- FINAL MANUSCRIPT -

Benchmarking urban eco-efficiency and urbanites' perception

Ramana Gudipudi[a,*], Matthias K.B. Lüdeke[a], Diego Rybski[a], Jürgen P. Kropp[a,b]

[a] Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, P.O. Box 60 12 03, Potsdam, D-14412, Germany.
[b] Dept. of Geo- and Environmental Sciences, University of Potsdam, Potsdam 14476, Germany

A B S T R A C T

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

1. Introduction

Cities, like organisms, are the outcome of numerous bottom up evolutionary processes (Batty, 2012; Portugali, 2000). Thriving on natural resources, cities release pollution and waste as by-products. Harbouring more than 50% of the global population, contemporary cities generate 80% of the GDP while consuming approximately 70% of energy supply and releasing bulk of environmental pollution (UN, 2014; Seto & Dhakal, 2014). Projected to be crucibles for humanity by the end of this century (Batty, 2013), contemporary cities are acknowledged to play a pivotal role in global sustainability and climate change mitigation (Creutzig, Baiocchi, Bierkandt, Pichler, & Seto, 2015).

Addressing issues concerning global sustainability with cities as foci relies heavily on the way they transform their energy and material flows at a local scale (Kennedy et al., 2015). Studies on urban meta-bolism address such issues concerning long-term sustainability by fo-cusing on resource and energy flows in human settlements. These stu-dies can have practical implications in urban sustainability reporting, greenhouse gas (GHG) accounting, urban design and policy analysis (Kennedy, Pincetl, & Bunje, 2011). The aim of sustainability according to previous studies on urban metabolism is to enhance socioeconomic outcomes in cities while reducing the resource inputs and environmental pollution (Kennedy et al., 2011; Newman, 1999). Parallels can be drawn between this definition and the concept of eco-efficiency in cities as defined by the World Business Council for Sustainable Devel-opment (UNESCAP, 2011). Eco-efficiency couples economic and eco-logical performance of a city with an aim to improve socioeconomic outcomes while reducing environmental burden and waste production. Apart from a study by Kennedy et al. (2015) for 27 megacities and a study by Goldstein, Birkved, Quitzau, and Hauschild (2013) for 5 cities, the concept of urban metabolism is applied to very few cities globally largely owing to data constraints (Kennedy, Cuddihy, & Engel-Yan, 2007; Minx et al., 2011).

This paper contributes to the current literature on urban metabolism by applying the concept of eco-efficiency to a large set of cities where consistent data is available. With an aim to identify the key factors determining urban eco-efficiency, we rank the performance of all considered cities. In order to achieve this aim, this paper merges the concept of urban eco-efficiency with a well-established methodological procedure in operational research, called benchmarking.

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

1.1. Urban metabolism and factors influencing eco-efficiency in cities

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

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

Urban metabolism and the subsequent eco-efficiency is influenced by a number of factors such as urban form and structure, quality of physical infrastructure, local climate, social, cultural and transportation priorities of urbanites and political economy (Gandy, 2004; Holmes & Pincetl, 2012; Kennedy et al., 2007; Newman, 1999; Weisz & Steinberger, 2010). It is often challenging to have a consistent city level data covering all these aspects and therefore limited urban metabolism to a few case studies so far (Kennedy et al., 2007). As mentioned earlier, we address this issue by merging the concept of urban eco-efficiency with benchmarking for a set of 88 European cities where comparable data is available. Having its roots in operational research, bench-marking is defined as a process characterized by the systematic search for efficient procedures and best practices for complicated problems (Dattakumar & Jagadeesh, 2003; Elmuti & Kathawala, 1997; Moriarty, 2011).

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

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

1.2. Quality of life in cities: subjective versus objective rankings

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

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

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

2. Data and methods

2.1. Data

A major pre-requisite for city benchmarking exercise is a consistent definition of cities. The EUROSTAT's Urban Audit data base[1] available as a part of the new OECD-EC definition of cities (Dijkstra & Poelman, 2012) enabled us to address this pre-requisite. Within this database, we identified three undesirable environmental burden/resource consumption and two desirable socioeconomic indicators for the year 2011. The indicator selection in this study is based on those suggested by Newman (1999) in his "extended metabolism model". We started the city selection by looking at the 100 most populated European cities and identified 88 cities where data on all these five indicators are

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

available.[2] In instances where a certain indicator for the year 2011 is not available, the value for the 2010 (or 2012) is considered. The population size of the cities considered in this analysis varied significantly. London is the most populous city considered in this study with a reported population of 8,173,941 inhabitants while Bonn is the least populated city with 324,899 inhabitants. The analysis includes 20 cities with a reported population of more than a million. The mean population of the 88 cities considered in this analysis is 874,037 with a standard deviation of 994,701.

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

Urban Audit database classifies cities into three spatial units: (1) 'city' as local administrative unit, (2) 'functional urban area' which includes city and its commuting zone and (3) 'greater city' as an approximation of the urban centre which stretches far beyond its administrative boundaries. Analyzing urban metabolism at spatial unit 'functional urban area' (as defined in the OECD-EU city definition) in the Urban Audit Database[3] will determine the broader factors influen-cing urban eco-efficiency. However, due to data unavailability, all the aforementioned indicators except the indicator GDP are obtained from the data available under the category 'Cities/Local Administrative Units' spatial units in the Urban Audit Database. The data on the GDP for these 88 cities is obtained from the spatial unit 'functional urban area'. The GDP reported here includes the income generated in the city together with its commuting zones. Since each city attracts commuters from neighboring towns which contribute to its GDP, this indicator provides a fair measure to depict GDP at city scale. Urban Audit data for European cities and a detailed description of the indicators used, their respective methodology can be found in the EUROSTAT Urban Audit website and methodological handbook (Eurostat, 2014). To our knowledge this is the best available, sufficiently large and consistent dataset which allows for an indication of the dimensions covering eco-efficiency of European cities. Table 1 shows the descriptive statistics of the indicators used in this study.

2.2. Methods

The methods currently used for city benchmarking in the state-of-the-art research can be broadly divided into four categories: (a) per capita ranking measures (Dhakal, 2009; Kennedy, Ramaswami, Carney, & Dhakal, 2009; Sovacool & Brown, 2010) in one dimensional indicator space; (b) multiple criteria decision making based on normalized and/or weighted measures (Boettle, Schmidt-Thomé, & Rybski, 2013; da Cruz & Marques, 2017; Jiang & Shen, 2013; Pinto, Costa, Figueira, & Marques, 2017; Singhal, McGreal, & Berry, 2013) in multi-dimensional indicator spaces; (c) ranking based on deviations in ordinary least squares regression analysis (OLS) and Stochastic Frontier Analysis (SFA) (Bettencourt, Lobo, Strumsky, & West, 2010; Castillo et al., 2005; Glaeser & Kahn, 2010; Larivière & Lafrance, 1999; Matas, 1998; Reckien, Ewald, Edenhofer, & Lüdeke, 2007; Wang, Long, & Chen, 2017; Yi & Fengyan, 2015) in one dimensional outcome space and multi-dimensional indicator spaces of independent variables and (d) ranking based on Data Envelopment Analysis (DEA) (Charnes et al., 1989; Munksgaard et al., 2005; Raab & Lichty, 2002; Sueyoshi, 1992) i n multi-dimensional input and outcome indicator spaces.

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

While the OLS method has its foundations in econometric theory, DEA is based on mathematical programming techniques (Bogetoft & Otto, 2011). In the OLS method, performance of each city with respect to each of its socioeconomic indicators (employment ratio and GDP) is compared with the average performance of cities with similar environmental variables. In DEA, a city's ranking is determined by comparing its performance with the best performing cities. While the DEA method can deal with multidimensional input and output spaces, the OLS method has been extended for that purpose as shown below.

2.2.1. City eco-efficiency rankings based on OLS and DEA

Eco-efficient cities maximize desirable socioeconomic factors relative to associated environmental burden/resource consumption factors. Therefore, the former are treated as dependent variables and the latter are considered as independent variables in the OLS ranking procedure. The residuals with respect to each of the dependent variables in the linear regression manifold determine the eco-efficiency of a city. The ranking of cities using OLS in this study follows two steps.

Firstly, we ranked the cities based on their residuals (V) for each dependent variable separately (E: employment ratio and P: GDP/cap), given their independent variables (N: NO_2, W: solid waste production and H: water consumption) as shown in Eq. (1) and Eq. (2).

$$V_i^P = P_i - (ß_o^P + ß_1^P \cdot N_i + ß_2^P \cdot W_i + ß_3^P \cdot H_i) \quad (1)$$

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

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

$$V_i^E = E_i - (ß_o^E + ß_1^E \cdot N_i + ß_2^E \cdot W_i + ß_3^E \cdot H_i) \quad (2)$$

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

Secondly, the rankings under both dependent variables are further aggregated into a consensus ranking using a branch and bound algorithm (D'Ambrosio, Amodio, & Iorio, 2015). For further details see supplementary information. The result is a new ranking which is closest to the two original rankings. As far as we are aware, such a non-parametric approach to solving the problem of multidimensional outcomes in OLS is unprecedented. We refer to this consensus ranking as enhanced OLS ranking in what follows.

The efficiency of a city in DEA method is calculated based on the

[2] Cities in the UK (except London) and Ireland (except Dublin) are not included in this study because of lack of data on water consumption.

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

Table 1
Descriptive statistics of the indicators used in this study for the year 2011.

Indicator	Category	Average	Minimum	Maximum
NO_2 concentration (in µg/m^3)	Environmental burden/resource consumption	26.88	10.18 (Stockholm)	51.36 (Milan)
Waste generation (in kilograms per capita)	Environmental burden/resource consumption	467.2	239.38 (Sofia)	848.57 (Copenhagen)
Water consumption per capita (m^3)	Environmental burden/resource consumption	75.52	35.53 (Szczecin)	155.69 (Oslo)
Employment ratio (%)	Socioeconomic	87.23	68.6 (Malaga)	97 (Oslo)
GDP per capita (in purchasing power standard)	Socioeconomic	30,523	9393 (Plovdiv)	51,382 (Munich)
"I am satisfied to live in this city: Completely Agree" (% of urban population)	Urbanites' perception for 45 cities	45.33	20 (Palermo)	73 (Zurich)

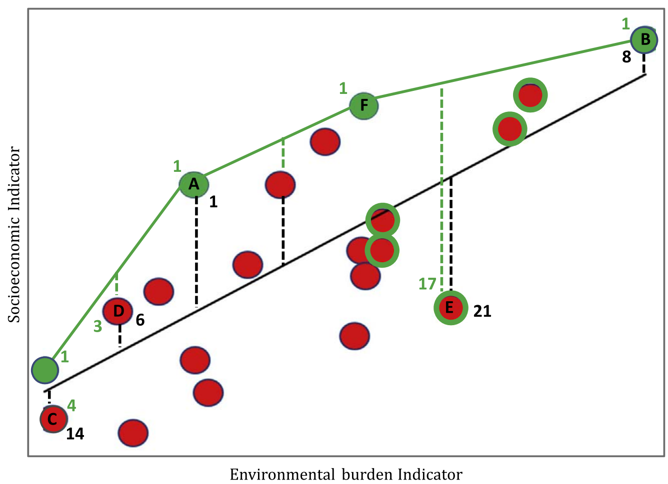

Fig. 1. An illustration of the difference between OLS and DEA methods in two dimensions. Ranking of the cities in DEA and OLS methods are shown in green and black colors respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ratio of its outputs to its inputs. Since our objective is to characterize an eco-efficient city by high socioeconomic measures and low environmental burden, the former were considered as outputs and the latter were considered as inputs in this study. DEA identifies the convex hull in data space which is spanned by the efficient cities and ranks the inefficient cities according to their (relative) distance to the hull. This hull is a piecewise linear manifold. Efficient cities which span the hull section an inefficient city is related to are called 'peers' (see Fig. 1 for details). These are positive, efficient examples for the inefficient cities. Changes in the indicator values necessary to reach the convex hull for an inefficient city are called 'slacks'. Slacks allow us to identify the most critical dimension for improving efficiency. For further details please refer to the supplementary information.

2.2.2. Methodological differences in ranking under OLS and DEA

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

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

3. Results

3.1. City ranking based on enhanced OLS method

As mentioned earlier, the OLS method ranks cities based on their residuals in the regression manifold. Fig. 2 shows the city rankings of the 88 cities based on their residuals in employment ratio (Fig. 2.A) and GDP (Fig. 2.B). The results of the estimates (slopes) for the independent variables in the underlying multilinear regression are shown in Table 2. It can be inferred from Table 2 that the regression manifold is strongly and positively influenced by NO_2 concentration followed by waste generation. This means that an average increase in GDP and employment will go together with an average increase in the NO_2 concentration and waste generation. The weak R^2 values shown in Table 2 depict the considerable variation amongst these cities with regard to the linear regression manifold which is the basis for our ranking. The 40 cities that deviate above the linear regression manifold with respect to GDP have an average GDP of 14,000 euros more than those cities that de-viate below the regression manifold (the average GDP of all the 88 cities that are considered in this study is 30,523 euros). Similarly, the 52 cities that deviate above the linear regression manifold with respect to employment ratio in relation to the environmental burden have an employment ratio of 10 percentage points more than those that deviate below.

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

The enhanced OLS ranking post the rank aggregation algorithm using branch and bound method yielded 4 different ranking permutations in which 2 permutations ranked cities from 1 to 88. The only difference between these ranking permutations is the ranking of Malaga which is ranked 88th in one permutation and 87th in the other. The

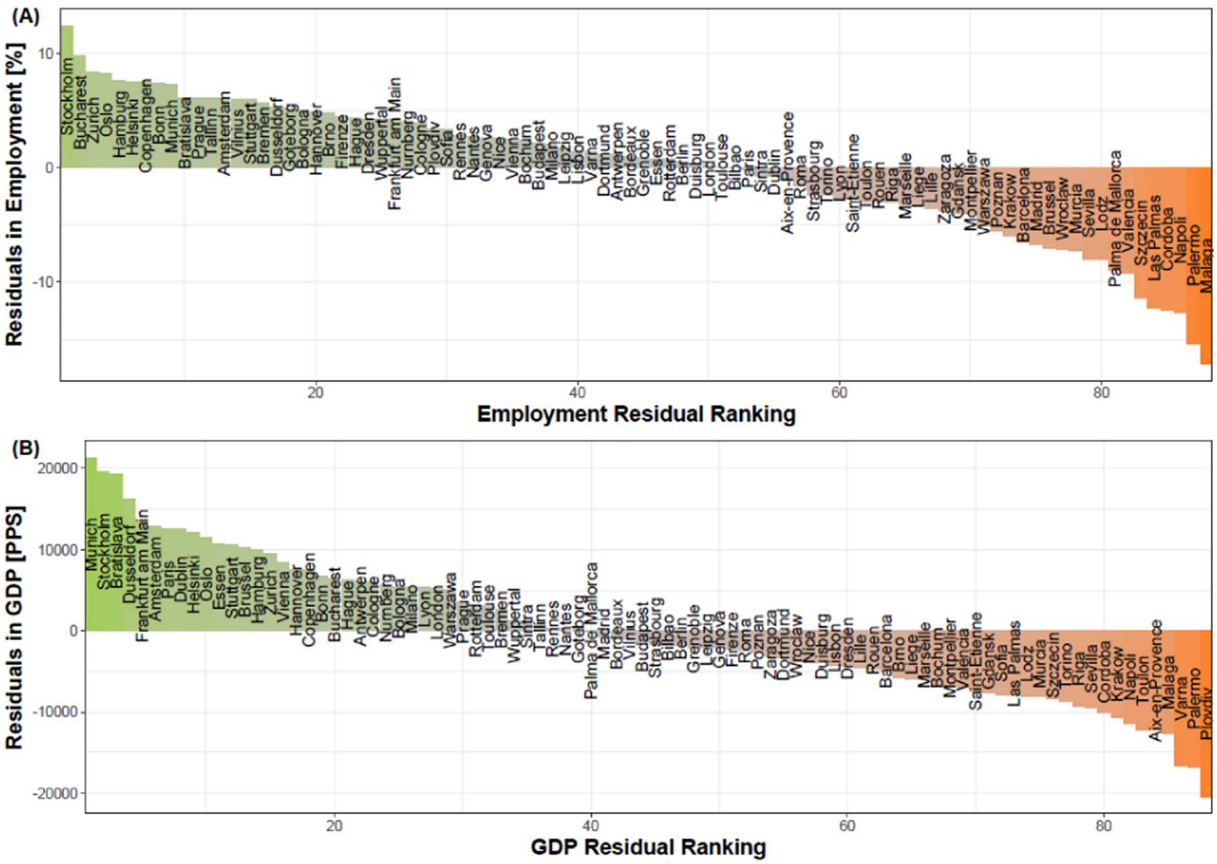

Fig. 2. Eco-efficiency ranks for 88 cities based on their residuals in Employment (A) and GDP (B) under the OLS method. Cities are sorted based on their ranking from left to right. Stockholm is ranked 1st with respect to employment while Munich is ranked 1st with respect to GDP. Malaga and Plovdiv are least ranked cities with respect to employment and GDP respectively.

Table 2
Coefficients of each of the independent variables in OLS method.

Dependent variable	Coefficients of the independent variables			
	NO_2 concentration (*N*)	Waste generation (*W*)	Water consumption (*H*)	Correlation Coefficient (R^2)
Employment in %	0.268	0.002	− 0.036	0.083
GDP (per capita in PPS)	311.6	9.320	17.50	0.089

other two permutations ranked cities from 1 to 52 and 51 respectively (with ties in ranking). Since each of these permutations is Kemeny optimal (for further details refer to supplementary information), we considered the permutation which ranked cities without any ties. The results of the enhanced OLS method show that Stockholm, Munich, Bratislava, Oslo and Helsinki are the most eco-efficient cities. These cities perform better both in terms of employment and GDP. Malaga, Plovdiv, Palermo and Varna ranked as the least eco-efficient cities. These cities have either lower GDP or employment ratio compared to other cities. Enhanced OLS ranking all these 88 cities can be found in Fig. 4 (values on the Y-axis).

3.2. City ranking based on DEA method

The efficiency of a city in DEA method is calculated based on the ratio of a linear combination of its socioeconomic indicators to that of its environmental burden/resource consumption parameters. While the OLS method of residual ranking have unique city rankings (without ties), the DEA method identified 23 cities which are ranked 1st. This is inherently because of the basic assumptions made under each method. As mentioned in Section 2.2, slacks determine the critical dimensions for improving efficiency of inefficient cities. Fig. 3 shows the ratio of slacks in each variable to their present value. It can be observed in Fig. 3 that the slack in GDP is a common factor determining inefficiency in most of the cities. The employment ratio in Brussels must be in-creased by 8% in order to be on the convex hull whereas NO_2 con-centration in Poznan has to be decreased by 12% in order to be effi-cient. Plovdiv reportedly has a GDP of 9393 in PPS and has to increase its GDP by almost 300% in order to be an efficient city. Malaga, the least ranked city has to improve its GDP by 57% while decreasing its waste generation and water consumption by 35% and 7% respectively.

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

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

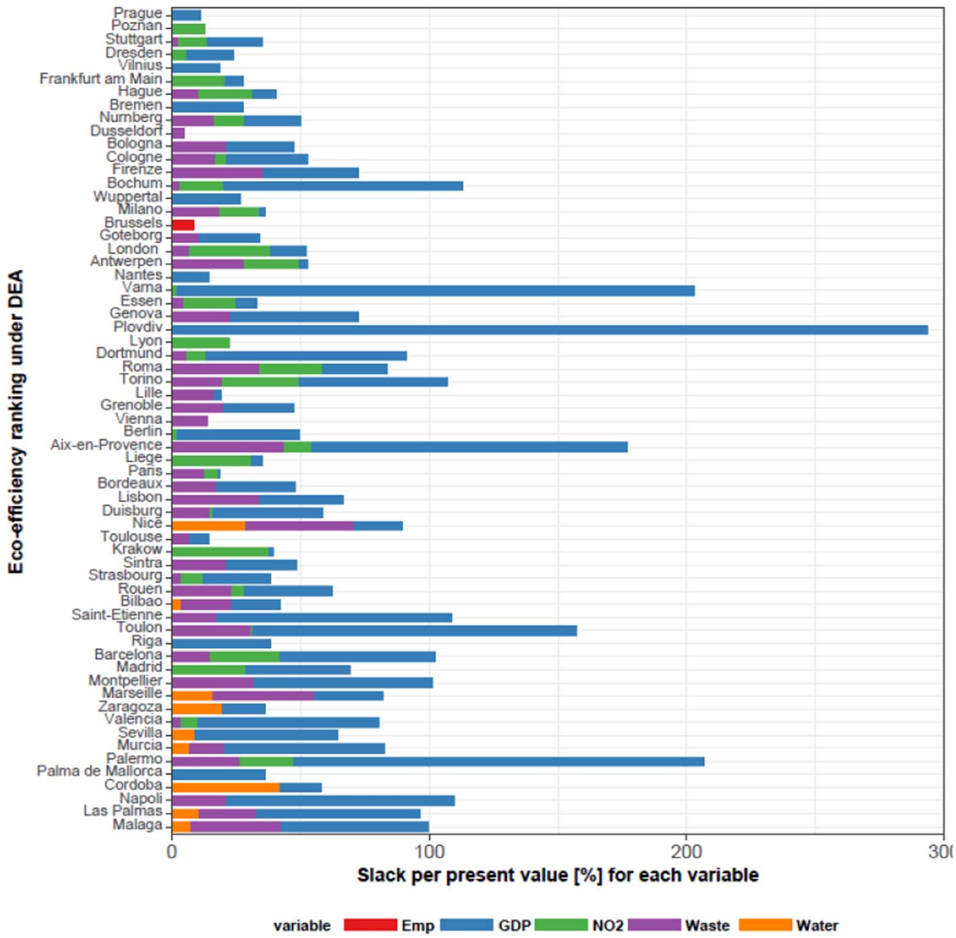

Fig. 3. Eco-efficiency ranking of inefficient cities under DEA method. Prague is ranked 2nd and Malaga is the least ranked city under this method. The bars represent the percentage of slack per present value for each input and output variables.

choices regarding the methods, we continued our further analysis with the original DEA result including ties.

The second caveat is that DEA ranking is highly sensitive to outliers (Banker & Chang, 2006). This is the major drawback of this method especially with respect to city benchmarking exercises since researchers usually do not have any control on the measurement errors of the published data (in our case Urban Audit Database). Existing literature has identified two possibilities to address this issue. The first possibility is the usage of so-called partial frontier methods (Aragon, Daouia, & Thomas-Agnan, 2005; Cazals, Florens, & Simar, 2002). The second possibility is identifying various methods to detect and deal with the outliers. For instance, a study by De Witte and Marques (2010) combined five complementary outlier detection procedures in one model to identify a broad range of atypical observations. Here, observations which are identified as outliers in at least two procedures are considered to be atypical. A detailed overview of methods to detect outliers in DEA are mentioned in (Ahamed, Naidu, & Reddy, 2015).

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

3.3. *Comparison of enhanced OLS and DEA rankings*

Fig. 4A compares the ranking of 88 cities in DEA and enhanced OLS methods and Fig. 4B shows the number of inefficient cities an efficient city in DEA serves as a peer. The objective of Fig. 4B is to depict that a majority of cities which are ranked well under both methods serve as a peer to many inefficient cities under DEA method. The Pearson's correlation coefficient of the rankings under both methods is found to be 0.64. With few exceptions such as Marseille, Barcelona and Madrid, the ranking of all the cities above 1 million population remained between medium to best under both methods. Although the number of cities with more than one million population represents approximately only a quarter of the number of cities considered in this study, this result suggests that large cities per se are not detrimental to the environment considering the socioeconomic benefits they offer compared to smaller cities. However, from a global perspective, European cities are relatively small in terms of their population size. Although subject to data availability, there is a need to extend this analysis to global cities to further validate this finding.

The 10 best performing cities under the enhanced OLS method are ranked as the most eco-efficient cities under the DEA method (except Helsinki and Dusseldorf which are ranked 6th and 12th under the DEA method). A comparison of the individual rankings of the two methods

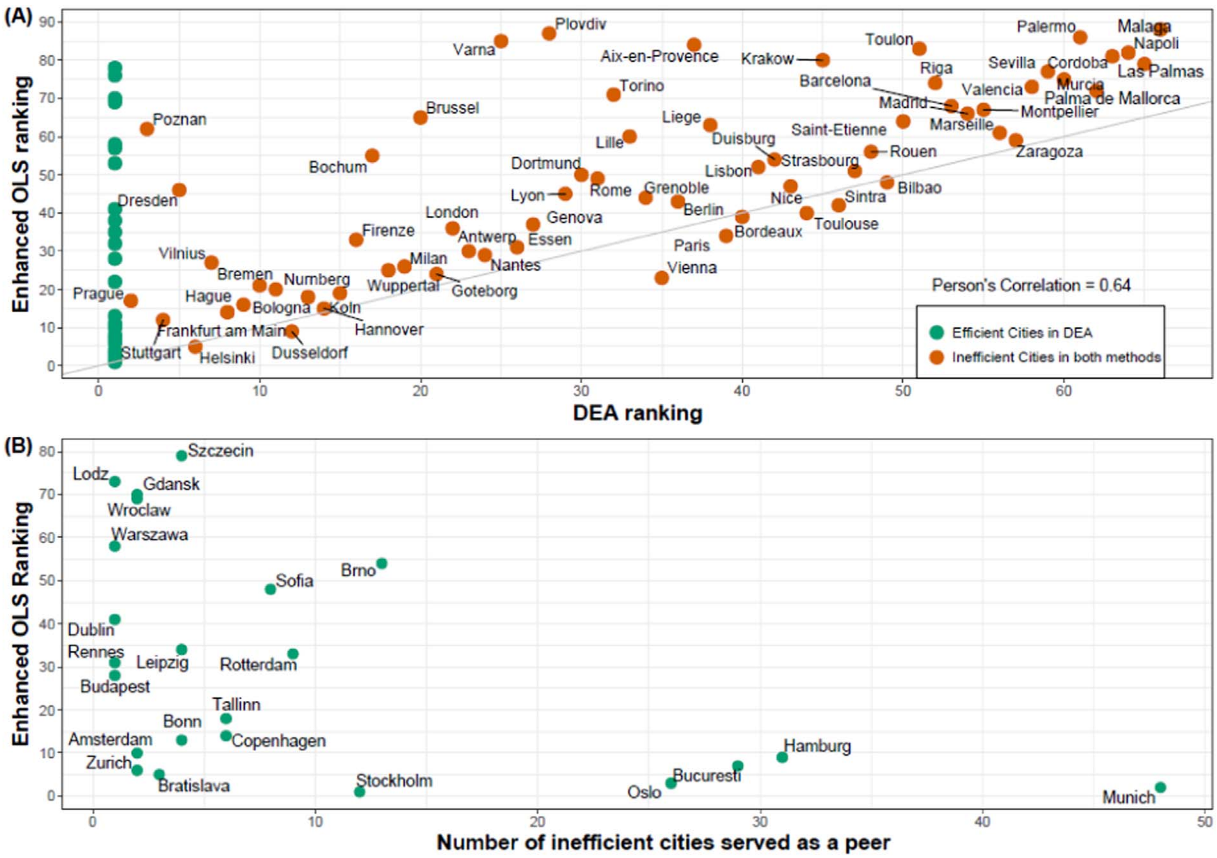

Fig. 4. Comparison of city rankings in DEA and enhanced OLS method. Each dot represents the ranking of a given city in enhanced OLS and DEA method respectively. The grey line (with slope 1) in 4A shows how far the rankings agree under both methods. 4B shows that cities which are ranked well in OLS serve as a peer to many inefficient cities in DEA method.

revealed that cities such as Stockholm, Munich, Oslo, Bratislava and Zurich are ranked as the best performing cities irrespective of the method used. Therefore these cities are the most eco-efficient cities according to this study. Cities such as Malaga, Palermo, Napoli, Cordoba and Las Palmas are ranked poorly under both methods and can be considered as inefficient cities.

As mentioned in Section 2.2.1, the eco-efficiency ranking of a city in DEA is based on the ratio of its socioeconomic measures to its environmental burden. Therefore, despite performing poorly with respect to socioeconomic measures, a city can still be efficient if it has lower environmental/resource consumption compared to other cities. This is because the efficiency of such a city is measured against the convex hull which is a piecewise manifold. OLS ranks city eco-efficiency based on its positive residual compared to one linear manifold defined by all cities. Therefore, cities such as Szczecin, Lodz, Gdansk, Wroclaw, Warsaw are ranked as the most efficient cities under the DEA method while being ranked poorly in the enhanced OLS rankings. On an average basis, the per capita water consumption and waste generation in these cities is 41% and 34% lower than all the other cities in this analysis. None of these cities serve as a peer for more than five cities under DEA method (Fig. 4B). Therefore these cities can be considered as cities in the periphery of the indicator space in the DEA method and the convex hull is determined mainly by these cities in that indicator space. However, with respect to OLS rankings, these cities have negative re-siduals either in employment or in GDP (see Fig. 2). Therefore, these cities are ranked poorly under the enhanced OLS method.

3.4. Comparison of public perception and objective city rankings

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

The correlation between the rankings of environmental parameters to that of the perception ranking is found to be low compared to that of socioeconomic indicators (Table 3). The correlation of employment and GDP rankings is similar (0.48). We found that eco-efficiency rankings from enhanced OLS method to be strongly correlated with subjective perception ranking (0.61). Considering the ties in DEA ranking, the correlation between subjective perception ranking and DEA (0.47) is also relatively good. This result demonstrates that urbanites' perception about quality of life is determined by the combination of socioeconomic well-being and lower environmental burden. Further, we show that the

Table 3
Results of the statistical analysis for the correlation between perception ranking with the ranking of the variables and objective eco-efficiency rankings. *p*-Value significance codes: 0 = ***, 0.001 = **, 0.01 = *.

Variable	Correlation coefficient	p-Value	95% Confidence interval	
			Lower	Upper
NO_2 ranking	0.25	0.09	− 0.04	0.51
Water ranking	0.21	0.16	− 0.08	0.48
Waste ranking	0.03	0.82	− 0.26	0.32
Employment ranking	0.48	0.00***	0.22	0.68
GDP ranking	0.48	0.00***	0.22	0.68
DEA ranking	0.47	0.00***	0.20	0.67
Enhanced OLS ranking	0.60	0.00***	0.39	0.77

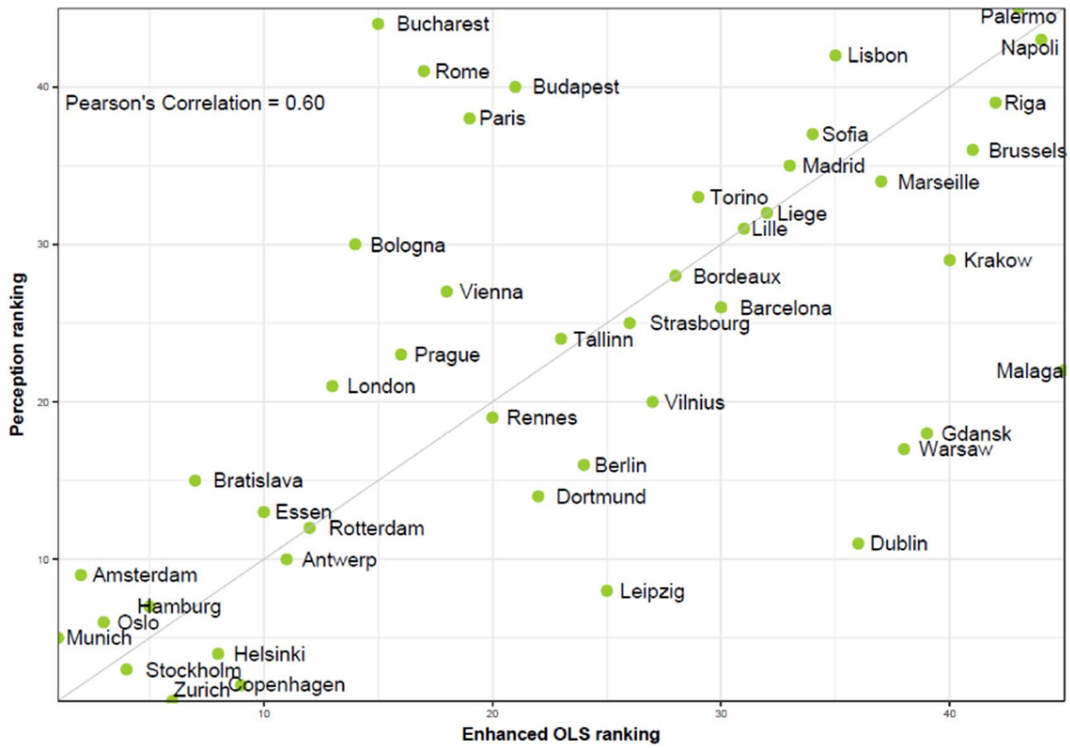

Fig. 5. Comparison of enhanced OLS ranking with public perception ranking for the 45 cities. Each dot represents ranking of a given city in enhanced OLS ranking and urbanites' perception ranking respectively.

correlation of perception ranking to enhanced OLS ranking is larger than that to DEA ranking indicating that urbanites' perceptions reflect the eco-efficiency performance of their city compared to the typical performance of similar cities. This result illustrates that urbanites' perception about quality of life in their city is less influenced by a city which performs exceptionally well (Munich for instance).

Since the OLS rankings are correlated the most to the perception rankings, we had a closer look at how the subjective perception ranking is interrelated to enhanced OLS rankings (Fig. 5). Our results show that there are three groups of cities. The first group consists of cities where perception rankings are in line with the enhanced OLS rankings. Cities like Zurich, Copenhagen, Stockholm, Helsinki and Munich which are amongst the top five best ranked cities with respect to urbanites' perception are amongst the best ranked cities in enhanced OLS method. Similarly, cities such as Palermo, Napoli, Lisbon, Rome and Riga being the least ranked cities under public perception are also amongst the inefficient cities under OLS rankings.

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

The third group belongs to cities such as Dublin, Warsaw and Gdansk. Despite being ranked poorly in the objective ranking, these cities are perceived relatively well (ranked 11th, 1 7 th and 18th respec-tively). Although the perception rankings of most of southern European cities are poor, the city of Malaga is found to be an exception. Despite being the least ranked city in enhanced OLS ranking (45th), the city stands 22nd with respect to perception rankings. Since this analysis is done for a relatively smaller sample (45 cities), the slope of regression line depends on the few outliers (Malaga, Gdansk and Warsaw). In general, our results depict that public perception about the quality of life in western European cities is guided by the prevailing social, economical and environmental dimensions. There seem to be other factors (for e.g. political) that influence the public perception in southern and east European cities.

4. Conclusion

City benchmarking studies such as those conducted by economic intelligence unit EIU, 2017 available at https://www.eiu.com/public/topical_report.aspx?campaignid=liveability17 (last accessed 20th November 2017) and the Mercer quality of living rankings available at: https://www.imercer.com/content/mobility/quality-of-living-city-rankings.html (accessed 20th November 2017) usually attract a lot of attention ranging from the scientific community to general public and the media. These rankings can influence the scale and direction of public/private investment and inform urbanites' perception regarding the quality of life.

Broadly all environmental indicators used in this study reflect either the environment burden and/or resource consumption. The NO_2 concentration can serve as a proxy for air pollution. For instance, road transport accounted for a major fraction (41%) of the NO_x emissions in Europe in the year 2011 (European Environment Agency, 2014), a major fraction of which can be attributed to the urban areas. Waste generated and water consumption can serve as a proxy for resource consumption and environmental pollution in case a city lacks proper treatment and disposal facilities. City efficiency benchmarking is highly sensitive to the selection of the indicators which define efficiency and the data quality. The eco-efficiency ranking of the 88 cities considered in this study will differ when more cities and more/other indicators are used in the analysis. In both cases such an inclusion will influence the number of cities deviating from the regression manifold in OLS method and the convex hull in DEA method. However, the biggest challenge here is the consistency of the indicators used to define eco-efficiency of cities. Lack of consistent and reliable data constrained this study to only three environmental/resource burden and two socioeconomic indicators.

Our results show that cities with well-established urban economies such as Munich, Stockholm and Oslo are eco-efficient irrespective of ranking methods. The results of this study corroborate the hypothesis that the stage of city development influences the metabolic process (Kennedy et al., 2007) and the subsequent eco-efficiency of a city. A majority of cities in southern and east European cities considered in this study face a bigger challenge to simultaneously improve their socioeconomic conditions while decreasing their environmental burden. In order to decrease their current environmental burden, local governments should adopt a combination of top-down and bottom-up strategies. The top-down approaches include improving public transportation and encouraging non-motorized transportation in order to further decrease their NO_2 (and GHG) emissions, renovating the water supply network with an aim to decrease transmission losses and adopting reduce, reuse and recycle strategies to decrease waste generation. From a bottom-up perspective, addressing urbanites' attitudes towards energy and resource consumption is crucial to decrease environmental burden. Breaking away from current consumption practices is also crucial to achieve sustainable development goals (SDGs) (Pradhan, Costa, Rybski, Lucht, & Kropp, 2017). With respect to improving socioeconomic outcomes, a key entry point to improve their eco-efficiency is to develop and implement city specific green growth policies. The aim of these policies is to improve socioeconomic wellbeing in cities by improving investments in infrastructure and encouraging innovation while promoting green services (such as efficient public transportation) and consumption (OECD, 2011).

Although this study captures the eco-efficiency of cities within their boundaries, it is crucial to mention that the embodied urban environmental impacts (and GHG emissions) are not always confined to these boundaries (Pichler et al., 2017). For instance, factoring in cross-boundary activities Hillman and Ramaswami (2010) found out that embodied emissions for eight cities in the USA on an average contribute to 47% more emissions in comparison to direct emissions within the city boundary. Subject to data availability, incorporating these embo-died environmental impacts will capture the factors leading to eco-ef-ficiency in a holistic manner. Such an analysis should incorporate ur-banites' lifestyles and attitudes towards energy/resource consumption as they play a predominant role in determining urban metabolism and eco-efficiency (Minx et al., 2011).

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

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

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

Acknowledgments

We thank C. Walther, M. Boettle, B. Prahl and L. Costa for their useful suggestions. The main author thanks German Academic Exchange Service (Funding program ID: 57076385) (DAAD) for its generous scholarship. The research leading to these results has received funding from the European Community's Seventh Framework Program under Grant Agreement No. 308497 (Project RAMSES).

References

Ahamed, S. K., Naidu, M. M., & Reddy, C. S. R. (2015). Outliers in data envelopment analysis. *International Journal of Computer Science and Security (IJCSS), 9*(3), 164–173.
Ahmad, S., Baiocchi, G., & Creutzig, F. (2015). CO2 emissions from direct energy use of urban households in India. *Environmental Science & Technology, 49*(19), 11312–11320. http://dx.doi.org/10.1021/es505814g.
Aragon, Y., Daouia, A., & Thomas-Agnan, C. (2005). Nonparametric frontier estimation: A conditional quantile-based approach. *Econometric Theory, 21*. http://dx.doi.org/10.1017/S0266466605050206.
Arribas-Bel, D., Kourtit, K., & Nijkamp, P. (2013). Benchmarking of world cities through self-organizing maps. *Cities, 31*, 248–257. http://dx.doi.org/10.1016/j.cities.2012.06.019.
Banker, R. D., & Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research, 175*(2), 1311–1320. http://dx.doi.org/10.1016/j.ejor.2005.06.028.
Batty, M. (2012). Building a science of cities. *Cities, 29*, S 9 –S16.
Batty, M. (2013). The future cities agenda. *Environment and Planning. B, Planning & Design, 40*(2), 191–194. http://dx.doi.org/10.1068/b4002ed.
Bettencourt, L. M. A., Lobo, J., Strumsky, D., & West, G. B. (2010). Urban scaling and its deviations: Revealing the structure of wealth, innovation and crime across cities. *PLoS One, 5*(11), 20–22. http://dx.doi.org/10.1371/journal.pone.0013541. Boettle, M., Schmidt-Thomé, P., & Rybski, D. (2013). Coastal protection and multi-criteria decision analysis: Didactically processed examples. *Climate change adaptation in practice: From strategy development to implementation* (pp. 35–49). . http://dx.doi.org/10.1002/9781118548165.ch4.
Bogetoft, P., & Otto, L. (2011). *Benchmarking With DEA, SFA, and R. 157*New York, NY: Springer New Yorkhttp://dx.doi.org/10.1007/978-1-4419-7961-2.
Caragliu, A., & Del Bo, C. F. (2015). Do smart cities invest in smarter policies? Learning from the past, planning for the future. *Social Science Computer Review,* 1–16. http://dx.doi.org/10.1177/0894439315610843.
Castillo, N. H., El-Haram, M., Walton, J. S., Hardcastle, C., Price, A. D. F., & Horner, R. M. W. (2005). Integrated assessment of urban sustainability. *Proceedings of the ICE - Engineering Sustainability, 158*(2), 57–65. http://dx.doi.org/10.1680/ensu.2005.158.2.57.
Cazals, C., Florens, J. P., & Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of Econometrics, 106*(1), 1–25. http://dx.doi.org/10.1016/S0304-4076(01)00080-X.
Charnes, A., Cooper, W. W., & Li, S. (1989). Using data envelopment analysis to evaluate efficiency in the economic performance of Chinese cities. *Socio-Economic Planning Sciences, 23*(6), 325–344. http://dx.doi.org/10.1016/0038-0121(89)90001-3.
Creutzig, F., Baiocchi, G., Bierkandt, R., Pichler, P. P., & Seto, K. C. (2015). Global typology of urban energy use and potentials for an urbanization mitigation wedge. *Proceedings of the National Academy of Sciences, 112*(20), 6283–6288. http://dx.doi.org/10.1073/pnas.1315545112.
da Cruz, N. F., & Marques, R. C. (2014). Scorecards for sustainable local governments. *Cities, 39*, 165–170. http://dx.doi.org/10.1016/j.cities.2014.01.001.
da Cruz, N. F., & Marques, R. C. (2017). An application of a multicriteria model to assess the quality of local governance. *Urban Affairs Review, 107808741773304*. http://dx.doi.org/10.1177/1078087417733049.
Cummins, R. (2000). Objective and subjective quality of life: An interactive model. *Social Indicators Research, 52*, 5 5 –72. http://dx.doi.org/10.1023/A:1007027822521.
D'Ambrosio, A., Amodio, S., & Iorio, C. (2015). Two algorithms for finding optimal solutions of the Kemeny rank aggregation problem for full rankings. *Electronic Journal of Applied Statistical Analysis, 8*(2), 198–213. http://dx.doi.org/10.1285/i20705948v8n2p198.
Dattakumar, R., & Jagadeesh, R. (2003). A review of literature on benchmarking. *Benchmarking: An International Journal, 10*(3), 176–209. http://dx.doi.org/10.1108/14635770310477744.
De Witte, K., & Marques, R. C. (2010). Influential observations in frontier models, a robust

non-oriented approach to the water sector. *Annals of Operations Research, 181*(1), 377–392. http://dx.doi.org/10.1007/s10479-010-0754-6.

Dhakal, S. (2009). Urban energy use and carbon emissions from cities in China and policy implications. *Energy Policy, 37*(11), 4208–4219. http://dx.doi.org/10.1016/j.enpol.2009.05.020.

Dijkstra, L., & Poelman, H. (2012). Cities in Europe: The new OECD-EC definition. *Regional and Urban Policy, Regional Focus, 1*.

Du, Q., Wang, Y., Ren, F., Zhao, Z., Liu, H., Wu, C., & Shen, Y. (2014). Measuring and analysis of urban competitiveness of Chinese provincial capitals in 2010 under the constraints of major function-oriented zoning utilizing spatial analysis. *Sustainability (Switzerland), 6*(6), 3374–3399. http://dx.doi.org/10.3390/su6063374.

Elmuti, D., & Kathawala, Y. (1997). An overview of benchmarking process: A tool for continuous improvement and competitive advantage. *Benchmarking: An International Journal, 4*(4), 229–243. http://dx.doi.org/10.1108/14635779710195087. European Environment Agency (2014). *Nitrogen oxides (NOx) emissions.* (Copenhagen). Eurostat (2014). *Eurostat Regional Yearbook 2014.* Publications Office of the European Unionhttp://dx.doi.org/10.2785/54659.

Fancello, G., Uccheddu, B., & Fadda, P. (2014). Data envelopment analysis (D.E.A.) for urban road system performance assessment. *Procedia - Social and Behavioral Sciences, 111*, 780–789. http://dx.doi.org/10.1016/j.sbspro.2014.01.112.

Gandy, M. (2004). Rethinking urban metabolism: Water, space and the modern city. *City, 8*(3), 363–379. http://dx.doi.org/10.1080/1360481042000313509.

Glaeser, E. L., & Kahn, M. E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics, 67*(3), 404–418. http://dx.doi.org/10.1016/j.jue.2009.11.006.

Goldstein, B., Birkved, M., Quitzau, M.-B., & Hauschild, M. (2013). Quantification of urban metabolism through coupling with the life cycle assessment framework: Concept development and case study. *Environmental Research Letters, 8*, 035024. http://dx.doi.org/10.1088/1748-9326/8/3/035024.

Grubler, A., Bai, X., Buettner, T., Dhakal, S., Fisk, D. J., Ichinose, T., ... J. S. and H. W. (2013). Urban energy systems. *Global Energy Assessment — Toward a Sustainable Future*Routledgehttp://dx.doi.org/10.4324/9780203066782.

Hillman, T., & Ramaswami, A. (2010). Greenhouse gas emission footprints and energy use benchmarks for eight U.S. cities. *Environmental Science & Technology, 44*(6), 1902–1910. http://dx.doi.org/10.1021/es9024194.

Hilmola, O. P. (2011). Benchmarking efficiency of public passenger transport in larger cities. *Benchmarking: An International Journal, 18*(1), 23–41. http://dx.doi.org/10.1108/14635771111109805.

Holmes, T., & Pincetl, S. (2012). *Metabolism literature review.* Center For Sustainable Urban Systems, Ucla Institute of The Environment Urban1–28.

Jiang, Y., & Shen, J. (2010). Measuring the urban competitiveness of Chinese cities in 2000. *Cities, 27*(5), 307–314. http://dx.doi.org/10.1016/j.cities.2010.02.004. Jiang, Y., & Shen, J. (2013). Weighting for what? A comparison of two weighting methods for measuring urban competitiveness. *Habitat International, 38*, 167–174. http://dx.doi.org/10.1016/j.habitatint.2012.06.003.

Keirstead, J. (2013). Benchmarking urban energy efficiency in the UK. *Energy Policy, 63*, 575–587. http://dx.doi.org/10.1016/j.enpol.2013.08.063.

Kelly, J. M., & Swindell, D. (2002). A multiple-indicator approach to municipal service evaluation: Correlating performance measurement and citizen satisfaction across jurisdictions. *Public Administration Review, 62*, 610–621. http://dx.doi.org/10.1111/1540-6210.00241.

Kennedy, C. A., Cuddihy, J., & Engel-Yan, J. (2007). The changing metabolism of cities. *Journal of Industrial Ecology, 11*(2), 43–59. http://dx.doi.org/10.1162/jie.2007.1107.

Kennedy, C. A., Pincetl, S., & Bunje, P. (2011). The study of urban metabolism and its applications to urban planning and design. *Environmental Pollution, 159*(8–9), 1965–1973. http://dx.doi.org/10.1016/j.envpol.2010.10.022.

Kennedy, C. A., Ramaswami, A., Carney, S., & Dhakal, S. (2009). Greenhouse gas emission baselines for global cities and metropolitan regions. *Cities,* 1–34.

Kennedy, C. A., Stewart, I., Facchini, A., Cersosimo, I., Mele, R., Chen, B., ... Sahin, A. D. (2015). Energy and material flows of megacities. *Proceedings of the National Academy of Sciences, 112*(19), 5985–5990. http://dx.doi.org/10.1073/pnas.1504315112. Kresl, P. K., & Singh, B. (1999). Competitiveness and the urban economy: Twenty-four large U.S. metropolitan areas. *Urban Studies, 36*(5), 1017–1027. http://dx.doi.org/10.1080/0042098993330.

Larivière, I., & Lafrance, G. (1999). Modelling the electricity consumption of cities: Effect of urban density. *Energy Economics, 21*(1), 53–66. http://dx.doi.org/10.1016/S0140-9883(98)00007-3.

Le Lannier, A., & Porcher, S. (2014). Efficiency in the public and private French water utilities: Prospects for benchmarking. *Applied Economics, 46*(5), 556–572. http://dx.doi.org/10.1080/00036846.2013.857002.

Marans, R. W. (2015). Quality of urban life & environmental sustainability studies: Future linkage opportunities. *Habitat International, 45*(P1), 47–52. http://dx.doi.org/10.1016/j.habitatint.2014.06.019.

Markovits-Somogyi, R. (2011). Ranking efficient and inefficient decision making units in data envelopment analysis. *International Journal for Traffic and Transport Engineering, 1*(4), 245–256 http://doi.org/UDC: 519.852.

Marques, R. C., da Cruz, N. F., & Pires, J. (2015). Measuring the sustainability of urban water services. *Environmental Science & Policy, 54*, 142–151. http://dx.doi.org/10.1016/j.envsci.2015.07.003.

Matas, A. (1998). Technical characteristics and efficiency of urban bus companies: The case of Spain. *Transportation, 25*, 243–263. http://dx.doi.org/10.1023/A:1005078830008.

McCrea, R., Shyy, T.-K., & Stimson, R. (2006). What is the strength of the link between objective and subjective indicators of urban quality of life? *Applied Research in Quality of Life, 1*(1), 79–96. http://dx.doi.org/10.1007/s11482-006-9002-2.

Minx, J., Creutzig, F., Medinger, V., Ziegler, T., Owen, A., & Baiocchi, G. (2011). *Developing a pragmatic approach to assess urban metabolism in Europe — a report to the environment agency. Berlin.*

Moriarty, J. P. (2011). A theory of benchmarking. *Benchmarking: An International Journal, 18*, 588–611. http://dx.doi.org/10.1108/14635771111147650.

Munksgaard, J., Wier, M., Lenzen, M., & Dey, C. (2005). Using input-output analysis to measure the environmental pressure of consumption at different spatial levels. *Journal of Industrial Ecology, 9*(1), 169–186. http://dx.doi.org/10.1162/1088198054084699.

Newman, P. W. G. (1999). Sustainability and cities: Extending the metabolism model. *Landscape and Urban Planning, 44*(4), 219–226. http://dx.doi.org/10.1016/S0169-2046(99)00009-2.

Novaes, A. (2001). Rapid-transit efficiency analysis with the assurance-region DEA method. *Pesquisa Operacional,* 179–197. Retrieved from http://www.scielo.br/scielo.php?pid=S0101-74382001000200004&script=sci_arttext.

OECD (2011). *Cities and Green Growth: A Conceptual Framework. OECD Regional Development Working Papers. 2011/08*, 1 –141. http://dx.doi.org/10.1787/5kg0tflmzx34-en.

Okulicz-Kozaryn, A. (2013). City life: Rankings (livability) versus perceptions (satisfaction). *Social Indicators Research, 110*(2), 433–451. http://dx.doi.org/10.1007/s11205-011-9939-x.

Oswald, A. J., & Wu, S. (2010). Objective confirmation of subjective measures of human well-being: Evidence from the U.S.A. *Science, 327*(5965), 576–579. http://dx.doi.org/10.1126/science.1180606.

Pichler, P. P., Zwickel, T., Chavez, A., Kretschmer, T., Seddon, J., & Weisz, H. (2017). Reducing urban greenhouse gas footprints. *Scientific Reports, 7*(1), 14659. http://dx.doi.org/10.1038/s41598-017-15303-x.

Pina, V., & Torres, L. (2001). Analysis of the efficiency of local government services delivery: An application to urban public transport. *Transportation Research, Part A (Policy and Practice), 35A*(10), 929–944. http://dx.doi.org/10.1016/s0965-8564(00)00033-1.

Pinto, F. S., Costa, A. S., Figueira, J. R., & Marques, R. C. (2017). The quality of service: An overall performance assessment for water utilities. *Omega, 69*, 115–125. http://dx.doi.org/10.1016/j.omega.2016.08.006.

Portugali, J. (2000). *Self-organization and the City.* New York: Springer New York.

Pradhan, P., Costa, L., Rybski, D., Lucht, W., & Kropp, J. P. (2017). A systematic study of sustainable development goal (SDG) interactions. *Earth's Future*. Accepted https://doi.org/10.1002/2017EF000632.

Raab, R., & Lichty, R. (2002). Identifying subareas that comprise a greater metropolitan area: The criterion of county relative efficiency. *Journal of Regional Science, 42*(3), 579–594. http://dx.doi.org/10.1111/1467-9787.00273.

Reckien, D., Ewald, M., Edenhofer, O., & Lüdeke, M. K. B. (2007). What parameters influence the spatial variations in CO2 emissions from road traffic in Berlin? Implications for urban planning to reduce anthropogenic CO2 emissions. *Urban Studies, 44*(2), 339–355. http://dx.doi.org/10.1080/00420980601136588.

Sáez, L., & Periáñez, I. (2015). Benchmarking urban competitiveness in Europe to attract investment. *Cities, 48*, 7 6 –85. http://dx.doi.org/10.1016/j.cities.2015.06.002.

Schneider, M. (1975). The quality of life in large American cities: Objective and subjective social indicators. *Social Indicators Research, 1*(4), 495–509. http://dx.doi.org/10.1007/BF00353066.

Seto, K., & Dhakal, S. (2014). *Chapter 12: Human Settlements, Infrastructure, and Spatial Planning. Climate Change 2014: Mitigation of Climate Change.*

Singhal, S., McGreal, S., & Berry, J. (2013). An evaluative model for city competitiveness: Application to UK cities. *Land Use Policy, 30*(1), 214–222. http://dx.doi.org/10.1016/j.landusepol.2012.03.018.

Sovacool, B. K., & Brown, M.a. (2010). Twelve metropolitan carbon footprints: A preliminary comparative global assessment. *Energy Policy, 38*(9), 4856–4869. http://dx.doi.org/10.1016/j.enpol.2009.10.001.

Sueyoshi, T. (1992). Measuring the industrial performance of Chinese cities by data envelopment analysis. *Socio-Economic Planning Sciences, 26*(2), 75–88. http://dx.doi.org/10.1016/0038-0121(92)90015-W.

UNESCAP (2011). *Are we Building Competitive and Liveable Cities? Guidelines for Developing Eco-efficient and Socially Inclusive Infrastructure.* Bangkok: United Nations.

United Nations (2014). *World Urbanization Prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352). New York, United.* http://dx.doi.org/10.4054/DemRes.2005.12.9.

Wang, L., Long, R., & Chen, H. (2017). Study of urban energy performance assessment and its influencing factors based on improved stochastic frontier analysis: A case study of provincial capitals in China. *Sustainability, 9*(7), 1110. http://dx.doi.org/10. 3390/su9071110.

Weisz, H., & Steinberger, J. K. (2010). Reducing energy and material flows in cities. *Current Opinion in Environmental Sustainability*. http://dx.doi.org/10.1016/j.cosust.2010.05.010.

Wolman, A. (1965). *The metabolism of cities.* Scientific Americanhttp://dx.doi.org/10.1038/scientificamerican0965-178.

Yi, S., & Fengyan, C. (2015). Regional innovation systems based on stochastic frontier analysis: A study on thirty-one provinces in China. *Science, Technology and Society, 20*(2), 204–224. http://dx.doi.org/10.1177/0971721815579808.

Yu, Y., & Wen, Z. (2010). Evaluating China's urban environmental sustainability with data envelopment analysis. *Ecological Economics, 69*(9), 1748–1755. http://dx.doi.org/10.1016/j.ecolecon.2010.04.006.