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Sustainability Performance of European Smart Cities: A Novel DEA Approach with Double Frontiers

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ABSTRACT

Sustainability is the crux of urban renaissance. Imbibed with utopian technological planning, understanding the convergence between smart development and sustainable practices for city development is necessary. Smart cities have succeeded in bringing high standards of living to its residents. This article evaluates the long-term sustainability performance of 35 leading European smart cities over time from 2015 till 2020 to understand on how these cities address sustainability to make the concept of smart sustainable cities more actionable. A novel Double-Frontier Slack Based Measure Data Envelopment Analysis (DFSBM-DEA) model considering undesirable factors in the technology set is proposed for the assessment. An integrated relative sustainability performance assessment model considering both the optimistic and pessimistic viewpoint simultaneously, in terms of interval efficiency is used to determine the most efficient smart city under 6 various dimensions of sustainable development. These key dimensions include; Energy and Environmental Resource, Governance and Institution, Economic dynamism, Social cohesion and solidarity, Climate Change and, Safety and Security. A productivity progress assessment from a double frontier perspective using a modified Malmquist-DEA model is then used to capture the response of each smart city in terms of their productivity growth towards achieving sustainable development. Results show Dublin (ranked 1st) as the most smart and sustainable European city under all the proposed dimensions of sustainable development from the double-frontier perspective. Along with Dublin lies Oslo, Zurich and Amsterdam as the cities with high aggregate sustainability performance. The results also revealed significant difference in the productivity progress values from the optimistic and pessimistic viewpoint, thus exemplifying the significance for the proposed aggregate productivity progress measurement model. The findings of the present study contribute to knowledge and practice for smart city modellers, decision makers and urban planners, by aiding methodological clarity in assessing sustainable capacity of cities from a double frontier perspective and, in particular, by drawing attention to underlying assumptions about the role of sustainability in smart city development. This research stands as a breakthrough in the field of relative sustainability assessment using non-parametric approaches and a benchmark for global smart cities to shape their development in light of sustainability.

1. Introduction

1.1. Theoretical Background

Smart cities are undoubtedly the engines of global prosperity and innovation, but a litany of prodigious challenges (Yigitcanlar et al., 2020; Bibri, 2021a). With an expected population growth rate of 33% by 2050 in smart cities, bringing out an equitable balance between the production and consumption patterns, carbon neutrality goals, sustainable urban growth and quality of life could be at stake (Shamsuzzoha et al., 2021; Singh and Ohri, 2021). Experiencing an increase in the urban ecological footprint has left smart cities to mobilize actions for embracing nature based solutions targeting long-term Sustainable Development (SD) (Kutty et al., 2020; Way and Peng, 2021; D'Amico

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et al., 2021; Glaeser, 2021). Illuminating smart cities with global SD practices can help address several development challenges such as human development, pollution and climate change adaption, biodiversity, circular economy, natural calamity preparedness and energy consumption (Kutty et al., 2020; Kourtit, 2021; Elhmoud and Kutty, 2021). The "United Nations' Sustainable Development Goals (SDGs)" offer untapped opportunities for cities and urban spaces to drive powerful transformations and nullify the prevailing development challenges (Mata, 2018; Yigitcanlar, 2021). Accounting to the sustainable urbanization practices can help smart cities significantly in not only shaping their energy and resource utilization, but also tackling all the development challenges across each SDGs to bring smartness and sustainability practices under one umbrella (Yigitcanlar et al., 2019a; Repette et al., 2021).

Smart cities can be perceived as one that utilizes the possibilities offered by information and communication technologies (ICTs) in enhancing the local prosperity and competitiveness by adopting an integrated urban development approach that involves multiple actors, stakeholders and multi-dimensional perspectives (Paskaleva, 2009). Cities driven by ICT-based technocentric approaches can help in reducing the root causes associated with most of the pressing concerns (Margarita et al., 2020). However, ICT-centered approaches often face risk when attempting to stabilize unsustainable development patterns, as tech-driven smart cities often focus on smart targets which does not automatically bring sustainability, in turn makes development models obsolete over time (Yigitcanlar and Kamruzzaman, 2019). For instance, the question of sustainable accessibility of smart public transportation system in cities is a social concern due to the territorial allocation of public transit infrastructure networks and regionalized development around profitable territories paving ways to "smart territories" than smart sustainable cities (Kamruzzaman, Shatu, and Habib, 2020). On the contrary, these emergent systems prioritize development that rise to prominence by adapting to the market behavior and not evolving over time (Esmaeilpoorarabi et al., 2020; Kutty et al., 2020). However, attempting to optimize systems do not deliver complete efficiency (Mora et al., 2019; Kourtit et al., 2021). In addition, most self-designed smart cities are business-driven models that function on public-private collaboration that target the cash-cow maturity curves than equitable growth and sustainable development (Yigitcanlar et al., 2019b). Thus, smart cities are focusing more onto profit-driven strategies than extending wings to address sustainability and sustainable growth patterns.

Smart cities have succeeded in bringing high standards of living to its residents (Angelidou and Mora, 2019). The British Standards Institute (BSI), the national standards body of the United Kingdom, supported that a smart city includes the efficient integration of physical, digital and human systems in the built infrastructure in order to create a sustainable, prosperous and inclusive future for its inhabitants (BSI, 2014). This emphasis on the habitability and inclusivity of the urban environments particularly underlines the social nature of smart cities. Via the use of digital intelligence, tools can be designed that save lives, prevent crime, and reduce the disease burden. These can save time, reduce waste, and even help boost social connectedness (McKinsey, 2018). In other words, smart cities strive to improve city services and urban management for the citizens, by creating a socially advanced environment. The ultimate goal of these processes is to improve the sustainability and liveability of the city (Toppeta, 2010; Shehab et al., 2021). City planners argue that the use of advanced technologies will by-nature improve the environmental outcomes of the city based on the pervasive use of real-time data and monitoring systems (Bibri, 2021b). For instance, the installation of smart trash bins that monitor real-time waste alert municipality officials in understanding the fill and assist in taking necessary actions in collecting the waste for appropriate disposal. Similarly, the self-powered smart streetlights respond to the urban density flow and illuminate in accordance so as to support the energy saving initiatives through smart practices. However, several contradictory studies (see: Kutty et al., 2020; Bibri, 2021c) in recent years show that these smart technologies require continuous communication through internet channels to acquire data to keep these smart systems running. This requires a great deal of energy usage and outweighs the potential benefits acquired through the use of smart infrastructures (Bibri, 2021d). Thus, smart cities despite the sworn oath to sustainability, in reality is a zero-sum-game due to the fact that "the positive and negative impacts tend to cancel each other out". A better understanding on "how sustainable are smart cities in long-run ?" is an area of research to conquer so as to tackle the deficiencies in the existing cities to plan better for a next-generation city.

1.2. Research significance and objectives

The urban revolution in smart cities needs to be backed by sustainable development, since smart cities are the epicenter of untapped opportunities for the future generation. At city level, functions and environments are more consistent, with input and output variables designed with the coverage of considerations of economic, environmental, and societal aspects (Kucukvar et al., 2021). Assessing the sustainable development capacity of smart cities is often crucial when planning development strategies. The insurmountable challenges of smart cities can reach better conclusions when assessed through the lens of sustainable development goals. For the same, several approaches are being used to understand the sustainable development capacity of smart cities. Till date, the literature contains two assessment techniques namely the parametric and non-parametric approach for the sustainability performance assessment, in general efficiency assessment. The frequently applied non-parametric linear programming based performance assessment technique is the "Data Envelopment Analysis" (DEA). DEA is one of the mainstream methods for evaluating sustainability performance of cities; during the infancy of this method, the DEA method was considered suitable for studying economically complex cities, and it was also used to evaluate 28 major cities in China by the pioneer of the method (Charnes et al., 1989). Zhu, (1996) built on this research and compared the results of the DEA method with those obtained using other contemporary methods, and provided evidence for the effectiveness of this method. These studies were focused on evaluating the economic output of cities, and it was only later when the DEA method was used to evaluate the environment and sustainability of Chinese cities. Yuan et al., (2015) used the DEA method to study the ability of 65 cities to respond to natural disasters, while Yang et al., (2016) used this method to evaluate the sustainability of cities in Taiwan. However, no comprehensive assessment of the sustainable development ability of European smart cities has been performed. The reason for the low frequency of usage of the DEA method, as noted by Li et al. (2005), is the limited availability of statistical data at the city level. In reality, the DEA method is perfectly suitable for comprehensive evaluation of a city's efficiency, and several case studies that have already been performed abroad using this method (Honma and Hu, 2008; Storto, 2016). In addition to a comprehensive assessment, as noted by Mega (1996), an increasing number of researchers has regarded sustainability in cities as a process rather than as an endpoint.

The use of DEA to assess the sustainability of smart cities hold the ability to include multiple inputs and outputs without defining any functional forms to these input and output variables. These inputs and outputs can be both desirable and undesirable. Several approaches exist when dealing with undesirable factors in DEA (see Koopmans, 1951; Golany and Roll, 1989; Ali and Seiford 1990; Seiford & Zhu, 2002). Most tend to ignore these undesirable factors from the "production possibility set" (PPS), while others undergo treatment and case-dependent transformations. However, a true reflection of the production process is often lost when desirability is not accounted while calculating the relative performance. This is the case of many of the existing approaches in the literature. Furthermore, it is essential to understand the relative sustainability performance considering both the efficiency and anti-efficiency frontiers of decision making units to arrive at better understanding while framing policies. Smart cities of today need to steer away from a capitalism-centric approach to a holistic approach, which encompasses environmental concerns, energy needs, standard of living and economic growth in order to ensure sustainable development. At present, the problem confronting the policy makers of all smart cities is on how to formulate a set of effective policies regarding the impacts of global warming potential on weather patterns, environmental protection, energy conservation, people-centric governance all in the pursuit of economic development. However, this involves a wide range of decision-support variables such as climate change adaption, geo-political stability, environmental and energy resource utilization, societal well-being concerns which significantly increases the complexity of policy making. Understanding the performance of cities based on these decision-support variables often tend to be from the optimistic point of view that inevitably ignores some very useful informations compared to their performance measured from different points of view. This fails to cover the panoramic view of sustainable outcomes leading to hindering the policy making process in smart cities. Here lies the rationale in undertaking this research which intends to quantify the sustainability performance of smart cities from multiple points of view by using a double frontier non-parametric approach. To this end, this research thus attempts to address the aforementioned concerns by accomplishing the following objectives namely;

a) Construct a Double Frontier (DF) Slacks-Based Measure (SBM) DEA model to address the occurrence of undesirability in the technology set for sustainability performance assessment.
b) Assess the overall sustainable development capacity of leading European smart cities using the proposed DF-SBM DEA model over time.
c) Understand the grouped sustainability performance of smart cities under the double-frontier approach to identify the best and worst performing smart city in terms of sustainable development in Europe.
d) Evaluate the change in productivity and sustainable capacity over time using an aggregate-DF-Malmquist productivity index (MPI) based DEA model from pessimistic, optimistic and double-frontier perspective.

2. Literature review

2.1. Sustainability assessment in smart cities

Despite technology playing a prominent role in transforming a city into being smart, there are several desired outcomes that need to be addressed when trying to mitigate several social, economic and urban challenges in a city, which hinders urban development in a sustainable manner (Kamruzzaman and Giles-Corti, 2019; Bibri, 2020). Smart city concepts have been perceived as an ICT driven concept focusing on improving the quality of life of the citizens (Bibri and Krogstie, 2020). However, smart cities need to extend their focus from the perspective of sustainable urban development (Yigitcanlar et al., 2019c). Initially, the concept of smart city was regarded as a strategic tool to underline the increasing importance of ICT and social and environmental capital in sculpting the competitiveness of modern cities (Schaffers et al., 2012). Consequently, smart city definitions that encompass the environmental dimension of sustainability frequently include the social dimension. Schaffers et al. (2012) argued that this is due to the distinctive attributes that social and environmental capital can offer to smart cities compared to the "more technologyladen counterparts," frequently mentioned in the literature as digital or intelligent cities. Thus, the distinction between digital or intelligent cities and smart cities appears to be the prevalence of the human element in the latter.

As an attempt to understand the methodological approaches, and tools developed to assess urban sustainability in smart cities, a review was carried out based on a series of latest research studies, and several indexing reports published in the field. The screening process of both scientific and gray literature was conducted with the aid of several search engines and Scopus online database, with a view to include a wide spectrum of journals, books, and technical reports with high relevance to smart city and urban sustainability assessment. The purpose of this bibliographical search was to identify the most well-known and widely-accepted sustainability assessment tools, indices, and methodologies used in smart cities for sustainability assessment from the last decade. We note that even though sustainability goes beyond local and urban areas, and several composite indices tackle country or global scale evaluation, we have restricted our study to urban sustainability in smart cities alone. Our research indicates that a variety of models and tools have been developed for the evaluation and comparability of sustainability in smart cities. These tools are based on composite indices that assess critical dimensions of sustainability. A good example of a composite index offered also as an interactive tool, that introduces both technology maturity and sustainability aspects in urban development is the Networked Society City Index (Ericsson, 2016). The Green City tool is another initiative on an European Union (EU) level and under the European Green Capital framework (European Green Capital, 2021), aiming to facilitate sustainable urban planning with a prime focus on offering best practices and guidance. It provides a simple, straightforward tool, limited to generic qualitative inputs of self-assessment for cities. In general, composite indices provide some key outcomes, such as ranking and benchmarking of cities, facilitating research and analysis in the urban design (Buldeo Rai et al., 2018) and assisting in sharing knowledge for the development of smart and sustainable cities (Abu-Rayash and Dincer, 2021). However, given that city sustainability entails a multitude of aspects and domains (Ali-Toudert and Ji, 2017), all these evaluation frameworks and indices present methodological gaps and conflicts, as they capitalize on different definitions of urban performance and development (Molinaro, 2020), while showing imbalance between smartness and sustainability.

Although there are many similarities among characteristics of evaluation frameworks, rating systems, or composite indices, they differ considerably in conceptualization, focus, and goals, due to the determined diverse city needs, boundaries and expected outcomes of the smart and sustainable cities under assessment, as well as the perspectives of the relevant stakeholders and experts. A majority of applications, experiments, projects and initiatives use as a guiding principle the "triple bottom line (TBL)" in order to evaluate sustainability performance which integrates social, economic, and environmental variables (Chen and Zhang, 2020). A good illustration of this is the China's urban sustainability indices (USI), the last version of which launched in 2016 and uses 23 indicators categorized under the 3 dimensions of TBL for ranking 185 Chinese cities of diverse sizes and development stages assessing their sustainability performance level between 2006 and 2014 (The China Urban Sustainability Index, 2016). Furthermore, some indices represent strong sustainability while others present a weak sustainability assessment. A representative index with strong sustainability criteria is the sustainable development of energy, water, and environment systems index (SDEWES) that assesses the sustainable performance of 120 cities across 7 dimensions, while identifying best practices for policy learning and adoption (Kılkış, 2016). There are also indices that primarily focus on environmental sustainability, such as the European Green City Index, grounded on 30 individual indicators to assess and compare the environmental performance of 30 big European cities from different countries (Shields et al., 2009), or indices that explore only specific urban aspects, such as urban mobility, air quality, business development, etc. (Akande et al., 2019), e.g., the index developed by Collins et al. (2019) that builds upon geographic, meteorological, and socio-economic data and k-means clustering to determine which out of 119 U.S. cities included in the analysis are bicycling-friendly cities (Collins et al., 2020).

Several indices used to assess sustainability also hold drawbacks that lie in the difference and multiplicity of the data sources used for results' comparison, owing to lack of data for some indicators or even due to inconsistency of the framework approach. In some cases, country-level data are utilized or extrapolation techniques are implemented, while data are also obtained from other indices to calculate a number of their metrics (for example see., e.g., Cohen, 2012; Innovation Cities Index, 2019). In the case of a city evaluated by two or more different indices, results lead to diverse type of rankings, implying an indication of subjectivity. A good illustration of this is the city of London when assessed via the IESE Cities in Motion Index 2020 and the IMD Smart City Index 2020. The city ranks top in the first index and on the 15th place in the second, due to the different approaches in the smart and sustainable city concept and its dimensions, as well as the number of cities and indicators of city evaluation between the two indices, leading to extremely difficult comparison of results. In addition, it is also to note that several major differences and incoherences are observed among composite indices regarding the normalization, weighting, and aggregation methods used to evaluate sustainability performance. However, non-parametric approaches such as the Data Envelopment Analysis (DEA) uses normalized values for all the indicators from linear scaling in the min-max range. The technique allows the analyst to endogenously assign weights for the partial indicators, yielding an overall score that depicts the analyzed decision making unit in its best possible light relative to the other observations.

2.2. DEA models for sustainability assessment

Data Envelopment Analysis (DEA) is a non-parametric quantitative optimization-based benchmarking technique developed by Charnes, Cooper, and Rhodes, (1978) to assess the relative efficiency of productive units. In this approach, the values of the selected input and output parameters are multiplied with appropriate weights calculated to obtain the desirable efficiency scores. The proposed model by Charnes, Cooper and Rhodes, (1978) (formally known as the CCR model) based on "constant returns to scale (CRS)" was further modified by Banker, Charnes, and Cooper, (1984) (so called BCC model) entitling "variable returns to scale (VRS)". In a classic DEA model, appropriate weights for each "Decision Making Units" (DMU) are formulated using mathematical programming. In contrast to DEA, a less frequently used non-parametric technique for efficiency calculation is the "Free disposal hull (FDH) approach" proposed by Deprins et al., (1994), which later on was modified by Lovell et al., (1994). Till date, DEA models are based on two measures, the radial DEA model proposed by Charnes, Cooper, & Rhodes, (1978) and the Slack based measure (SBM) DEA model developed by Tone, (2001).

Through the years, various DEA models have been extended from the classical CCR and BCC models to calculate the relative efficiency of the DMUs. Tayala et al., (2020) applied the BCC model with constant input to calculate the efficiency and select the most sustainable facility layout plan, combined with machine learning, K-means clustering and meta heuristics approaches. An SBM-DEA model combined with emergy analysis was used to assess the urban metabolic performance of eight Chinese communities by Tang et al., (2020). The frontier approach has brought all the sustainability assessment indicators under the composite sustainability framework. A metafrontier DEA approach was used to study the territorial eco-efficiency patterns in 282 European regions for the years from 2006 till 2014 by (Bianchi et al., 2020). Yasmeen et al., (2020) used a "super-efficiency" DEA model combined with a system generalized method of moment estimator to study the ecological productivity of 30 provinces of Mainland China under the COP-21 agreement. The impact of pivotal factors contributing towards national and regional sustainability were also identified and targeted for possible improvements. A multi power system network-based DEA model was used to monitor the degree of sustainability by Tavassoli et al., (2020) within the context of Iran's electricity distribution grid. The model included several undesirable outputs, excess inputs and system re-work indicators whose weights were assigned based on expert judgements. A similar network DEA approach was used by Wang & Song, (2020) to measure the degree of sustainable airport development for 12 Asian airports from the grey model using real time and forecasted data. Castellano et al., (2020) made use of a "multi-stage DEA" model to assess the relative environmental and economic prosperity of 24 Italian seaports. The model estimated the diligence of economic efficiency when considerable adjustments were made in the ecological costs and pro-ecological commitments. A multi stage DEA-ratio data model developed by Mozaffari et al., (2020) was used to estimate the sustainable efficiency of 20 fire station supply chain (SC) based on a set of dependent variables. The model utilized the Genetic Algorithm (GA) as a means to obtain the productive weights of a multi-echelon SC model. Ibrahim & Alola, (2020) applied an "Autoregressive Distributed Lag (ARDL)" method with "Pooled Mean Group (PMG) estimation" approach to understand the non-renewable resource efficiency for a set of response variables like GDP growth rate, energy usage and aggregate natural resource rent. While, a similar study was conducted using a DEA model to evaluate the efficiency for renewable energy and, socio-economic and ecological development. Thus, DEA can be seen as a powerful tool in assessing sustainable development capacity across several domains.

Progressive efficiency can be assessed by understanding the technological changes as a whole over the years. Productivity measurement is an important topic to account for when understanding sustainability. The DEA based Malmquist Productivity Index (MPI), as an effective tool has long been used to measure the productivity change in efficiencies over time for a set of representative units. A DEA-MPI model was used by Pan et al., (2021) to measure the sustainable development of electronic agriculture-based infrastructure in 31 provinces of China. The integrated approach rules out bias in estimation of production efficiency associated with the use of cross-sectional or time series data. To assess the ecological productivity of 30 Chinese cities from a time series perspective, Zhu et al., (2019) developed a common weight DEA approach combined with Biennial-MPI. Zhang et al., (2020) employed a super efficiency DEA-MPI to create an evaluation index system to understand the impact of IoT with real economy for an economic sustainability assessment. To study the productivity change in eco-efficiency and technology catch-up indices, a non-radial metafrontier Malmquist-Luenberger DEA model was used by Tang et al., (2020a) over time on 30 Chinese provinces. Double bootstrapped MPI was used by Kularatne et al., (2019) to analyze on how environmentally sustainable practices can make Sri Lankan hotel industry more efficient, by measuring productivity change over period from 2010-2014. Wang and Li, (2018) employed DEA-MPI to analyze the carbon emission performance of petrochemical producers in United States over time. Combined with super efficiency DEA-MPI and kernel density estimation, Ge et al., (2021) studied the eco-efficiency performance of 40 growing cities. DEA-Malmquist-Luenberger productivity index was used in combination with Difference in Difference-Propensity Score Matching (PSM-DID) approach to estimate the productivity progress of low-carbon emission pilot cities of China by Fu et al., (2021). Wang, (2019) used DEA-MPI to understand the sustainability performance and productivity change of 40 world-wide cities across 6 prime dimensions.

2.3. DEA with undesirable factors

The literature till date provides two intuitive approaches when dealing with undesirability while calculating the efficiency performance. The most commonly employed approach is the application of suitable data transformation to the undesirable factors in the PPS to make them desirable. Non-data transformation approaches are also used to preserve the true input-output relationship of the production process. A non-parametric DEA model using the directional distance function (DDF) under the assumption of weak free disposability was proposed by Färe & Grosskopf (2004) and Yu (2004) to treat both undesirable inputs and outputs in the linear conventional BCC-DEA model. A single-process

Table 1
Comparative study on the existing literature for the sustainability assessment of cities using DEA models with undesirability considerations

Authors	Application scheme	Undesirable factors X^{UI}	Y^{UO}	DEA Models	Undesirability consideration	Productivity change	Frontier consideration Efficiency	Anti-efficiency
Calzada-Infante et al., (2020)	45 global tech-cities	No	Yes	Slack-Based Inefficiency models	Weak disposability assumption	-	Yes	No
Wang et al., (2018)	285 Chinese cities	No	Yes	Directional distance function based DEA	Null-jointness assumptions	Malmquist-Luenberger productivity index (MLPI)	Yes	No
Meng et al., (2018)	31 Chinese provinces	Yes	Yes	Synthesized DEA	Multiplicative inverse transformation	Malmquist productivity index (MPI)	Yes	No
Chen, (2017)	Taiwanese cities	No	Yes	Multi-activity DEA	Weak disposability assumption	Malmquist-Luenberger index	Yes	No
Sueyoshi and Yuan, (2017)	30 Chinese province-equivalents	No	Yes	Intermediate radial and non-radial DEA models under unified efficiency concept	Natural disposability with double efficiency frontier	-	Yes	No
Song et al., (2016)	31 Chinese cities	No	Yes	Principal compound analysis (PCA)-DEA approach	Reciprocal transformation $f(\mathrm{Y}) = 1/\mathrm{Y}^{UO}$		Yes	No
Wang and Wei, (2014)	30 major cities in China	No	Yes	Variable Returns to Scale (VRS) DEA model	Weak disposability assumption for VRS setting	-	Yes	No
Alper et al., (2015)	30 Israeli municipalities	No	Yes	CCR, BCC, Cross-efficiency (CE) and 2-stage DEA models	Reciprocal transformation $f(\mathrm{Y}) = 1/\mathrm{Y}^{UO}$	-	Yes	No
Chen et al., (2012)	Taiwanese city transit systems	Yes	Yes	Standard additive and super-efficiency SBM-DEA models	Standard strong disposability	-	Yes	No
Bian, (2009)	71 Chinese cities	No	Yes	Modified-CCR DEA model	-1 multiplication of Y^{UO} with adding translation vector v for $f(\mathrm{Y}) = -\mathrm{Y}^{UO} + \beta$	-	Yes	No
Lian et al., (2009)	17 cities in Anhui province, China	No	Yes	CCR based PCA-DEA model	-1 multiplication of Y^{UO} with increasing monotone transformation of principal components	-	Yes	No

X^{UI}: Undesirable inputs; Y^{UO}: Undesirable output

DDF approach to treat undesirable outputs in a network DEA model was proposed by Lozano et al., (2013) when computing the airport efficiency scores. Based on the classification invariance property, the performance of the inefficient DMU can be improved by maximizing the undesirable inputs and desirable outputs with minimizing the undesirable outputs and desirable inputs. This was applied by Seiford & Zhu, (2002) in understanding the performance of 30 paper production mills in the United States. The undesirable input $\mathrm{X}^{UI}{}_{ko}$ was multiplied by "-1" and then a translational vector "*w*" was added to convert the negative $\mathrm{X}^{UI}{}_{ko}$ to a positive form. Here, the undesirable input $\mathrm{X}^{UI}{}_{ko}$ is increased. A "Semi--Oriented Radial Measure DEA (SORM-DEA)" model presented by Emrouznejad (2010) dealt with negative undesirable inputs/outputs. A modified extension to the conventional SBM-DEA model proposed by Tone (2001) was used by Sharp et al., (2007) to addresses the desirability concerns in the input and output variables that are present in the technology set. A restricted DEA model using optimal shadow pricing taking into account the undesirability in the output was used by Guo and Wu (2013) to rank DMUs based on "Maximal Balance index".

Several data transformational approaches exist in literature to deal with desirability concerns in inputs and/or outputs when measuring relative performance. Lovell et al., 1995 used the multiplicative inverse approach to treat the undesirable outputs (monotone decreasing transformation) to achieve the desirable state. For instance, any undesirable output can be treated in the form $f(\mathrm{Y}) = 1/\mathrm{Y}^{UO}{}_{vj}$ $\{(v = 1,2,3,\ldots\ldots.t) \in T_c\}$ to use it as a set of desirable output for the efficiency assessment. Data translations of the form $f(\mathrm{Y}) = -\mathrm{Y} + \delta$ was used in the studies conducted by Pastor (1996) and Scheel (2001) to transform undesirable outputs to their desirable forms. Reducing dimensionality of the data set to its intrinsic dimension can help in capturing the significant inputs and outputs to be included while measuring the relative efficiency scores. Liang et al., (2009) used a monotone increasing data transformation on a selected set of principal components to rule out negative undesirable outputs when attempting to understand the ecological performance of 17 Chinese cities. Table 1 shows several studies that employed DEA models to assess the sustainability performance of cities with due consideration on undesirable factors.

2.4. Novelty and state-of-art contribution

The 2030 Agenda for Sustainable Development accentuates the importance of techno-centric development in transforming urban spaces to more smarter living units (World Urban Forum, 2018). However, it is unclear on how well these technological retrofits and advancements can bring sustainable outcomes or improve sustainability. Studies over the years have focused on attempts to transform smart cities into smarter living units in belief that technological advancements can pave ways to sustainability. Nevertheless, recent research contradicts this paradigm to support the smart sustainable city concept. This study tries to explore the true essence of the concept of sustainable development in leading European smart cities through a novel data-driven analytical approach for performance assessment.

In addition, traditional production theories, as seen in our literature analysis, often ignores the presence of undesirability (undesirable input and undesirable output) in the technology set while computing relative efficiencies for representative units to rule out the computational difficulties. However, this does not reflect the true production possibility set. Studies have considered the inclusion of undesirable outputs from an efficiency frontier perspective for sustainability assessment. However, no mention on the undesirable input and simultaneous inclusion of undesirable input and output reflecting their true technology set characteristics could be seen in the literature. In the real-world scenario, the efficiency measure for each representative units or DMU depends on the presence of certain undesirable inputs and outputs in the technology set, which rarely can be ignored as it does not reflect the real situation, ending up giving bias in the results. Furthermore, most of all the studies conducted till date analyzed the relative sustainability performance based on the efficiency frontier alone, disregarding the anti-ideal frontier. Recent research has revealed the essence of simultaneous inclusion of the efficiency and anti-efficiency frontiers for the performance assessment of representative units (see Entani et al., 2002; Azizi and Ajirlu, 2010; Azizi, 2011; Azizi, 2014; Ganji and Rassafi, 2019). However, all the studies ignored the presence of undesirability (undesirable inputs and undesirable outputs) and their simultaneous inclusion while computing the pessimistic and optimistic efficiencies from the double-frontier approach. Furthermore, in some of the DEA models, optimistic and pessimistic efficiencies are used to form an interval (see Entani et al., 2002; Wang and Yang, 2007; Jahanshahloo et al., 2011). These models considered the efficiency of a DMU as the interval between the optimistic and pessimistic values. However, these DEA models for computation of the pessimistic efficiency of each DMU holds a major drawback; namely, it does not consider some of the input and output data. These methods practically considers the data of only one input and one output for the DMU under evaluation and ignores the rest of the input and output data. Similarly, these models are not able to identify DEA-inefficient DMUs adequately. In addition, our literature review reveals that existing MPIs for productivity measurement are all proposed from the optimistic DEA point of view by using optimistic DEA models. No attempt has been made to examine the MPI from the pessimistic DEA point of view with due consideration to the input-output undesirability. This inevitably ignores some very useful information on productivity changes because the MPI values measured from different points of view are hardly the same and none of them can be replaced by each other. More importantly, measuring the MPIs from both the optimistic and the pessimistic DEA points of view can provide a comprehensive assessment and panoramic view of the productivity changes over time. To this end, this research targets to bridge the existing knowledge gaps identified by;

a) Proposing a novel modified DF-SBM bounded Malmquist-DEA model, extending the desirability inclusive DEA model of Liu et al., (2010) to a unified presentation of sustainability performance based on the DF-SBM approach.
b) Including desirability while considering the technology set for the sustainability assessment to simultaneously increase some selected set of input indicators (along with decreasing the desirable input indicators) and decrease selected set of output indicators (maximum value outputs included). The proposed model simultaneously considers the inclusion of undesirable factors to reflect the true production possibility set.
c) Conducting the first of its kind sustainability performance assessment of leading European smart cities in view of both the optimistic and pessimistic performances simultaneously (as bounded efficiency scores), with a true reflection of the technology set with multiple indicators across several dimensions of sustainable development, to make the concept of smart sustainable cities actionable.

3. Method

3.1. Double frontier SBM (DF-SBM) approach

This section describes the double frontier optimistic and pessimistic Slack Based Measure (SBM) DEA model used to assess the relative sustainable development capacity considering the case of smart cities. The model assumes to evaluate $\boldsymbol{n}$ smart cities, represented by the response unit DMU_j (j = 1,2,3,….*n*) were each DMU consumes $\boldsymbol{m}$ desirable inputs $X^{DI}{}_{ij}$ (i = 1,2,3,…....m) ϵ T and $\boldsymbol{p}$ undesirable inputs $X^{UI}{}_{kj}$ (k = 1,2,3,…... p) ϵ T to produce $\boldsymbol{s}$ desirable outputs $Y^{DO}{}_{rj}$ (r = 1,2,3,…...s) ϵ T and $\boldsymbol{t}$ undesirable outputs $Y^{UO}{}_{vj}$ (v = 1,2,3,…....t) ϵ T.

Assuming extended strong disposability and convexity, the technology set $T_{optimistic} \subseteq T$, for the optimistic SBM (represented by OSBM) reads:

$$T_{\text{optimistic}} = \left\{ \left(\mathbf{X}_{\mathbf{k}}^{\mathbf{UI}}, \mathbf{X}_{\mathbf{i}}^{\mathbf{DI}}; \mathbf{Y}^{\mathbf{DO}}\mathbf{v}, \mathbf{Y}_{\mathbf{r}}^{\mathbf{DO}}\right): \mathbf{XU_k} \leq \sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{X}_{\mathbf{kj}}^{\mathbf{UI}}\lambda_{\mathbf{j}}, \mathbf{X}_{\mathbf{i}}^{\mathbf{DI}} \geq \sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{X}_{\mathbf{ij}}^{\mathbf{DI}}\lambda_{\mathbf{j}} \right.$$
$$\left. \mathbf{Y}_{\mathbf{v}}^{\mathbf{UO}} \geq \sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{Y}_{\mathbf{vj}}^{\mathbf{UO}}\lambda_{\mathbf{j}}; -\mathbf{Y}_{\mathbf{r}}^{\mathbf{DO}} \leq -\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{Y}_{\mathbf{rj}}^{\mathbf{DO}}\lambda_{\mathbf{j}}, \sum_{\mathbf{j=1}}^{\mathbf{n}} \lambda_{\mathbf{j}} = \mathbf{1}, \lambda_{\mathbf{j}} \geq \mathbf{0}; \forall \mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{v} \right\} \tag{1}$$

The OSBM approach to find whether the response unit DMU_j lies in the efficient frontier or not can be achieved through the fractional programming model:

$$\text{Minimize } \boldsymbol{\Gamma}_{\text{optimistic}} = \frac{1 - \left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} s_i^{XD-} / X_{io}^{DI} + \sum_{v=1}^{t} s_v^{YU-} / Y_{vo}^{UO}\right)}{1 + \left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} s_r^{YD+} / Y_{ro}^{DO} + \sum_{k=1}^{p} s_k^{XU+} / X_{ko}^{UI}\right)} \tag{2}$$

Subject to

$$\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{X}_{\mathbf{kj}}^{\mathbf{UI}}\lambda_{\mathbf{j}} - \mathbf{s_k XU+} = \mathbf{X_{ko}UI}$$
$$\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{X}_{\mathbf{ij}}^{\mathbf{DI}}\lambda_{\mathbf{j}} + \mathbf{s_i XD+} = \mathbf{X_{io}DI}$$
$$\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{Y}_{\mathbf{rj}}^{\mathbf{DO}}\lambda_{\mathbf{j}} - \mathbf{s_r YD+} = \mathbf{Y_{ro}DO}$$
$$\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{Y}_{\mathbf{vj}}^{\mathbf{UO}}\lambda_{\mathbf{j}} + \mathbf{s_v YU-} = \mathbf{Y_{vo}UO}$$
$$\sum_{j=1}^{n} \lambda_j \mathbf{1 for Variable Returns to Scale}(\mathbf{VRS})$$
$$\Lambda_{\mathbf{j}}, \mathbf{s_k XU+}, \mathbf{s_i XD}, \mathbf{s_r YD+}, \mathbf{s_v YU} \geq \mathbf{0}; \forall \mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{v}$$

Where,

$X^{DI}{}_{ij}$	The i th desirable input of DMU_j
$Y^{DO}{}_{rj}$	The r th desirable output of DMU_j
$X^{UI}{}_{kj}$	The k th undesirable input of DMU_j
$Y^{UO}{}_{vj}$	The v th undesirable output of DMU_j
λ_j	weights of efficient DMU
$s_k{}^{XU+}$	slack variable for the undesirable input
$s_i{}^{XD-}$	slack variable for the desirable input
$s_r{}^{YD+}$	slack variable for the desirable output
$s_v{}^{YU-}$	slack variable for the undesirable output

The proposed OSBM-DEA model simultaneously minimizes the input and output inefficiencies. The mean rate of input minimization and the inverted mean rate of output maximization can be defined through the equations $(1/|m| + |t|)\ [\sum_{i=1}^{m}(X_{io}^{DI} - - s_i^{XD-})/ X_{io}^{DI} + \sum_{v=1}^{t}(Y_{vo}^{UO} - - s_v^{YU-})/ Y_{vo}^{UO}]$ and, $[(1/|s| + |p|)\ \{\sum_{r=1}^{s}(Y_{ro}^{DO} + s_r^{YD+})/ Y_{ro}^{DO} + \sum_{k=1}^{p}(X_{ko}^{UI} + s_k^{XU+})/ X_{ko}^{UI}\}]^{-1}$ respectively. The fractional programming model (2) can be converted into a linear programming (LP) model (3) by multiplying both the numerator and denominator of model (3) using a positive scalar variable $f > 0$ to form:

$$\mathbf{Minimize}\,\eta_{\text{optimistic}} = f - \left[\left(\frac{1}{|\mathbf{m}| + |\mathbf{t}|}\right)\left(\sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} / \mathbf{X}_{\mathbf{io}}^{\mathbf{DI}} + \sum_{\mathbf{v=1}}^{\mathbf{t}} \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} / \mathbf{Y}_{\mathbf{vo}}^{\mathbf{UO}}\right)\right] \tag{3}$$

Subject to

$$1 = f + \left[\left(\frac{1}{|\mathbf{s}| + |\mathbf{p}|}\right)\left(\sum_{r=1}^{s} \mathbf{S}_{r}^{\mathbf{YD}+}/\mathbf{Y}_{ro}^{\mathbf{DO}} + \sum_{k=1}^{p} \mathbf{S}_{k}^{\mathbf{XU}+}/\mathbf{X}_{ko}^{\mathbf{UI}}\right)\right]$$

$$\sum_{J=1}^{n} \mathbf{X}_{kj}^{\mathbf{UI}}\Lambda_j - \mathbf{S}_k^{\mathbf{XU}+} = f\mathbf{X}_{ko}\mathbf{UI}$$

$$\sum_{J=1}^{n} \mathbf{X}_{ij}^{\mathbf{DI}}\Lambda_j + \mathbf{S}_I^{\mathbf{XD}-} = f\mathbf{X}_{io}^{\mathbf{DI}}$$

$$\sum_{J=1}^{n} \mathbf{Y}_{r}^{\mathbf{DO}}\Lambda_j - \mathbf{S}_r^{\mathbf{YD}+} = f\mathbf{Y}_{ro}^{\mathbf{DO}}$$

$$\sum_{J=1}^{n} \mathbf{Y}_{vj}^{\mathbf{UO}}\Lambda_j + \mathbf{S}_v^{\mathbf{YU}-} = f\mathbf{Y}_{vo}\mathbf{UO}$$

$$\sum_{J=1}^{n} \Lambda\mathbf{j} = 1\mathbf{forVariableReturnstoScale}(\mathbf{VRS})$$

$$\Lambda_j, \mathbf{S}_k^{\mathbf{XU}+}, \mathbf{S}_I^{\mathbf{XD}-}, \mathbf{S}_r^{\mathbf{YD}+}, \mathbf{S}_v^{\mathbf{YU}-} \geq 0; \forall\mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{vand}f > \mathbf{0}$$

where $\Lambda_j = f\lambda_j$, $\mathbf{S}_I^{\mathbf{XD}-} = f s_I^{XD-}$, $\mathbf{S}_v^{\mathbf{YU}-} = f s_v^{YU-}$, $\mathbf{S}_r^{\mathbf{YD}+} = f s_r^{YD+}$, $\mathbf{S}_k^{\mathbf{XU}+} = f s_k^{XU+}$. The index $\eta_{optimistic}$ and $\Gamma_{optimistic}$ ranges between a value from 0 to 1. Greater the value of the index, greater the performance of each smart city towards sustainable development. The optimal solutions for model (2) and model (3) are ($\eta^* = \Gamma^*$, Λ_j^*, f^*, $\mathbf{S}_I^{\mathbf{XD}-}*$, $\mathbf{S}_v^{\mathbf{YU}-}*$, $\mathbf{S}_r^{\mathbf{YD}+}*$, $\mathbf{S}_k^{\mathbf{XU}+}*$) and ($\Gamma^* = \eta^*$; $\lambda_j^* = \Lambda_j^*/f^*$; $s_k^{XU\,*+} = \mathbf{S}_k^{\mathbf{XU}+}*/f^*$; $s_i^{XD\,*-} = \mathbf{S}_I^{\mathbf{XD}-}*/f^*$; $s_r^{YD\,*+} = \mathbf{S}_r^{\mathbf{YD}+}*/f^*$, $s_v^{YU\,*-} = \mathbf{S}_v^{\mathbf{YU}-}*/f^*$) respectively. The DMU is termed to be efficient when, $\eta^*_{optimistic} = \Gamma^*_{optimistic} = 1$. Here, the input excess: $s_k^{XU\,+}$, $s_i^{XD\,-}$ and, the output shortfall: $s_r^{YD\,+}$, $s_v^{YU\,-}$ should be equal to zero. In other case, the DMU is termed to be inefficient.

Considering the pessimistic SBM (represented by PSBM) DEA model, the technology set $T_{pessimistic} \subseteq T$ for the model reads as follows:

$$T_{\text{pessimistic}} = \left\{(\mathbf{X}_k^{\mathbf{UI}}, \mathbf{X}_i^{\mathbf{DI}}; \mathbf{Y}_v^{\mathbf{UO}}, \mathbf{Y}_r^{\mathbf{DO}}) : \mathbf{X}^{\mathbf{UI}}\mathbf{k} \geq \sum_{j=1}^{n} \mathbf{X}_{kj}^{\mathbf{UI}}\lambda_j, \mathbf{X}_i^{\mathbf{DI}} \leq \sum_{j=1}^{n} \mathbf{X}_{ij}^{\mathbf{DI}}\lambda_j \right.$$
$$\left. \mathbf{Y}_v^{\mathbf{UO}} \leq \sum_{j=1}^{n} \mathbf{Y}_{vj}^{\mathbf{UO}}\lambda_j, \mathbf{Y}_r^{\mathbf{DO}} \geq \sum_{j=1}^{n} \mathbf{Y}_{rj}^{\mathbf{DO}}\lambda_j, \sum_{j=1}^{n} \lambda_j = \mathbf{1}, \lambda_j \geq \mathbf{0}; \forall\mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{v}\right\} \tag{4}$$

The fractional programming model to calculate the anti-efficiency for each DMU can be achieved from:

$$\text{Maximize } \Gamma_{\text{pessimistic}} = \frac{1 + \left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} s_i^{XD+}/X_{io}^{DI} + \sum_{v=1}^{t} s_v^{YU+}/Y_{vo}^{UO}\right)}{1 - \left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} s_r^{YD-}/Y_{ro}^{DO} + \sum_{k=1}^{p} s_k^{XU-}/X_{ko}^{UI}\right)} \tag{5}$$

Subject to

$$\sum_{J=1}^{n} \mathbf{X}_{kj}^{\mathbf{UI}}\lambda_j + \mathbf{s_k XU} = \mathbf{X}_{ko}\mathbf{UI}$$

$$\sum_{J=1}^{n} \mathbf{X}_{ij}^{\mathbf{DI}}\lambda_j - \mathbf{s_i XD+} = \mathbf{X}_{io}\mathbf{DI}$$

$$\sum_{J=1}^{n} \mathbf{Y}_{rj}^{\mathbf{DO}}\lambda_j + \mathbf{s_r YD-} = \mathbf{Y}_{ro}\mathbf{DO}$$

$$\sum_{J=1}^{n} \mathbf{Y}_{vj}^{\mathbf{UO}}\lambda_j - \mathbf{s_v YD+} = \mathbf{Y}_{vo}\mathbf{UO}$$

$$\sum_{J=1}^{n} \lambda_j = 1\mathbf{forVariableReturnstoScale}(\mathbf{VRS})$$

$$\Lambda_j, \mathbf{s_k XU-}, \mathbf{s_i XD+}, \mathbf{s_r YD}; \mathbf{s_v YU+} \geq \mathbf{0}; \forall\mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{v}$$

The proposed PSBM model (6) maximizes the mean rate of input expansion as well as the inverted mean rate of output reduction through $(1/|m| + |t|)\ [\sum_{i=1}^{m}(X_{io}^{DI} + s_i^{XD+})/X_{io}^{DI} + \sum_{v=1}^{t}(Y_{vo}^{UO} + s_v^{YU+})/Y_{vo}^{UO}]$ and, $[(1/|s| + |p|)\ \{\sum_{r=1}^{s}(Y_{ro}^{DO} - - s_r^{YD-})/Y_{ro}^{DO} + \sum_{k=1}^{p}(X_{ko}^{UI} - - s_k^{XU-})/X_{ko}^{UI}\}]^{-1}$ respectively. The fractional programming PSBM model (5) can be converted into a LP model by multiplying both the numerator and denominator using a positive scalar variable $f > 0$, similar to the OSBM to form:

$$\text{Maximize}\,\boldsymbol{\eta}_{\text{pessimistic}} = f + \left[\left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} \mathbf{S}_I^{\mathbf{XD}+}/X_{io}^{DI} + \sum_{v=1}^{t} \mathbf{S}_v^{\mathbf{YU}+}/Y_{vo}^{UO}\right)\right] \tag{6}$$

Subject to

$$1 = f - \left[\left(\frac{1}{|\mathbf{s}| + |\mathbf{p}|}\right)\left(\sum_{r=1}^{s} \mathbf{S}_r^{\mathbf{YD}-}/\mathbf{Y}_{ro}^{\mathbf{DO}} + \sum_{k=1}^{p} \mathbf{S}_k^{\mathbf{XU}} - /\mathbf{X}_{ko}^{\mathbf{UI}}\right)\right]$$

$$\sum_{J=1}^{n} \mathbf{X}_{kj}^{\mathbf{UI}}\Lambda_j + \mathbf{S}_k^{\mathbf{XU}-} = f\mathbf{X}_{ko}\mathbf{UI}$$

$$\sum_{J=1}^{n} \mathbf{X}_{ij}^{\mathbf{DI}}\Lambda_j - \mathbf{S}_I^{\mathbf{XD}} + = f\mathbf{X}_{i0}\mathbf{DI}$$

$$\sum_{J=1}^{n} \mathbf{Y}_r^{\mathbf{DO}}\Lambda_j + \mathbf{S}_r^{\mathbf{YD}} - f\mathbf{Y}_{ro}\mathbf{DO}$$

$$\sum_{J=1}^{n} \mathbf{Y}_{vj}^{\mathbf{UO}}\Lambda_j - \mathbf{S}_v^{\mathbf{YU}} + = f\mathbf{Y}_{vo}\mathbf{UO}$$

$$\sum_{J=1}^{n} \Lambda\mathbf{j} = 1\mathbf{forVariableReturnstoScale}(\mathbf{VRS})$$

$$\Lambda_j, \mathbf{S}_k^{\mathbf{XU}-}, \mathbf{S}_I^{\mathbf{XD}+}, \mathbf{S}_r^{\mathbf{YD}-}, \mathbf{S}_v^{\mathbf{YU}+} \geq 0; \forall\mathbf{j}, \mathbf{k}, \mathbf{i}, \mathbf{r}, \mathbf{vand}\theta > \mathbf{0}$$

where $\Lambda_j = f\lambda_j$, $\mathbf{S}_I^{\mathbf{XD}\,+} = f s_I^{XD\,+}$, $\mathbf{S}_v^{\mathbf{YU}\,+} = f s_v^{YU\,+}$, $\mathbf{S}_r^{\mathbf{YD}\,-} = f s_r^{YD\,-}$, $\mathbf{S}_k^{\mathbf{XU}\,-} = f s_k^{XU\,-}$. All the optimality conditions for the PSBM approach is equivalent to that of the optimistic SBM model. The DMU is termed to be anti-efficient when, $\eta^*_{pessimistic} = \Gamma^*_{pessimistic} = 1$. This highlights the fact that the corresponding DMU lies on the anti-efficient frontier. Such a condition should have all the slack variables $s_I^{XD\,+}$, $s_v^{YU\,+}$, $s_r^{YD\,--}$ and $s_k^{XU\,-} = 0$. To measure the relative sustainable development capacity of $\boldsymbol{n}$ European smart cities over time *t*, *t*+*1*,…*t*+*n*, refer the optimistic and pessimistic SBM in time (Eq. S1 Supporting information SI-file).

3.2. Bounded model for aggregate sustainability performance

The aggregate sustainability performance of each smart city will be studied using Azizi, (2011)'s bounded-DEA model, which is modified further to include undesirable factors both in the inputs and outputs. Both the pessimistic and optimistic efficiency scores are represented within an interval, after considerable modifications to the pessimistic efficiency scores. The modified pessimistic efficiency is $\tilde{\varphi_j}^* = \alpha \times \eta_{pessimistic}^*$. φ_{vj}^* is the pessimistic efficiency of the virtual (*v*) DMU 'j', where φ_{vj}^* is obtained using the LP model applying Charnes and Cooper, (1962)'s transformation. The model reads as follows;

$$\text{Min}\,\varphi\text{vj}* = 1 + \left(\sum_{i=1}^{m} X_{io}^{min}\lambda_i + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right) - \left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right) \tag{7}$$

Subject to

$$\left(\sum_{i=1}^{m} X_{ij}^{DI}\lambda_{ij} + \sum_{v=1}^{t} Y_{vj}^{UO}\lambda_{vj}\right) - \left(\sum_{r=1}^{s} Y_{rj}^{DO}\lambda_{rj} + \sum_{k=1}^{p} X_{kj}^{UI}\lambda_{kj}\right) \geq 0;$$

$$\left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right) \leq \left(\frac{1}{|m| + |t|}\right)$$

Table A1
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the climate change dimension

Smart cities	SBM Optimistic				SBM Pessimistic				DF-SBM Bounded η	
			η distribution				η distribution			
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_1\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	1.0000	1	0.000	1.000	0.6697	20	0.6697	0.3303	[0.1582, 1.0000]	7
Sofia	0.7923	27	0.208	0.792	0.3808	10	0.3808	0.6192	[0.0899, 0.7923]	32
Prague	0.7991	26	0.201	0.799	0.5331	15	0.5331	0.4669	[0.1259, 0.7991]	28
Copenhagen	1.0000	1	0.000	1.000	0.2876	5	0.2876	0.7124	[0.0679, 1.0000]	18
Munich	0.9570	20	0.043	0.957	0.4264	13	0.4264	0.5736	[0.1007, 0.9570]	20
Tallinn	1.0000	1	0.000	1.000	0.7377	24	0.7377	0.2623	[0.1742, 1.0000]	5
Dublin	1.0000	1	0.000	1.000	0.5036	14	0.5036	0.4964	[0.1189, 1.0000]	11
Athens	1.0000	1	0.000	1.000	0.3219	7	0.3219	0.6781	[0.0760, 1.0000]	16
Bilbao	0.7660	30	0.234	0.766	1.0000	35	1.0000	0.0000	[0.2362, 0.7660]	25
Lyon	1.0000	1	0.000	1.000	0.9112	27	0.9112	0.0888	[0.2152, 1.0000]	2
Dusseldorf	1.0000	1	0.000	1.000	0.6680	19	0.6680	0.3320	[0.1578, 1.0000]	8
Bologna	0.9493	21	0.051	0.949	1.0000	35	1.0000	0.0000	[0.2362, 0.9493]	4
Hamburg	1.0000	1	0.000	1.000	0.6778	21	0.6778	0.3222	[0.1601, 1.0000]	6
St. Petersburg	0.8390	25	0.161	0.839	0.7132	22	0.7132	0.2868	[0.1685, 0.8390]	24
Marseille	1.0000	1	0.000	1.000	0.4211	12	0.4211	0.5789	[0.0995, 1.0000]	12
Geneva	1.0000	1	0.000	1.000	0.9359	28	0.9359	0.0641	[0.2211, 1.0000]	1
Budapest	0.7782	29	0.222	0.778	0.5740	17	0.5740	0.4260	[0.1356, 0.7782]	29
Manchester	1.0000	1	0.000	1.000	0.3811	11	0.3811	0.6189	[0.0900, 1.0000]	13
Amsterdam	1.0000	1	0.000	1.000	0.5955	18	0.5955	0.4045	[0.1407, 1.0000]	9
Vienna	1.0000	1	0.000	1.000	0.8443	26	0.8443	0.1557	[0.1994, 1.0000]	3
Warsaw	0.8492	24	0.151	0.849	1.0000	35	1.0000	0.0000	[0.2362, 0.8492]	14
Lisbon	1.0000	1	0.000	1.000	0.2627	3	0.2627	0.7373	[0.0620, 1.0000]	19
Bucharest	0.9645	19	0.036	0.965	0.7298	23	0.7298	0.2702	[0.1724, 0.9645]	10
Krakow	0.7900	28	0.210	0.790	0.8100	25	0.8100	0.1900	[0.1913, 0.7900]	26
Bratislava	0.7156	31	0.284	0.716	1.0000	35	1.0000	0.0000	[0.2362, 0.7156]	27
Helsinki	1.0000	1	0.000	1.000	0.3036	6	0.3036	0.6964	[0.0717, 1.0000]	17
Stockholm	1.0000	1	0.000	1.000	0.3526	9	0.3526	0.6474	[0.0833, 1.0000]	15
London	0.8500	23	0.150	0.850	0.2661	4	0.2661	0.7339	[0.0629, 0.8500]	30
Zaragoza	0.6094	34	0.391	0.609	1.0000	35	1.0000	0.0000	[0.2362, 0.6094]	33
Oslo	1.0000	1	0.000	1.000	0.1938	2	0.1938	0.8062	[0.0458, 1.0000]	21
Zurich	1.0000	1	0.000	1.000	0.1044	1	0.1044	0.8956	[0.0247, 1.0000]	22
Moscow	0.6836	32	0.316	0.684	0.3482	8	0.3482	0.6518	[0.0822, 0.6836]	34
Kiev	0.5022	35	0.498	0.502	1.0000	35	1.0000	0.0000	[0.2362, 0.5022]	35
Rome	0.8913	22	0.109	0.891	0.5565	16	0.5565	0.4435	[0.1314, 0.8913]	23
Ankara	0.6617	33	0.338	0.662	1.0000	35	1.0000	0.0000	[0.2362, 0.6617]	31

$\varphi_{vj}{}^*$: 2.1262, $\theta_j{}^*$: 0.5022, α_1: 0.2362

$$\left(\sum_{i=1}^{m} X_{io}^{min}\lambda_i + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right) \leq \left(\frac{1}{|s| + |p|}\right)\left[1 + \left(\sum_{i=1}^{m} X_{io}^{min}\lambda_i + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right) - \left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right)\right]$$

For $\lambda_i, \lambda_v, \lambda_r, \lambda_k \geq \varepsilon; \forall$ k, i, r, v
Where

$$X_i^{min} = \min_j\{X_{ij}^{DI}\},\ \text{For } i = 1,2,3,\ldots\ldots.m;$$

$$X_k^{max} = \max_j\{X_{kj}^{UI}\},\ \text{For } k = 1,2,3,\ldots\ldots.p;$$

$$Y_r^{max} = \max_j\left\{Y_{rj}^{DO}\right\},\ \text{For } r = 1,2,3,\ldots\ldots.s;$$

$$Y_v^{min} = \min_j\{Y_{vj}^{UO}\},\ \text{For } v = 1,2,3,\ldots\ldots.t;$$

The value of α is determined as $\alpha = \theta\min*/\varphi vj*$, where the aggregate sustainability performance score is represented within an interval of [α, 1]. It is to note that the estimate value "α" must satisfy the criterion $\alpha\eta_{pessimistic}{}^* \leq \theta\min* \ \forall\ [\alpha\eta_{pessimistic}{}^*, \theta j*]$ (j= 1,2,3…$\boldsymbol{n}$).

We have, $\theta\min* = \min\{\eta_{optimistic}\}\forall$ j= 1,2,3...$\boldsymbol{n}$ and $\varphi_{vj}{}^* \geq \max\{\eta_{pessimistic}\}\forall$ j= 1,2,3...$\boldsymbol{n}$. The interval efficiency is represented as $[\alpha\eta_{pessimistic}{}^*, \theta j*] = [\widetilde{\varphi_j}{}^*, \theta j*] = [\eta_o{}^{L*}, \eta_o{}^{U*}]$ where L = lower bound efficiency and U = upper bound efficiency measured from the pessimistic and optimistic perspective respectively.

To rank each smart city based on the interval efficiency score, the midpoint $m(A_i)$ and range $w(A_i)$ of each interval efficiency score obtained using model (7) is calculated. Smart cities are then ranked in the ascending order based on the midpoint values. The smart city with the largest $m(A_i)$ value is ranked 1 followed by other smart cities in the descending order of their $m(A_i)$ values. The $m(A_i)$ and $w(A_i)$ are calculated as;

$$m(Ai) = \frac{1}{2}\ (\eta oL* + \eta oU*)\ \text{and}\ w(Ai) = \frac{1}{2}\ (\eta oU* - \eta oL*) \tag{8}$$

3.3. Malmquist Productivity Index

Smart cities are often driven by technology and their progressive efficiency can be assessed by understanding the technological changes as

Table A2
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the Governance and institution dimension

Smart cities	SBM Optimistic		η distribution		SBM Pessimistic		η distribution		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_2\eta_{pessimistic}{}^*, \theta_j^*]$	Rank
Brussels	1.0000	1	0.000	1.000	0.4079	11	0.4079	0.5921	[0.0591, 1.0000]	6
Sofia	0.4420	33	0.558	0.442	1.0000	35	1.0000	0.0000	[0.1449, 0.4420]	31
Prague	0.2090	35	0.791	0.209	1.0000	35	1.0000	0.0000	[0.1449, 0.2090]	35
Copenhagen	0.7130	19	0.287	0.713	0.6749	26	0.6749	0.3251	[0.0978, 0.7130]	18
Munich	0.4590	32	0.541	0.459	1.0000	35	1.0000	0.0000	[0.1449, 0.4590]	30
Tallinn	0.5490	29	0.451	0.549	1.0000	35	1.0000	0.0000	[0.1449, 0.5490]	25
Dublin	0.8840	15	0.116	0.884	0.4762	17	0.4762	0.5238	[0.0690, 0.8840]	15
Athens	0.9010	14	0.099	0.901	0.3837	10	0.3837	0.6163	[0.0556, 0.9010]	14
Bilbao	0.4980	31	0.502	0.498	0.2041	3	0.2041	0.7959	[0.0296, 0.4980]	34
Lyon	0.5780	26	0.422	0.578	0.4323	13	0.4323	0.5677	[0.0627, 0.5780]	28
Dusseldorf	1.0000	1	0.000	1.000	0.3043	8	0.3043	0.6957	[0.0441, 1.0000]	8
Bologna	0.7270	18	0.273	0.727	0.6715	25	0.6715	0.3285	[0.0973, 0.7270]	17
Hamburg	0.9550	13	0.045	0.955	0.3288	9	0.3288	0.6712	[0.0477, 0.9550]	13
St. Petersburg	1.0000	1	0.000	1.000	0.4123	12	0.4123	0.5877	[0.0598, 1.0000]	5
Marseille	0.5960	24	0.404	0.596	0.4956	18	0.4956	0.5044	[0.0718, 0.5960]	27
Geneva	0.6230	22	0.377	0.623	0.5718	21	0.5718	0.4282	[0.0829, 0.6230]	22
Budapest	0.6000	23	0.400	0.600	0.5784	22	0.5784	0.4216	[0.0838, 0.6000]	26
Manchester	1.0000	1	0.000	1.000	0.1583	1	0.1583	0.8417	[0.0229, 1.0000]	12
Amsterdam	0.8260	16	0.174	0.826	0.2669	6	0.2669	0.7331	[0.0387, 0.8260]	16
Vienna	0.5110	30	0.489	0.511	0.5065	19	0.5065	0.4935	[0.0734, 0.5110]	32
Warsaw	0.7420	17	0.258	0.742	0.2964	7	0.2964	0.7036	[0.0430, 0.7420]	19
Lisbon	0.5530	28	0.447	0.553	1.0000	35	1.0000	0.0000	[0.1449, 0.5530]	23
Bucharest	1.0000	1	0.000	1.000	0.2198	5	0.2198	0.7802	[0.0319, 1.0000]	9
Krakow	1.0000	1	0.000	1.000	0.1794	2	0.1794	0.8206	[0.0260, 1.0000]	11
Bratislava	0.9730	12	0.027	0.973	0.5466	20	0.5466	0.4534	[0.0792, 0.9730]	7
Helsinki	1.0000	1	0.000	1.000	0.5938	23	0.5938	0.4062	[0.0861, 1.0000]	4
Stockholm	1.0000	1	0.000	1.000	0.6345	24	0.6345	0.3655	[0.0920, 1.0000]	3
London	1.0000	1	0.000	1.000	0.7034	28	0.7034	0.2966	[0.1020, 1.0000]	2
Zaragoza	0.6620	21	0.338	0.662	0.4541	14	0.4541	0.5459	[0.0658, 0.6620]	21
Oslo	1.0000	1	0.000	1.000	0.7080	29	0.7080	0.2920	[0.1026, 1.0000]	1
Zurich	1.0000	1	0.000	1.000	0.2111	4	0.2111	0.7889	[0.0306, 1.0000]	10
Moscow	0.5540	27	0.446	0.554	0.4688	15	0.4688	0.5312	[0.0680, 0.5540]	29
Kiev	0.3910	34	0.609	0.391	1.0000	35	1.0000	0.0000	[0.1449, 0.3910]	33
Rome	0.6760	20	0.324	0.676	0.4711	16	0.4711	0.5289	[0.0683, 0.6760]	20
Ankara	0.5940	25	0.406	0.594	0.7008	27	0.7008	0.2992	[0.1016, 0.5940]	24

φ_{vj}*: 1.4419, θ_j*: 0.2090, α_2: 0.14495

a whole over the years. The MPI $_{optimistic}$ for each smart city represented by DMU_j for optimistic efficiencies can be calculated using the following formulation;

$$MPI_{optimistic} = \left[\frac{\alpha_0^t(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})}{\alpha_0^t(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)} \cdot \frac{\alpha_0^{t+1}(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})}{\alpha_0^{t+1}(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)}\right]^{1/2} \tag{9}$$

Where, $\alpha_0^t(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)$ is the OSBM in time t;and $\alpha_0^{t+1}(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})$ is the OSBM in time $t+1$. Similarly, $\alpha_0^t(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})$ calculates the optimistic efficiency in time $t+1$ utilizing the technology in time t; and $\alpha_0^{t+1}(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)$ evaluates the optimistic efficiency in time t, making use of the technology in time $t+1$. To better understand on the growth index for productivity change measurement, see Sueyoshi, (1998).

Model (9) measures the productivity change in efficiencies for smart cities from time t to $t+1$. A progress is marked in productivity when MPI $_{optimistic}$ > 1, while if MPI $_{optimistic}$ $= 1$, then there is no change in the level of productivity, and an MPI $_{optimistic}$ < 1 indicates a decrease in the productivity level from time t to $t+1$ (Färe et al., 1992).

Similarly, from a pessimistic point of view, the productivity change in efficiencies can be calculated taking the geometric mean of the pessimistic efficiencies, $\alpha_0^t(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1}) / \alpha_0^t(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)$ and $\alpha_0^{t+1}(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1}) / \alpha_0^{t+1}(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)$. The MPI $_{pessimistic}$ for each smart city in time t to $t+1$ can be calculated as follows:

$$MPI_{pessimistic} = \left[\frac{\alpha_0^t(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})}{\alpha_0^t(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)} \cdot \frac{\alpha_0^{t+1}(w_{io}^{t+1}, x_{ko}^{t+1}, y_{ro}^{t+1}, z_{vo}^{t+1})}{\alpha_0^{t+1}(w_{io}^t, x_{ko}^t, y_{ro}^t, z_{vo}^t)}\right]^{1/2} \tag{10}$$

Table A3
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the dimension economic dynamism

Smart cities	SBM Optimistic				SBM Pessimistic				DF-SBM Bounded η	
			η distribution				η distribution			
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_3\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	0.570	32	0.430	0.570	1.0000	35	1.0000	0.0000	[0.1846, 0.5700]	27
Sofia	1.000	1	0.000	1.000	0.1522	1	0.1522	0.8478	[0.0281, 1.0000]	12
Prague	0.544	33	0.456	0.544	0.4378	5	0.4378	0.5622	[0.0808, 0.5440]	34
Copenhagen	0.651	19	0.349	0.651	0.5817	11	0.5817	0.4183	[0.1074, 0.6510]	24
Munich	0.651	19	0.349	0.651	0.3661	3	0.3661	0.6339	[0.0676, 0.6510]	31
Tallinn	0.571	31	0.429	0.571	1.0000	35	1.0000	0.0000	[0.1846, 0.5710]	26
Dublin	0.961	9	0.039	0.961	0.8694	28	0.8694	0.1306	[0.1605, 0.9610]	3
Athens	1.000	1	0.000	1.000	0.6065	13	0.6065	0.3935	[0.1119, 1.0000]	4
Bilbao	0.606	25	0.394	0.606	0.4898	6	0.4898	0.5102	[0.0904, 0.6060]	32
Lyon	0.775	16	0.225	0.775	0.6996	20	0.6996	0.3004	[0.1291, 0.7750]	16
Dusseldorf	0.903	13	0.097	0.903	0.3882	4	0.3882	0.6118	[0.0716, 0.9030]	13
Bologna	0.591	29	0.409	0.591	1.0000	35	1.0000	0.0000	[0.1846, 0.5910]	22
Hamburg	0.850	14	0.150	0.850	0.5139	8	0.5139	0.4861	[0.0948, 0.8500]	14
St. Petersburg	0.932	10	0.068	0.932	0.6860	18	0.6860	0.3140	[0.1266, 0.9320]	9
Merseille	0.838	15	0.162	0.838	0.4918	7	0.4918	0.5082	[0.0908, 0.8380]	15
Geneva	1.000	1	0.000	1.000	0.2062	2	0.2062	0.7938	[0.0381, 1.0000]	10
Budapest	0.909	12	0.091	0.909	0.6524	16	0.6524	0.3476	[0.1204, 0.9090]	11
Manchester	1.000	1	0.000	1.000	0.5341	10	0.5341	0.4659	[0.0986, 1.0000]	6
Amsterdam	0.596	28	0.404	0.596	0.9787	29	0.9787	0.0213	[0.1806, 0.5960]	21
Vienna	0.530	34	0.470	0.530	0.6708	17	0.6708	0.3292	[0.1238, 0.5300]	33
Warsaw	0.639	22	0.361	0.639	0.5909	12	0.5909	0.4091	[0.1091, 0.6390]	28
Lisbon	0.703	17	0.297	0.703	0.6393	15	0.6393	0.3607	[0.1180, 0.7030]	17
Bucharest	0.625	23	0.375	0.625	0.5229	9	0.5229	0.4771	[0.0965, 0.6250]	30
Krakow	0.929	11	0.071	0.929	0.8467	27	0.8467	0.1533	[0.1563, 0.9290]	8
Bratislava	0.672	18	0.328	0.672	0.7014	21	0.7014	0.2986	[0.1295, 0.6720]	20
Helsinki	0.598	27	0.402	0.598	0.7561	23	0.7561	0.2439	[0.1396, 0.5980]	29
Stockholm	0.579	30	0.421	0.579	0.9886	30	0.9886	0.0114	[0.1825, 0.5790]	23
London	0.605	26	0.395	0.605	0.8284	25	0.8284	0.1716	[0.1529, 0.6050]	25
Zaragoza	0.651	19	0.349	0.651	0.8433	26	0.8433	0.1567	[0.1556, 0.6510]	19
Oslo	0.991	6	0.009	0.991	0.8081	24	0.8081	0.1919	[0.1491, 0.9910]	1
Zurich	1.000	1	0.000	1.000	0.7455	22	0.7455	0.2545	[0.1376, 1.0000]	2
Moscow	0.984	7	0.016	0.984	0.6118	14	0.6118	0.3882	[0.1129, 0.9840]	7
Kiev	0.238	35	0.762	0.238	1.0000	35	1.0000	0.0000	[0.1846, 0.2380]	35
Rome	0.980	8	0.020	0.980	0.6949	19	0.6949	0.3051	[0.1283, 0.9800]	5
Ankara	0.625	23	0.375	0.625	1.0000	35	1.0000	0.0000	[0.1846, 0.6250]	18

φ_{vj}*: 1.2895, θ_j*: 0.2380, α_3: 0.18457

Where, $\alpha_0{}^t$ ($w^t{}_{io}$, $x^t{}_{ko}$, $y^t{}_{ro}$, $z^t{}_{vo}$) is the PSBM in time t;and $\alpha_0{}^{t+1}$ ($w^{t+1}{}_{io}$, $x^{t+1}{}_{ko}$, $y^{t+1}{}_{ro}$, $z^{t+1}{}_{vo}$) is the PSBM in time $t+1$. Similarly, here $\alpha 0t$ $(w\ t+1io,\ x\ t+1ko,\ y\ t+1ro,\ z\ t+1\ vo)$ calculates the pessimistic efficiency in time $t+1$ utilizing the technology in time t; and $\alpha 0t$ $+1(w\ tio,\ x\ tko,\ y\ tro,\ z\ t\ vo)$ evaluates the pessimistic efficiency in time t, making use of the technology in time $t+1$.

Similar to the MPI $_{\textbf{optimistic}}$ based on to Färe et al., (1992) assumptions, an increase in the productivity level is noticed when MPI $_{\textbf{pessimistic}} > 1$. A regression over time t to t+1 is when MPI $_{\textbf{pessimistic}} < 1$. There is no noticeable change in the productivity over time when MPI $_{\textbf{pessimistic}} = 1$.

To achieve consistency in the evaluation of the Malmquist productivity index and arrive at concrete conclusions, it is essential to integrate the proposed point of views to accurately understand the productivity changes for each smart city under selected dimensions over time. Thus, combining the geometric means of Eq. (9) and (10), we obtain the Double Frontier Malmquist productivity index (DF-MPI) for the j^{th} smart city, which is as follows;

$$DF-MPIj = \left[MPI_{\ \textbf{optimistic}}\ .\ MPI_{\ \textbf{pessimistic}}\right]^{1/2} \tag{11}$$

4. Empirical analysis: The case of European smart cities

Despite the pervasive use of technology, the steep growth in urban population and the subsequent increase in resource consumption has inevitably created numerous challenges for smart cities. This fact highlights the importance of shifting paradigms in the way cities work in terms of sustainability. For the purpose of the present study, it is important to establish a working definition of sustainability in the context of smart cities. Allen and Hoekstra (1993) highlights the importance of establishing the scale on which a system is being assessed in terms of its progress towards sustainability. Achieving sustainability on a global scale requires different type of actions than on a city level. There is no single best-established definition in terms of sustainability in the regional scale nevertheless there is a commonly-used set of characteristics of urban sustainability (Kutty and Abdella, 2020; Abdella et al., 2021). These include intergenerational equity, intra-generational equity (social, geographical, and governance and institutional equity), conservation of the natural and built environment, significant reduction of the use of non-renewable energy and resources, climate change, economic vitality and diversity, autonomy in communities, citizen well-being, gratification of fundamental human needs and secure living (Maclaren, 1996). For the context of this research an urban space can be sustainable when adaption to climatic changes, social equity, conservation of the natural environment and energy resources, economic dynamism, Social cohesion and solidarity, and quality of life are achieved. Urban sustainability appears to be one of the prevailing themes in smart city literature, but to what extent is the concept embedded in the understanding of smart cities and how comprehensively is it addressed, is what this study investigates. Thus, to better understand on whether smart cities address sustainability and principles of sustainable urban development?, the proposed desirability inclusive DF-SBM DEA approach is used to study the performance of 35 leading European smart cities over time from 2015 till 2020. The smart cities were selected based on the ranks assigned to these cities by the Smart City Index 2020,

Table A4
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the energy and environmental resource dimension

Smart cities	SBM Optimistic				SBM Pessimistic				DF-SBM Bounded η	
			η distribution				η distribution			
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_4\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	0.5507	25	0.449	0.551	0.3731	8	0.3731	0.6269	[0.0724, 0.5507]	26
Sofia	0.4154	33	0.585	0.415	0.3411	7	0.3411	0.6589	[0.0662, 0.4154]	34
Prague	0.3995	34	0.601	0.399	1.0000	35	1.0000	0.0000	[0.1939, 0.3995]	29
Copenhagen	1.0000	1	0.000	1.000	0.8603	26	0.8603	0.1397	[0.1668, 1.0000]	7
Munich	1.0000	1	0.000	1.000	0.9104	29	0.9104	0.0896	[0.1766, 1.0000]	4
Tallinn	0.3844	35	0.616	0.384	1.0000	35	1.0000	0.0000	[0.1939, 0.3844]	32
Dublin	1.0000	1	0.000	1.000	0.9065	28	0.9065	0.0935	[0.1758, 1.0000]	5
Athens	0.4178	32	0.582	0.418	0.2209	5	0.2209	0.7791	[0.0428, 0.4178]	35
Bilbao	0.4829	30	0.517	0.483	0.3807	9	0.3807	0.6193	[0.0738, 0.4829]	33
Lyon	0.7190	17	0.281	0.719	0.6413	20	0.6413	0.3587	[0.1244, 0.7190]	17
Dusseldorf	0.7779	14	0.222	0.778	0.6568	21	0.6568	0.3432	[0.1274, 0.7779]	14
Bologna	1.0000	1	0.000	1.000	0.1995	4	0.1995	0.8005	[0.0387, 1.0000]	10
Hamburg	0.7587	15	0.241	0.759	0.6318	18	0.6318	0.3682	[0.1225, 0.7587]	16
St. Petersburg	1.0000	1	0.000	1.000	0.1988	3	0.1988	0.8012	[0.0386, 1.0000]	11
Merseille	0.6370	21	0.363	0.637	0.5493	17	0.5493	0.4507	[0.1065, 0.6370]	21
Geneva	1.0000	1	0.000	1.000	0.9788	32	0.9788	0.0212	[0.1898, 1.0000]	1
Budapest	0.6118	23	0.388	0.612	0.4477	13	0.4477	0.5523	[0.0868, 0.6118]	24
Manchester	1.0000	1	0.000	1.000	0.1294	2	0.1294	0.8706	[0.0251, 1.0000]	12
Amsterdam	0.6494	20	0.351	0.649	0.7427	24	0.7427	0.2573	[0.1440, 0.6494]	18
Vienna	1.0000	1	0.000	1.000	0.9646	31	0.9646	0.0354	[0.1871, 1.0000]	2
Warsaw	0.5088	29	0.491	0.509	0.3931	10	0.3931	0.6069	[0.0762, 0.5088]	31
Lisbon	0.4686	31	0.531	0.469	1.0000	35	1.0000	0.0000	[0.1939, 0.4686]	25
Bucharest	0.5220	28	0.478	0.522	0.4755	15	0.4755	0.5245	[0.0922, 0.5220]	28
Krakow	0.5305	27	0.470	0.531	0.4516	14	0.4516	0.5484	[0.0876, 0.5305]	27
Bratislava	0.6674	18	0.333	0.667	0.4130	11	0.4130	0.5870	[0.0801, 0.6674]	20
Helsinki	1.0000	1	0.000	1.000	0.9206	30	0.9206	0.0794	[0.1785, 1.0000]	3
Stockholm	0.6589	19	0.341	0.659	0.6373	19	0.6373	0.3627	[0.1236, 0.6589]	19
London	1.0000	1	0.000	1.000	0.8005	25	0.8005	0.1995	[0.1552, 1.0000]	8
Zaragoza	1.0000	1	0.000	1.000	0.6969	22	0.6969	0.3031	[0.1352, 1.0000]	9
Oslo	1.0000	1	0.000	1.000	0.9033	27	0.9033	0.0967	[0.1752, 1.0000]	6
Zurich	0.7507	16	0.249	0.751	0.7265	23	0.7265	0.2735	[0.1409, 0.7507]	15
Moscow	1.0000	1	0.000	1.000	0.1099	1	0.1099	0.8901	[0.0213, 1.0000]	13
Kiev	0.6326	22	0.367	0.633	0.4328	12	0.4328	0.5672	[0.0839, 0.6326]	22
Rome	0.6033	24	0.397	0.603	0.5368	16	0.5368	0.4632	[0.1041, 0.6033]	23
Ankara	0.5427	26	0.457	0.543	0.2605	6	0.2605	0.7395	[0.0505, 0.5427]	30

$\varphi_{vj}{}^*$: 1.9821, $\theta_j{}^*$: 0.3844, α_4: 0.19394

categorizing them as the top ranked smart cities in Europe. The rationale behind selecting top ranked smart cities is to capture better the idea of whether these tech-driven cities that promise sustainability and smartness are truly sustainable or not. In addition, the European smart cities cover nearly 3/4th of the list of major smart cities in the world with 28 European cities included in the top 50 global smart cities. It is well evident that the sample size is large enough for the results to be extrapolated to a global level in terms of the sustainability performance of smart cities. A comprehensive assessment is carried out using 50 sustainability input-output indicators under 6 dimensions of sustainable urban development, based on the proposed working definition of sustainability, namely; Energy and Environmental Resources (ER), Governance and Institution (GI), Economic dynamism (E), Social cohesion and solidarity (SC), Climate Change (CC) and, Safety and Security (SS). For this purpose, this paper uses the longitudinal time-series data extracted from the European data portal (https://data.europa.eu/en) and EU city data statistics from 2015-2020. The indicators under each dimension is aligned to the 17 SDGs. The indicators were then categorized according to their desirability to be increased or decreased simultaneously based on managerial and computational reasoning. To understand better on preparing data for DEA assessment see Sarkis, (2007). Some selected set of input indicators were maximized (undesirable) along with simultaneously decreasing the desirable inputs and, some output indicators were minimized (undesirable) with maximum value outputs included. The input-output indicators used for the sustainability performance assessment under all the 6 dimensions of sustainable urban development can be seen in Table S1 (Supplementary Information-SI file). The selection of input and output indicators based on the number of smart cities chosen for the study satisfied Eq (9).

$$n \geq \max\{(m+p)*(s+t),\ 3[(m+p)+(s+t)]\} \tag{12}$$

Where $\boldsymbol{n}$ is the number of smart cities, $\boldsymbol{m}$ is the number of desirable inputs, $\boldsymbol{p}$ is the number of undesirable inputs, $\boldsymbol{s}$ is the number of desirable outputs and $\boldsymbol{t}$ is the number of undesirable outputs.

4.1. Sustainable development capacity assessment

This section evaluates and presents the sustainability performance of the 35 smart cities from the optimistic, pessimistic and aggregate double frontier perspectives. According to the results in Table A1 (Appendix A), under the climate change dimension, it is evident that the smart cities, namely Brussels, Copenhagen, Tallinn, Dublin, Athens, Lyon, Dusseldorf, Hamburg, Merseille, Geneva, Manchester, Amsterdam, Vienna, Lisbon, Helsinki, Stockholm, Oslo and Zurich are optimistic-efficient ($\eta_{optimistic} = 1.00$) based on model (3). These smart cities all-together make the efficiency frontier. All the other smart cities considered in the study are optimistic non-efficient ($\eta_{optimistic} < 1.000$) under the climate change dimension. It is found that Kiev, with an efficiency score, $\eta_{optimistic} = 0.5022$ is the most optimistic non-efficient smart city for all the inputs and outputs considered for the study under the climate change dimension. Taking into account the pessimistic viewpoint, it is identified that Bilbao, Bologna, Warsaw, Bratislava, Zaragoza, Kiev and Ankara are pessimistic inefficient with $\eta_{pessimistic} = 1.000$. The other smart cities ($\eta_{pessimistic} < 1.000$) are less worse performing under the climate change dimension than the DEA-inefficient smart cities. Similarly, Zurich with $\eta_{pessimistic} = 0.1044$ is the least worst performing

Table A5
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the safety and security dimension

Smart cities	SBM Optimistic		η distribution		SBM Pessimistic		η distribution		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_5\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	0.7277	29	0.272	0.728	0.4864	23	0.4864	0.5137	[0.1524, 0.7277]	6
Sofia	1.0000	14	0.000	1.000	0.1939	7	0.1939	0.8061	[0.0607, 1.0000]	17
Prague	1.0000	1	0.000	1.000	0.2308	13	0.2308	0.7692	[0.0723, 1.0000]	22
Copenhagen	0.7371	28	0.263	0.737	0.2266	10	0.2266	0.7734	[0.0710, 0.7371]	4
Munich	0.6227	34	0.377	0.623	0.1208	4	0.1208	0.8792	[0.0378, 0.6227]	1
Tallinn	1.0000	1	0.000	1.000	0.2219	9	0.2219	0.7781	[0.0695, 1.0000]	19
Dublin	0.7979	25	0.202	0.798	0.4897	24	0.4897	0.5103	[0.1534, 0.7979]	8
Athens	0.8854	22	0.115	0.885	0.7058	27	0.7058	0.2943	[0.2211, 0.8854]	28
Bilbao	0.6808	31	0.319	0.681	1.0000	35	1.0000	0.0000	[0.3133, 0.6808]	11
Lyon	0.9999	16	0.000	1.000	0.2996	17	0.2996	0.7004	[0.0939, 0.9999]	24
Dusseldorf	1.0000	1	0.000	1.000	0.1849	6	0.1849	0.8151	[0.0579, 1.0000]	16
Bologna	0.7837	26	0.216	0.784	1.0000	35	1.0000	0.0000	[0.3133, 0.7837]	26
Hamburg	1.0000	1	0.000	1.000	0.1066	2	0.1066	0.8934	[0.0334, 1.0000]	13
St. Petersburg	1.0000	1	0.000	1.000	0.2508	14	0.2508	0.7492	[0.0786, 1.0000]	23
Merseille	1.0000	1	0.000	1.000	0.2303	12	0.2303	0.7697	[0.0722, 1.0000]	21
Geneva	0.8937	21	0.106	0.894	0.7155	28	0.7155	0.2845	[0.2242, 0.8937]	29
Budapest	0.9793	17	0.021	0.979	0.7278	29	0.7278	0.2722	[0.2280, 0.9793]	34
Manchester	1.0000	15	0.000	1.000	0.2996	17	0.2996	0.7004	[0.0939, 1.0000]	25
Amsterdam	0.6874	30	0.313	0.687	0.0983	1	0.0983	0.9017	[0.0308, 0.6874]	2
Vienna	0.7480	27	0.252	0.748	0.2512	15	0.2512	0.7488	[0.0787, 0.7480]	5
Warsaw	1.0000	1	0.000	1.000	0.1114	3	0.1114	0.8886	[0.0349, 1.0000]	14
Lisbon	0.7979	24	0.202	0.798	0.5291	25	0.5291	0.4710	[0.1658, 0.7979]	10
Bucharest	1.0000	1	0.000	1.000	0.3206	19	0.3206	0.6794	[0.1004, 1.0000]	27
Krakow	0.8694	23	0.131	0.869	0.4493	22	0.4493	0.5507	[0.1408, 0.8694]	12
Bratislava	1.0000	1	0.000	1.000	0.3939	20	0.3939	0.6061	[0.1234, 1.0000]	30
Helsinki	1.0000	1	0.000	1.000	0.1366	5	0.1366	0.8634	[0.0428, 1.0000]	15
Stockholm	0.6728	32	0.327	0.673	0.2783	16	0.2783	0.7217	[0.0872, 0.6728]	3
London	0.5876	35	0.412	0.588	1.0000	35	1.0000	0.0000	[0.3133, 0.5876]	7
Zaragoza	1.0000	1	0.000	1.000	0.2302	11	0.2302	0.7698	[0.0721, 1.0000]	20
Oslo	0.9197	20	0.080	0.920	0.6623	26	0.6623	0.3377	[0.2075, 0.9197]	31
Zurich	0.6469	33	0.353	0.647	1.0000	35	1.0000	0.0000	[0.3133, 0.6469]	9
Moscow	1.0000	1	0.000	1.000	0.2016	8	0.2016	0.7984	[0.0632, 1.0000]	18
Kiev	0.9785	18	0.022	0.978	0.7439	30	0.7439	0.2561	[0.2331, 0.9785]	35
Rome	0.9591	19	0.041	0.959	0.7628	31	0.7628	0.2372	[0.2390, 0.9591]	33
Ankara	1.0000	1	0.000	1.000	0.4403	21	0.4403	0.5597	[0.1379, 1.0000]	32

φ_{vj}*: 1.8755, θ_j*: 0.5876, α_5: 0.3133

(pessimistic non-inefficient) smart city in Europe in terms of climate change and mitigation strategies. Contrastingly, under the integrated DF DEA-model, when observing the interval efficiencies, it is seen that Geneva is the most sustainably performing smart city under the climate change dimension. Without no surprise, Lyon, Vienna and Bologna backs the 1st, 2nd and 3rd runner up positions in addressing climate change concerns under the bounded model. It is evident from the interval efficiency scores [0.2362, 0.5022] and an m(A_i) value of 0.3692 that, Kiev is the least relatively sustainable smart city under the climate change dimension over time from 2015 till 2020. However, while measuring the best relative-efficiency for all the 35 European smart cities under the "Governance and institution" dimension (Table A2 in Appendix A), it is found that Brussels, Dusseldorf, Manchester, Helsinki, Stockholm, Oslo and Zurich have retained their position of being on the top list as in the climate change dimension ($\eta_{pessimistic} = 1.000$). The smart cities namely, St. Petersburg, Bucharest, Krakow and London were new add-ons to the list of the best relatively efficient smart cities under the "Governance and Institution" dimension. Nevertheless, Prague with an efficiency score of $\eta_{optimistic} = 0.2090$ was the most optimistic non-efficient smart city under this dimension. When analysing from the pessimistic view point under the Governance and Institution dimension, it can be noticed that 6 smart cities, i.e, Sofia, Prague, Munich, Tallinn, Lisbon and Kiev are pessimistic inefficient with worse performance ($\eta_{pessimistic} = 1.000$). It is seen that Manchester with $\eta_{pessimistic} = 0.1583$ is the least DEA-non-inefficient smart city when compared to all the other worst performing smart cities. Oslo with an interval efficiency of [0.1026, 1.0000] followed by London (η bounded = [0.1020, 1.0000]; Rank 2) and Stockholm (η bounded = [0.0920, 1.0000]; Rank 3) are the best performing smart cities in Europe under the dimension "governance and institution" from the bounded DEA perspective.

Similarly, when comparing the efficiency scores from the optimistic and pessimistic perspective, it can be found that under the dimension "economic dynamism", smart cities namely, Sofia, Athens, Geneva, Manchester and Zurich are optimistic efficient (see Table A3 in Appendix A). While Brussels, Tallinn, Bologna, Kiev and Ankara are pessimistic inefficient smart cities with $\eta_{pessimistic} = 1.000$. Kiev with an efficiency score, $\eta_{optimistic} = 0.2380$ is the most optimistic non-efficient smart city when compared with its peers. On the contrary, Sofia with $\eta_{pessimistic} = 0.1522$ has the least relative pessimistic performance under "economic dynamism". Under the bounded model for aggregate sustainability performance measurement, Oslo ranks 1st with an η bounded interval value [0.1491, 0.9910]. While Kiev ranks as the least sustainable smart city under the economic dynamism dimension with a bounded interval score [0.1846, 0.2380]. When considering smart cities under the dimension "energy and environmental resource" for the optimistic scenario, we can see that Copenhagen, Munich, Dublin, Bologna, St. Petersburg, Geneva, Manchester, Vienna, Helsinki, London, Zaragoza, Oslo and Moscow perform relatively efficient with a score $\eta_{optimistic} = 1.00$. While Tallinn ($\eta_{optimistic} = 0.238$) is the most optimistic non-efficient smart city under the respective dimension. On the other hand, Moscow with $\eta_{pessimistic} = 0.1099$ lies farthest away from the anti-efficiency frontier. Smart cities like Prague, Tallinn and Lisbon lies on the anti-efficient frontier, thus branded as the "anti-ideal" smart city with relatively worst efficiency performance (Table A4 in Appendix A). While, considering the bounded sustainability performance under the double frontier approach; Geneva, Vienna and Helsinki ranks 1st, 2nd

Table A6
Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities for the years from 2015 till 2020 under the social cohesion and solidarity dimension

Smart cities	SBM Optimistic				SBM Pessimistic				DF-SBM Bounded η	
			η distribution				η distribution			
	$\eta_{optimistic}$	Rank	d_1	d_2	$\eta_{pessimistic}$	Rank	d_1	d_2	$[\alpha_6\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	1.0000	1	0.000	1.000	0.2203	8	0.2203	0.7797	[0.0168, 1.0000]	13
Sofia	0.5695	33	0.430	0.570	1.0000	35	1.0000	0.0000	[0.0761, 0.5695]	33
Prague	1.0000	1	0.000	1.000	0.3087	12	0.3087	0.6913	[0.0235, 1.0000]	9
Copenhagen	0.7958	26	0.204	0.796	0.6258	18	0.6258	0.3742	[0.0477, 0.7958]	26
Munich	1.0000	1	0.000	1.000	0.8183	27	0.8183	0.1817	[0.0623, 1.0000]	3
Tallinn	0.8119	23	0.188	0.812	0.6704	21	0.6704	0.3296	[0.0510, 0.8119]	23
Dublin	1.0000	1	0.000	1.000	0.2022	7	0.2022	0.7978	[0.0154, 1.0000]	14
Athens	0.8742	21	0.126	0.874	0.7332	26	0.7332	0.2668	[0.0558, 0.8742]	21
Bilbao	1.0000	1	0.000	1.000	0.2394	9	0.2394	0.7606	[0.0182, 1.0000]	12
Lyon	0.8054	25	0.195	0.805	0.6304	19	0.6304	0.3696	[0.0480, 0.8054]	25
Dusseldorf	1.0000	1	0.000	1.000	0.1098	3	0.1098	0.8902	[0.0084, 1.0000]	18
Bologna	1.0000	1	0.000	1.000	0.1997	6	0.1997	0.8003	[0.0152, 1.0000]	15
Hamburg	1.0000	1	0.000	1.000	0.1897	4	0.1897	0.8103	[0.0144, 1.0000]	17
St. Petersburg	1.0000	1	0.000	1.000	0.2988	11	0.2988	0.7012	[0.0228, 1.0000]	10
Merseille	1.0000	1	0.000	1.000	0.2969	10	0.2969	0.7031	[0.0226, 1.0000]	11
Geneva	1.0000	1	0.000	1.000	0.6211	17	0.6211	0.3789	[0.0473, 1.0000]	6
Budapest	0.7031	28	0.297	0.703	0.6878	23	0.6878	0.3122	[0.0524, 0.7031]	29
Manchester	1.0000	1	0.000	1.000	0.5199	15	0.5199	0.4801	[0.0396, 1.0000]	7
Amsterdam	1.0000	1	0.000	1.000	0.9801	29	0.9801	0.0199	[0.0746, 1.0000]	1
Vienna	0.8054	24	0.195	0.805	0.6651	20	0.6651	0.3349	[0.0506, 0.8054]	24
Warsaw	0.7901	27	0.210	0.790	0.6833	22	0.6833	0.3167	[0.0520, 0.7901]	27
Lisbon	1.0000	1	0.000	1.000	0.3443	13	0.3443	0.6557	[0.0262, 1.0000]	8
Bucharest	0.5883	32	0.412	0.588	1.0000	35	1.0000	0.0000	[0.0761, 0.5883]	32
Krakow	0.5602	34	0.440	0.560	1.0000	35	1.0000	0.0000	[0.0761, 0.5602]	34
Bratislava	0.6946	29	0.305	0.695	0.4195	14	0.4195	0.5805	[0.0319, 0.6946]	31
Helsinki	1.0000	1	0.000	1.000	0.7205	25	0.7205	0.2795	[0.0549, 1.0000]	4
Stockholm	0.8327	22	0.167	0.833	0.6130	16	0.6130	0.3870	[0.0467, 0.8327]	22
London	1.0000	1	0.000	1.000	0.0492	2	0.0492	0.9508	[0.0037, 1.0000]	19
Zaragoza	1.0000	1	0.000	1.000	0.1903	5	0.1903	0.8097	[0.0145, 1.0000]	16
Oslo	1.0000	1	0.000	1.000	0.9399	28	0.9399	0.0601	[0.0716, 1.0000]	2
Zurich	1.0000	1	0.000	1.000	0.7121	24	0.7121	0.2879	[0.0542, 1.0000]	5
Moscow	0.6602	31	0.340	0.660	1.0000	35	1.0000	0.0000	[0.0761, 0.6602]	30
Kiev	0.2034	35	0.797	0.203	1.0000	35	1.0000	0.0000	[0.0761, 0.2034]	35
Rome	1.0000	1	0.000	1.000	0.0113	1	0.0113	0.9887	[0.0009, 1.0000]	20
Ankara	0.6811	30	0.319	0.681	1.0000	35	1.0000	0.0000	[0.0761, 0.6811]	28

φ_{vj}*: 2.6712, θ_j*: 0.2034, α_6: 0.07615

and 3rd respectively in terms of its performance under the energy and environmental resource dimension across the years from 2015 till 2020. It is seen those smart cities namely, Bilbao, Sofia and Athens perform relatively worse under the aggregated performance with ranks 33, 34 and 35 among all the European smart cities.

Based on the set of input and output indicators chosen under the "safety and security" dimension (Table A5 in Appendix A), it is found that the cities that show relatively best performance under the optimistic scenario are namely, Sofia, Prague, Tallinn, Dusseldorf, Hamburg, St. Petersburg, Merseille, Manchester, Warsaw, Bucharest, Bratislava, Helsinki, Zaragoza, Moscow and Ankara. It is noticed that Amsterdam is pessimistically non-inefficient ($\eta_{pessimistic} = 0.0983$); while Bilbao, Bologna, London and Zurich are pessimistic inefficient smart cities with a score $\eta_{pessimistic} = 1.000$. However, the results from the aggregate performance ranks Munich, Amsterdam and Stockholm as 1st, 2nd and 3rd best smart city that is safe and secure for the citizens and tourists visiting them. While smart cities namely, Rome (rank: 33), Budapest (rank: 34) and Kiev (rank: 35) are ranked as the least sustainably performing smart city from the "safety and security" perspective. Under the "society and well-being" dimension (Table A6 in Appendix A), it is found that Sofia, Copenhagen, Tallinn, Athens, Lyon, Budapest, Vienna, Warsaw, Bucharest, Bratislava, Krakow, Stockholm, Moscow, Kiev and Ankara are optimistic non-efficient smart cities. These smart cities lie outside the efficiency frontier ($\eta_{pessimistic} < 1.000$). While, among all the optimistic non-efficient smart cities, Kiev with an $\eta_{optimistic} = 0.2034$ performs as the most inefficient smart city under the optimistic scenario. The double frontier bounded model for aggregate performance assessment reveals, Amsterdam (η bounded = [0.0746, 1.0000]; Rank 1), Oslo (η bounded = [0.0716, 1.0000]; Rank 2) and Munich (η bounded = [0.0623, 1.0000]; Rank 3), as the best performing smart cities. On the other hand, Kiev, Krakow and Sofia ranks 35th, 34th and 33rd with bounded DEA scores [0.0761, 0.2034], [0.0761, 0.5602] and [0.0761, 0.5695] respectively.

4.2. Sustainability performance clustering

This section uses the Quartile clustering method to group the efficiency scores for each smart city under all the 6 dimensions of sustainable development depending on their performance. The method partitions the data set into 4 equal clusters (groups), where each cluster has 25% of the data. The semantics for each group is represented on a scale from High to Low sustainability performance (SP). Performance grouping helps in understanding the impact of having certain undesirable parameters in the production set on the total sustainability performance. Once the data set is divided into 4 equal intervals, each smart city is placed in appropriate quartile based on their efficiency scores to better understand the standing of each smart city relative to one another under respective viewpoints namely; optimistic, pessimistic and aggregate double frontier perspective.

Figure 2 shows the group-based sustainability performance along with their respective ranks for each smart city under the optimistic scenario. To better visualize the sustainability performance, conditional formatting is used to assign position-dependent colour gradience to each cluster relative to the smart city performance. Manchester ranks No.1 as the relatively best performing smart city in terms of sustainable development among all the 35 leading European smart cities under the

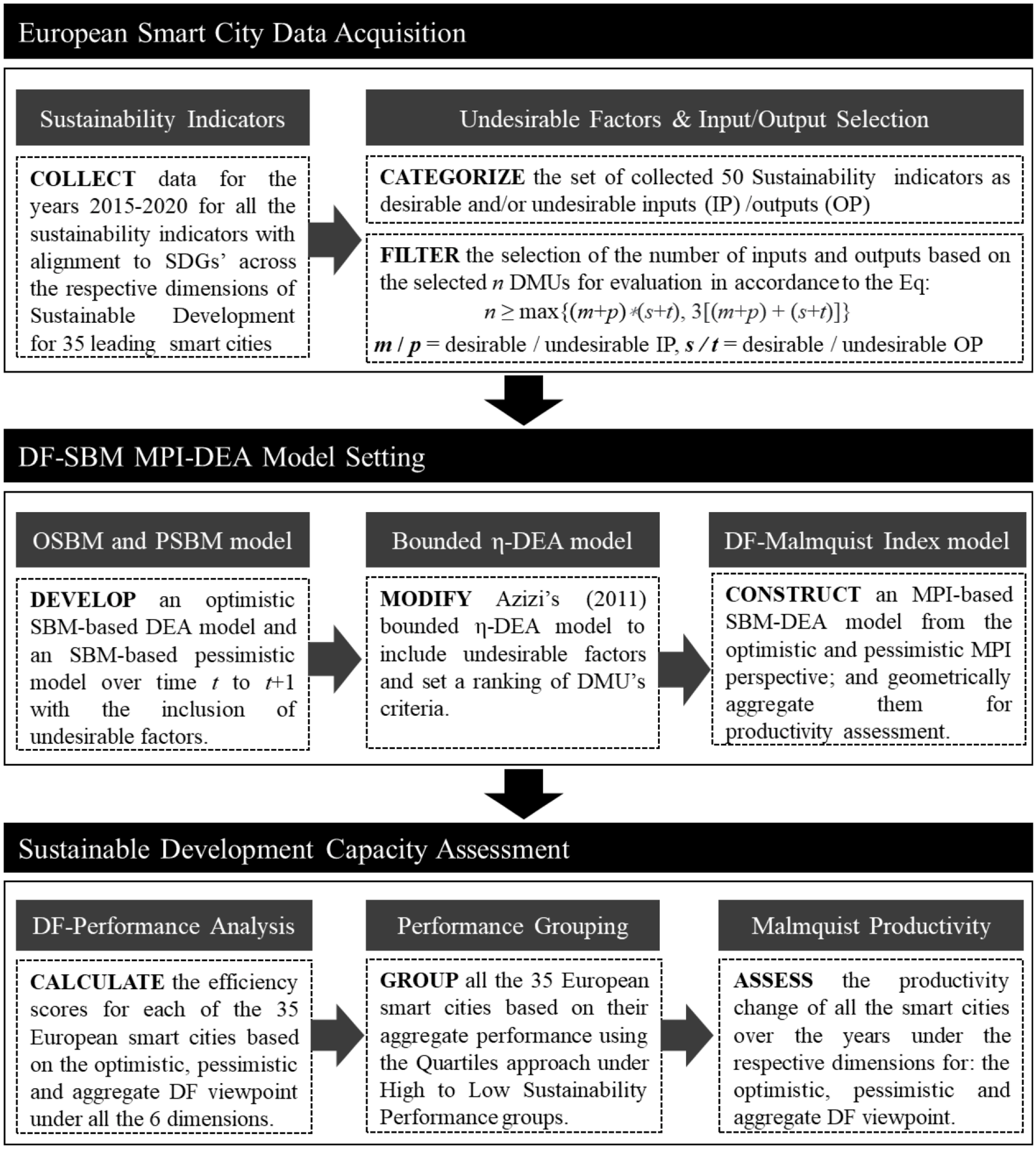


Figure 1. Schematics of research flow

optimistic scenario. Oslo, St. Petersburg and Dusseldorf backed the 1st, 2nd and 3rd runner up positions falling under the high sustainability performance cluster. It is seen that Kiev is the most under-performing smart city in terms of addressing sustainable development from the optimistic viewpoint, falling under the Low SP cluster. Smart cities namely; Brussels, Amsterdam, Stockholm, Bratislava, Bucharest, Munich, Krakow, Vienna and Budapest show a medium-to-low SP.

Figure 3 reveals Kiev, Tallinn, Ankara, Oslo, Bologna, Geneva, Vienna, Lisbon and Krakow as pessimistic inefficient smart cities with a relatively low sustainability performance from the pessimistic viewpoint. Oslo, Dublin, Geneva and Zurich which were grouped under the High SP category from the optimistic viewpoint were replaced by Rome, Moscow, Merseille and Athens in the High SP category under the pessimistic view point. These smart cities show less relatively worse performance or better termed less pessimistic non-inefficiency when compared to its peers in other clusters. It is seen that Manchester is ranked 35th under the High SP cluster and Kiev ranked 1st, falling under the Low SP cluster under the pessimistic scenario.

Figure 4 shows the performance grouping of smart cities from High SP to Low SP under the double frontier approach. Kiev remains the least sustainably performing smart city under all the viewpoints including the double frontier point of view (Fig. 4). It is seen that Dublin (ranked 1st) is the most smart and sustainable European city under all the dimensions of sustainable development. Along with Dublin in the High SP cluster lies Oslo, Zurich, Amsterdam, Geneva, Helsinki, Manchester, Dusseldorf and Hamburg. St. Petersburg that made itself into the High SP cluster under both the optimistic and pessimistic viewpoint is grouped under the High-Medium SP cluster under the DF scenario. It is surprising to see the position of Amsterdam pushed to the High SP cluster under the DF approach from the Medium-Low SP/Low-Medium SP cluster under the optimistic and pessimistic viewpoint respectively. Kiev, Ankara, Sofia and Prague that were grouped under the Low SP cluster from the optimistic point of view remained within the Low SP cluster under the aggregate DF scenario along with Budapest, Bilbao, Bucharest and

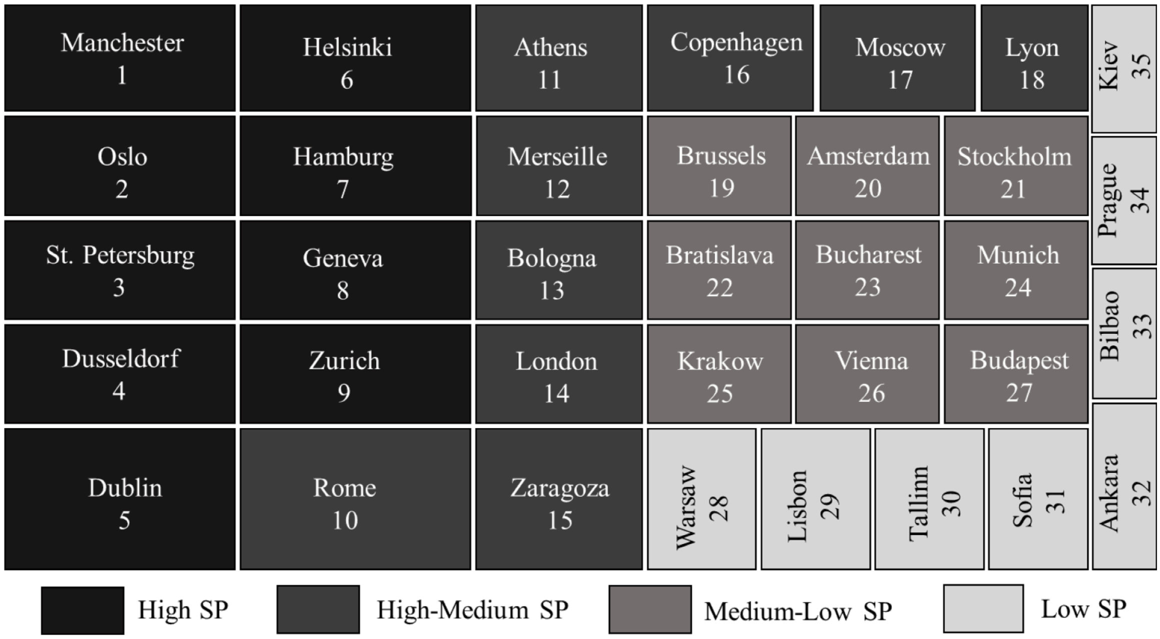


Figure 2. Grouped optimistic sustainability performance of smart cities

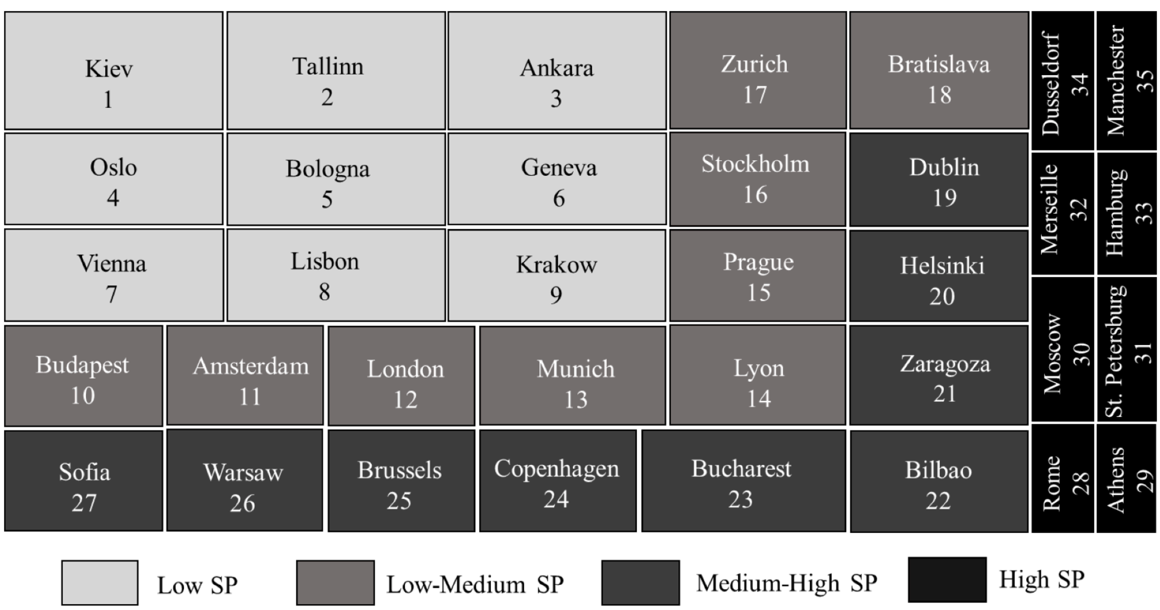


Figure 3. Grouped sustainability performance of smart cities under the pessimistic scenario

Bratislava.

4.3. *Productive performance through Malmquist Index*

In this section, the relative productivity change of each smart city over different period of time from 2015 till 2020 is presented under the Double-Frontier approach using an aggregate DEA-SBM Malmquist index (model 11). To discuss the change in the sustainability performance for all the smart cities under study, the MPI's were measured from different viewpoints: optimistic (model 9) and pessimistic (model 10) point of view under the dimensions; climate change, economic dynamism, governance and institution, social cohesion and solidarity, energy and environmental resource and, safety and security. A productivity progress is indicated when the DF-MPI >1. It is seen from Fig. 5 (a) under the climate change dimension that, Rome (DF − MPI =1.4827), Geneva (DF − MPI =1.0444), Stockholm (DF −MPI =1.0437), Tallinn (DF-MPI =1.0342) and Hamburg (DF-MPI =1.0326) showed the greatest positive productivity change from 2015 to 2020. The most decline in productivity is seen for Moscow (DF-MPI =0.9114), Prague (DF-MPI =0.9334), Bucharest (DF-MPI =0.9345), Athens (DF-MPI =0.9473), Lisbon (DF-MPI =0.9480) and Dublin (DF-MPI =0.9507). However, under the optimistic MPI (Table S4), Stockholm made the most cumulative productivity progress of 89.77%. While Manchester experienced the most regress in productivity with -54.26%. It is to note that, Athens failed to achieve productive progress under the double frontier integrated approach, while under the optimistic MPI, Athens achieved a progress in productivity by 68.98%. However, it is surprising to note that for the smart cities namely, Geneva, Stockholm, Zaragoza, Moscow, Kiev and Rome, there is no noticeable change in productivity during the years from 2015 till 2020 with $MPI_{pessimistic} = 1$. While, Zaragoza with $MPI_{optimistic} = 1$ and $MPI_{pessimistic} = 1$ has not achieved any progress under both the optimistic and pessimistic MPI scenarios. Similarly, under the dimension "economic dynamism" (see Table S5), from the optimistic perspective, it is seen that Bratislava has

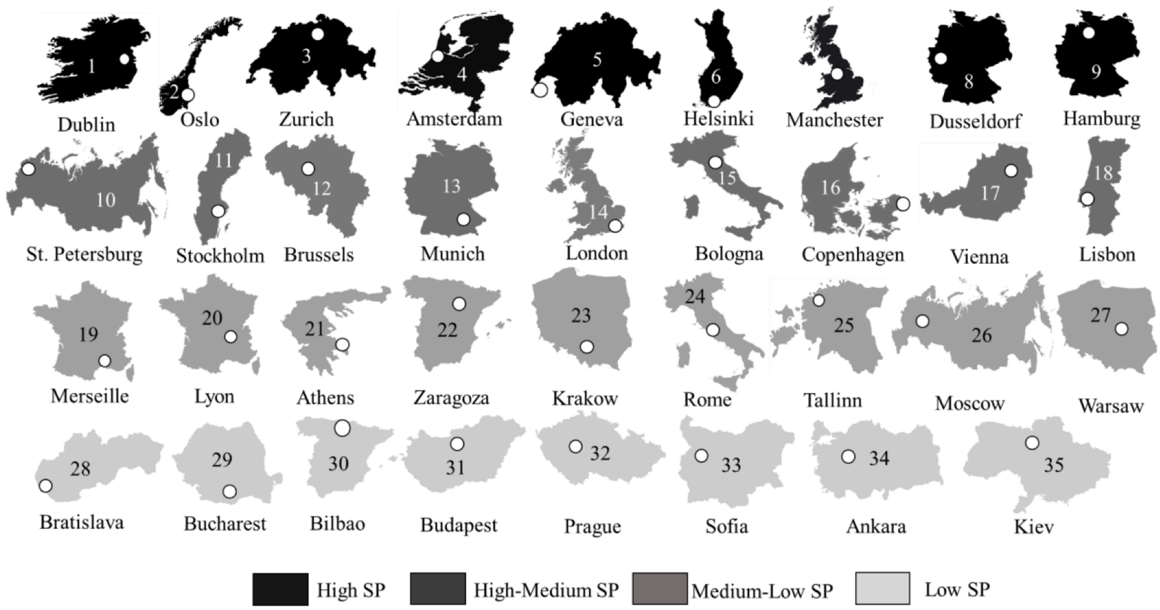


Figure 4. Grouped sustainability performance of smart cities with rank under the double frontier approach

made the greatest progress by 20.563% in terms of productivity followed by Kiev (7.274%), Athens (3.088%), Geneva (1.739%) and Hamburg (1.323%). All the other smart cities showed a regress in productive performance with Manchester showing a steady decline in productivity by -32.926% followed by Munich (-32.91%), Helsinki (-32.56%) and Bilbao (-20.63%). Contrastingly, from the pessimistic viewpoint, it is seen that Rome with a productivity regress of 54.21% ranks as the least productive smart city in terms of its progress towards achieving sustainable development across the years. Contrarily, Rome ranks 35th under the aggregate double frontier approach with a DF-MPI index that equals 0.87099 (Fig. 5b) for lowest productivity progress over the years, followed by Hamburg (DF-MPI =0.9309), Zaragoza (DF-MPI =0.93373), Lisbon (DF-MPI =0.93478) and Lyon (DF-MPI =0.94166). Figures B1(a-f) in Appendix B shows the productivity change for the 35 European smart cities over the years from 2015 till 2020 under respective dimensions of sustainable development from the optimistic viewpoint. Figures B2 (a-f) in Appendix B shows the change in productivity from the pessimistic view point over time for the smart cities under various dimensions.

While, investigating the productivity changes of all the European smart cities over the years, it is seen that St. Petersburg has made significant progress in terms of productivity under the governance and institution dimension from the optimistic viewpoint ($MPI_{optimistic}$ = 1.2949). An average productivity increase of 91.86% is seen under the optimistic viewpoint from 2015-2020 while, under the pessimistic view point, a decline of 13.604% over the years is seen ($MPI_{pessimistic}$ = 0.9924). However, the integrated DF-MPI value for St. Petersburg show an overall productivity progress (DF-MPI =1.1336) and ranks 1st as the smart city that achieved best productivity growth in terms of addressing the essence of the governance and institution theme from 2105-2020 (Fig. 5c). On the contrary, Zaragoza experienced a decline in productivity under both the optimistic and pessimistic scenarios with an average productivity regress rate of 18.41% and 15.45% respectively (Table S6 in SI file). However, under the integrated DF-MPI, Ankara stands as the first runner up (DF-MPI =1.0645) followed by Merseille (DF-MPI =1.0467), Bucharest (DF-MPI =1.0413) and Helsinki (DF-MPI =1.0143) in terms of its progressive performance growth under the governance and institution dimension of sustainable development. A distinct evaluation to understand the productivity progress under the "society and well-being" dimension was carried out using models from 6-8 for the smart cities under study. No noticeable change in the productivity over time was investigated under the pessimistic scenario for Munich, Merseille, Lisbon, Zaragoza, Oslo and Moscow (Table S7). This is evident from the $MPI_{pessimistic}$ value of 1.000. Paradoxically, a decline in productivity was noticed for all these smart cities under the optimistic scenario except for Munich with a progress of 0.522% over the years. Smart cities that showed rapid productivity growth under the aggregate pessimistic MPI values from 2015-2020 (Fig. A2-d) where; Dublin ($MPI_{pessimistic}$ = 1.0255), Lyon ($MPI_{pessimistic}$ = 1.0035), Geneva ($MPI_{pessimistic}$ = 1.011), Amsterdam ($MPI_{pessimistic}$ = 1.0304), Warsaw ($MPI_{pessimistic}$ = 1.0034), Helsinki ($MPI_{pessimistic}$ = 1.0158), London ($MPI_{pessimistic}$ = 1.0068) and Zurich ($MPI_{pessimistic}$ = 1.0037). Under the MPI based on double frontier, Brussels achieved the least productivity growth with a DF-MPI value of 0.93243.

When analyzig the MPI values for the European smart cities under the "energy and environmental resource" dimension, it is found that the smart cities that show the highest amount of increase in productivity under the integrated double frontier approach are namely; London (DF-MPI =1.2945; Rank: 1), Helsinki (DF-MPI =1.0681; Rank: 2), Oslo (DF-MPI =1.0656; Rank: 3), Manchester (DF-MPI =1.0311, Rank: 4), and Dublin (DF-MPI =1.0304, Rank: 5). A decline in productive performance over time was found for Geneva (DF-MPI =0.9578; Rank: 35), Moscow (DF-MPI =0.96686; Rank: 34), Hamburg (DF-MPI = 0.9737; Rank: 33), Munich (DF-MPI = 0.9895; Rank: 32) and St. Petersburg (DF-MPI = 0.9902; Rank: 31). However, Geneva shows a significant progress in terms of productivity by 30.517% under the optimistic view point (Table S8). While, a regress in productivity of 26.7% is found that has resulted in the overall productivity decline under the DF-MPI approach. Furthermore, London (progress rate: 62.73%, Rank: 1), Helsinki (progress rate: 43.90%, Rank: 2), St. Petersburg (progress rate: 28.45%, Rank: 4) and Zurich (progress rate: 10.91%, Rank: 5) exhibits a cumulative productive progress under the optimistic viewpoint. Howbeit, smart cities namely; Zaragoza (progress rate: 13.45%, Rank: 1), Brussels (progress rate: 7.584%, Rank: 2), Zurich (progress rate: 5.69%, Rank: 3), Helsinki (progress rate: 4.76%, Rank: 4) and Kiev (progress rate: 4.484%, Rank: 5) show improved productivity under the pessimistic scenario. Whilst, under the "safety and security" dimension (Table S9), Merseille (progress rate: 29.7%), Dusseldorf (progress rate: 29.49%) and Lisbon (progress rate: 19.803%) ranks 1st, 2nd and 3rd in terms of aggregate productive progress over time under the optimistic MPI scenario. However, a dip in productivity is shown most in the case of Moscow by 24.052%, Hamburg by 19.6% and Zaragoza by 17.764%

a) b)

Figure 5. Sustainable productivity comparison for 35 European smart cities from pessimistic, optimistic and double frontier perspective under a) Climate change b) Economic dynamism c) Governance and Institution d) Social cohesion and solidarity e) Energy and environmental resources f) Safety and security

under the optimistic MPI, while a productivity regress by 47.57%, 29.74% and 24.53% is shown under the pessimistic viewpoint by Geneva, Zurich and St. Petersburg respectively. For a change index of DF-MPI =0.8846, Bologna indicates the highest decrease in productivity level from 2015 till 2020 while, the greatest progress in productivity is marked for Kiev with a DF-MPI index of 1.0477 for the study duration. Furthermore, it is to note that, St. Petersburg under the optimistic scenario and Moscow under the pessimistic scenario show no change in productivity with MPI index values equal to 1.000. Productivity change for all the 35 European smart cities over the years from 2015 till 2020 under the 6 dimensions of sustainable urban development are shown in Tables S4-S9 (refer SI file). Fig. 5(a-f) shows the cumulative MPI values for all the 35 smart cities under the optimistic, pessimistic and double frontier approach over time from 2015 till 2020.

5. Conclusion

In this study, the sustainability performance of 35 leading European smart cities were studied from the optimistic, pessimistic and double-frontier perspective through a novel DF-SBM DEA model under the extended strong disposability assumptions. The change in productive performance over time for the smart cities from 2015 till 2020 was analysed using a modified DF-MPI model that accounted for the inclusion of undesirable factors while carrying out the assessment. After running the models to understand the optimistic and pessimistic DEA-MPI values for all the smart cities in the study, the findings clearly show that the productivity values vary significantly under both the perspectives. Thus, the traditional approach to only computing the optimistic MPI values when trying to understand the productivity change can lead to partial results and not a comprehensive overview of the productivity change. Thus, the DF-MPI approach used in the study to compute the sustainable productivity change of smart cities result in a panoramic view of how smart cities respond to the call of sustainable development over the years through technological change. They are geometrically averaged to produce a full ranking or an overall assessment of the DMUs. The results after running the models for the sustainable development capacity assessment also reveal the true essence of measuring the aggregate sustainability performance using the double-frontier approach. It is noticed that, under the social cohesion and solidarity dimension, about 57% of the efficiencies are overestimated by the SBM optimistic model to a score of $\eta_{\text{optimistic}} = 1.000$. Similarly, under the economic dynamism dimension, Stockholm ranks 30$^{\text{th}}$ under both the optimistic and pessimistic scenario, with $\eta_{\text{optimistic}}$ and $\eta_{\text{pessimistic}}$ values equal to 0.5793 and 0.9886, respectively. These variations in results can lead to different policies when decision making. Thus, a simultaneous evaluation of sustainability performance under both the viewpoints using the aggregated model as carried out in this study is best recommended. The preliminary application of the proposed DF-SBM DEA model in the case of European smart cities, confirmed its potential applicability for assessing and comparing cities that aspire a sustainable transformation. The authors plan to implement proposed methods in several case studies across various scopes of urban sustainability in the future, namely the sustainable city, the eco-city, the low-carbon city, the green city etc., to fine-tune the proposed steps and validate its applicability. The proposed approach focuses on a solid and unified evaluation process for a city-oriented progress assessment towards sustainability, capable of generating clear, sufficient, understandable, and ready-for-benchmarking results and conclusions for all cities globally with similar or different sets of sustainability indicators.

The math to perform better is sceptical and an intricate puzzle even for several best performing smart cities. It is best recommended that the sustainable growth patterns in cities need to be decoupled from carbon-intensive activities in attempts to encourage foreign investments for smarter transition of cities. Nevertheless, the increasing use of energy and environmental resources to exemplify the economy (examples of Athens, Tallinn and Sofia); declining employment rate in attempts to shut down carbon-intensive industries (Munich, Moscow and Vienna); lack of capacity to contrive with the judicial system to eliminate crime and theft (Kiev, Rome and Bratislava); political instability due to lack of will and opposition from public; and an imbalance in the share of renewables among the cities due to new energy dependant pathways in action (Kiev, Bucharest and Sofia); can all subpar the performance of smart cities, which can also be read from the empirical findings of this paper. The least performing European smart cities should set a specific timetable and objective for climate change mitigation, and distribute carbon reduction duties through top-down effects, which will help to monitor and facilitate achieving the objective. In recent years, it has been demonstrated that the technological advancements of energy, architecture, transportation, agriculture, fisheries, and manufacturing, which are driven by climate policies, are closely related to and promote the transformation of the current fossil fuels and black economy (high-pollution) into a green economy. If fiscal tax is taken as an incentive or punishment, it will involve an overall economic transformation (Al-Buenain et al., 2021). Thus, a combination of high-level decision--making and coordination among the different parts will facilitate change. Taking a top-down approach regarding the allocation of carbon reduction responsibilities, timeframes and targets in European smart cities is essential to the supervision and achievement of goals. The high awareness of environmental protection and the robustness of the regulatory framework can facilitate the effective implementation of policies in the least performing smart cities, as industries must comply with relevant laws and meet market demands by constantly improving production technology and efficiency. A delicate balance between the pillars of sustainable development, protectionist measure against unfair competition, building capacity to invite funds and investments without tampering the sustainable urban development initiatives and positioning as an ambitious de facto leader taking into account the success of the benchmarks can all pave ways for smart cities to target the ever-ambitious goal of transition into a smart sustainable city.

From a methodological point of view, the proposed OSBM and PSBM models are non-translation invariant and non-negative undesirable models, i.e., the proposed models are capable to only handle positive input and output data. The general case where there are negative data for inputs or outputs is non-trivial and deserves further discussions. Although technically it should be always possible to transfer such cases and then apply the proposed non-negative undesirable models, there are many reasons that people still prefer to use negative data in some applications. The authors suggest Range Directional (RD) models to derive merit functions that can be used to treat the presence of negative data for performance assessment. The authors further suggest using Evidential Reasoning algorithms with mass functions to aggregate the sustainability performance under the double frontier approach as a future work. Furthermore, if we wish to use a single ratio to measure the radial extension or contraction for both desirable and undesirable part of inputs or outputs, then we may have to deal with DEA models with objective functions like $\theta + 1/\theta$. Thus, it is difficult to directly combine the proposed Extended Strong Disposability model with standard radial measure while keeping the original input-output orientation. Alternatively, Super-SBM models can be used for the optimistic performance evaluation along with inverted-SBM models for pessimistic evaluations in future. Enhanced Russell Measurement (ERM) models can then be combined to understand the change in the input and output orientations, which can help support decision making by controlling outcomes for studies that are highly dependent on the input-output relationships. In addition, the proposed DF-DEA based MPI can be easily extended to the global MPI that measures the optimistic efficiencies with a unified efficiency frontier and the pessimistic efficiencies with a unified inefficiency frontier for time periods t and $t + 1$. Interested readers may refer to Pastor and Lovell, (2005) for the discussions on the global MPI. Eqn 1-12, Fig 1

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

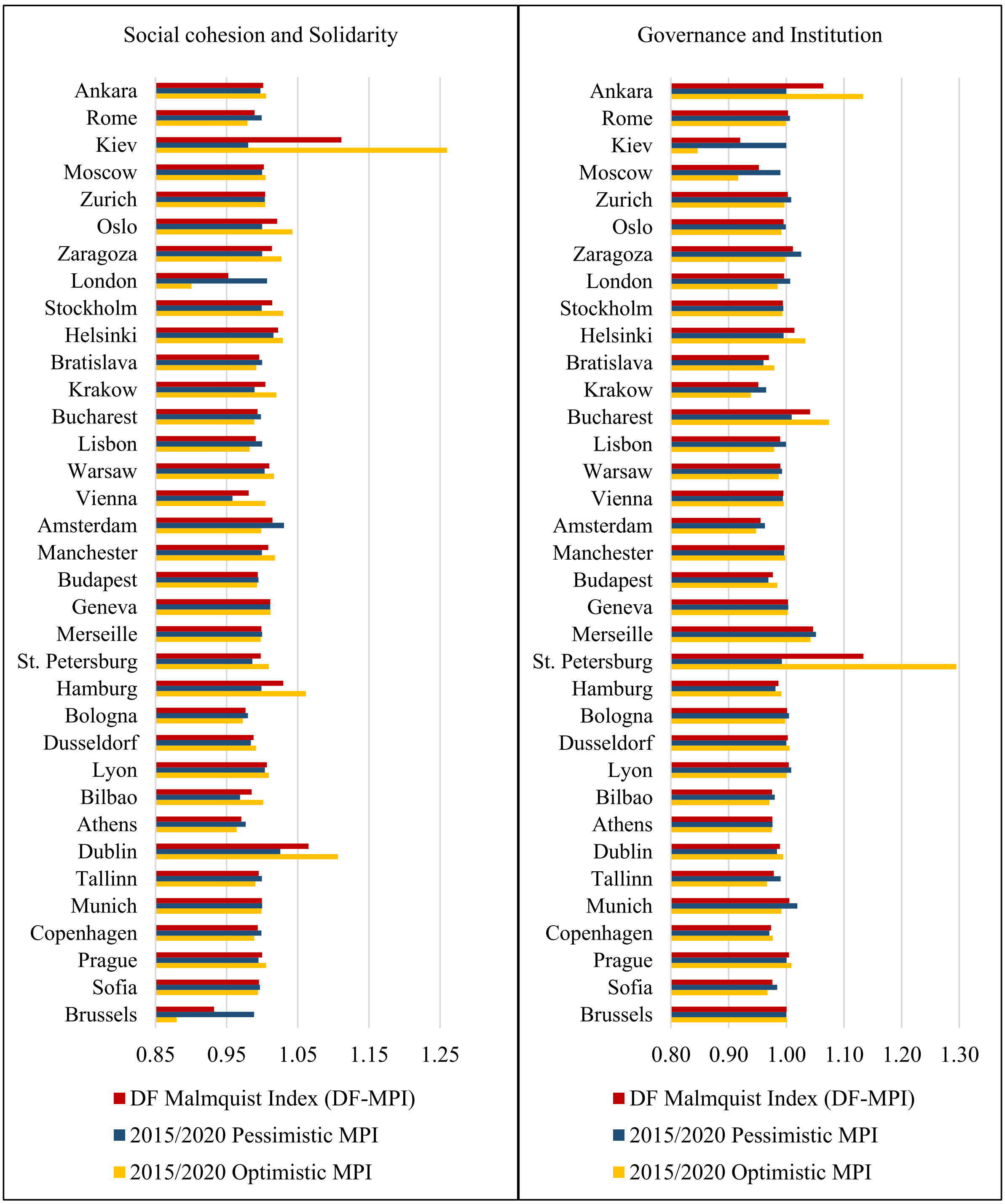
Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2022.103777.

Appendix A

Table A1, Table A2, Table A3, Table A4, Table A5, Table A6.

Appendix B

Fig B1, Fig B2



c) d)

Figure B1. Productive performance from optimistic viewpoint of 35 European smart cities over time from 2015 till 2020 under the dimensions a) climate change b) economic dynamism c) governance and institution d) social cohesion and solidarity e) energy and environmental resource f) safety and security

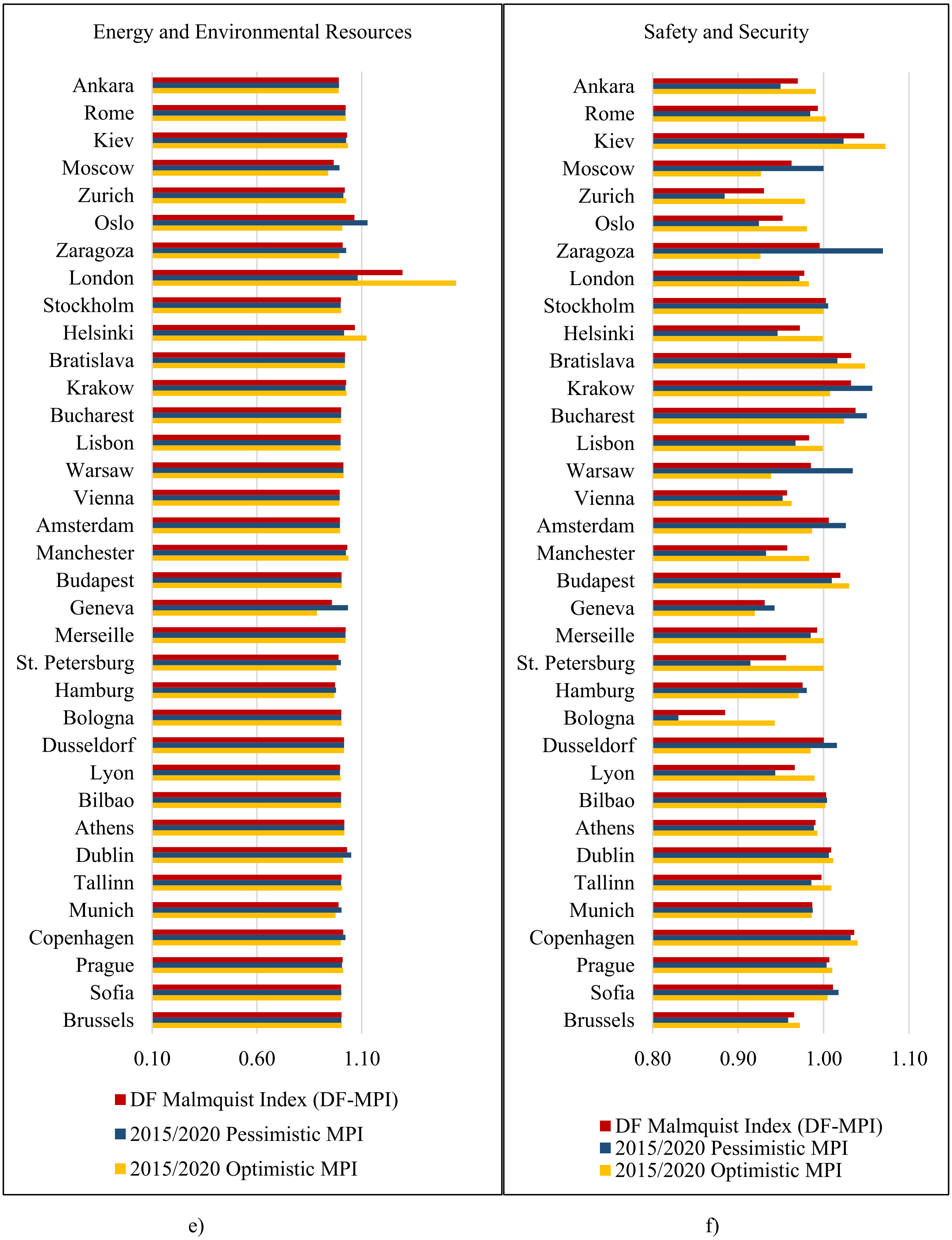


Figure B2. Productive performance from pessimistic view point of 35 European smart cities over time from 2015 till 2020 under the dimensions a) climate change b) economic dynamism c) governance and institution d) social cohesion and solidarity e) energy and environmental resource f) safety and security.

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