panama City	2.22	1	484261	11100	4526	1
Bogota	2.29	1	7102602	11960	4467	3
Riga	2.33	1	719928	10499	2376	4
Montevideo	2.38	1	1345010	11600	2538	3
Cali	2.44	1	2392877	12741	4372	1
Santo Domingo	2.49	1	913540	8000	10030	1
Quito	2.5	1	1559295	7300	9172	3

Karachi	2.54	1	9339023	6430	2648	2
Tunis	2.61	1	702330	7700	19847	3
Lima	2.62	1	8445211	12864	10557	2
Male	2.81	1	103693	4500	17884	1
Islamabad	2.84	1	529180	7181	4410	3
Cebu	2.95	1	718821	11371	2558	1
St. John's	2.98	1	99182	6374	222	4
Surabaya	3.06	1	2611506	6811	7440	1
Rabat	3.18	1	642000	8175	5321	3
Naihati	3.41	1	215303	6046	18641	1
Manila	3.48	1	1581082	13423	2575	1
Porto Alegre	3.57	1	19089	16667	45	3
Quezon City	3.65	1	2173831	14080	12661	1
Ulaanbaatar	3.92	1	1012733	3000	5038	4
Kolkata	3.96	1	4572876	7033	24718	1
Casablanca	4.04	1	2995000	10374	9244	3
Damascus	4.05	1	1658000	4700	2894	3
Amman	4.13	1	1204110	5100	717	2
Beirut	4.31	1	361366	10700	18437	3
Sao Paulo	4.42	1	11016703	20589	7234	3
Jakarta	4.52	1	8820603	10082	13284	1
Vilnius	4.73	1	543494	17400	1379	4
Curitiba	4.99	1	1788559	23268	4189	3
Chennai	5.02	2	4343645	8902	24963	2
Ankara	5.04	2	3517182	15608	1398	3
Bucharest	5.19	2	1931838	11500	8121	3
Belo Horizonte	5.21	2	2399920	24317	7164	3
Hyderabad	5.38	2	3637483	9538	21065	1
Kingston	5.59	2	579137	8800	26324	1
Cairo	5.72	2	6758581	12192	31582	2
Stockholm	5.82	2	789024	34668	4219	4
Istanbul	5.84	2	11174257	18090	6103	3
Delhi	5.91	2	9879172	10486	22922	3
Bangalore	5.93	2	5104047	10514	7199	1
Guadalajara	6.06	2	1640589	18837	10865	3
Santiago	6.08	2	4960815	20979	6823	3
London	6.1	2	7421209	41271	10505	3
Victoria, BC	6.34	2	289625	13539	15243	3
Bern	6.39	2	122256	41900	2368	3
Caracas	6.44	2	1975294	10915	4562	1
Budapest	6.45	2	1699212.5	19876	3237	3
Brasilia	6.55	2	2383784	30564	411	1
Mexico City	6.59	2	11285654	20496	7600	3
Geneva	6.71	2	178574	44017	10829	3
Sarajevo	6.91	2	527049	6300	3738	3

Copenhagen	7.1	3	505141	71164	5740	3
Dubai	7.27	2	1089000	11400	846	2
Ho Chi Minh City	7.28	2	3015743	13200	21541	1
Lisbon	7.43	2	504725.5	27292	5954	3
Sofia	7.76	2	1155403	12300	859	3
Belgrade	7.9	2	1313994	10300	3379	3
Minsk	8.1	2	1789098	10800	5847	4
Kiev	8.15	2	2676789	7200	3210	4
Berlin	8.63	2	3386667	28529	3801	3
Athens	8.67	2	789166	26042	20235	3
Ljubljana	8.83	2	250953	28900	1530	3
Kuala Lumpur	8.85	2	1551306	15000	6384	1
Ottawa	9.09	2	812129	19402	292	4
Abuja	9.15	2	107069	24411	1091	1
Dublin	9.53	2	495781	36721	4202	3
Tripoli	9.87	2	1500000	13900	4205	2
Warsaw	10.25	2	1704717	17977	3297	3
Barcelona	10.28	2	1605602	35976	516	3
Vladivostok	10.48	2	579811	12207	966	4
Buenos Aires	10.81	2	2965403	28292	51	3
Bangkok	10.86	2	5658953	17751	8084	1
Tehran	11.06	2	7088287	16131	9327	3
Nagoya	11.36	2	2215062	34811	6785	3
Paris	11.45	2	2125017	57027	20238	3
Madrid	11.81	2	3128600	41315	19509	3
Shenzhen	11.96	2	7008831	11047	17744	3
Osaka	12.05	2	2628811	36922	11836	3
Yokohama	12.1	2	3579628	37054	8184	3
Rome	12.19	2	2626640	43127	2009	3
Seoul	12.25	2	10020123	29706	16553	4
Milan	13.06	2	1306086	46180	7174	3
Prague	13.17	2	1188126	25500	9741	3
Vienna	13.52	2	1664146	53776	4013	3
Tokyo	13.53	2	8489653	41456	13663	3
Brussels	14.1	2	144784	45355	899	3
Singapore	14.37	2	4588600	51656	6582	1
Beijing	14.43	2	11509595	13325	8413	4
Guangzhou	15.21	3	8524826	14044	2218	3
Tel Aviv	16.26	3	387233.5	39003	7476	3
Hamburg	16.37	3	1704735	54103	2258	3
Shanghai	16.84	3	14348535	15547	7442	3
St. Petersburg	17.16	3	4569616	19987	7541	4
Bandar seri begawan	17.39	3	27285	53900	272	1

Amsterdam	17.45	3	742884	60514	4467	3
Helsinki	17.5	3	566526	44249	3040	4
Jerusalem	17.69	3	740475	42432	5914	3
Riyadh	18.08	3	4087152	23964	5109	2
Phoenix, AZ	18.66	3	1552259	41260	1168	2
Montreal	19.06	3	3268513	40709	8955	4
Detroit, MI	20.05	3	916952	44344	2552	4
Honolulu, HI	20.55	3	375571	45444	1692	1
Vancouver, BC	21.02	3	1837969	44884	16123	3
Toronto	21.32	3	4612191	45537	3677	4
Chicago, IL	22.09	3	2836658	48840	4819	4
Los Angeles, CA	22.11	3	3834340	48896	1616	3
Tashkent	23.9	3	2137218	11600	7124	3
Luxembourg-Ville	23.9	3	84644	70597	1660	3
Denver, CO	25.19	3	588349	55700	1558	2
New York, NY	25.39	3	8274527	56149	10350	3
Seattle, WA	25.68	3	594210	56788	2733	3
Melbourne	25.8	3	3806092	46137	495	3
Moscow	26.38	3	10456490	30712	9673	4
Boston, MA	26.54	3	599351	58686	4783	4
Manama	27.1	3	176909	36100	5897	2
Sydney	27.52	3	4336374	49226	357	3
Port-of-Spain	27.7	3	43396	23100	3616	1
Abu Dhabi	27.85	3	527000	43700	293	2
Anchorage, AK	28.74	3	279671	63549	64	4
Johannesburg	31.65	3	752349	32023	2364	3
Cape Town	31.66	3	3497097	32037	12059	3
Kuwait City	41.06	3	32403	55600	11900	2
Doha	56.3	3	344939	100300	2174	2