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Research Paper

Sustainable urban development indicators in Great Britain from 2001 to 2016

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HIGHLIGHTS

- Urban structure contributes to the sustainability of urban areas.
- Composite indicators represent a useful tool for measuring the internal structure of urban areas.
- There is a uniform increase in urban structure sustainability of areas in and around British city centres.
- Urban structure sustainability has been improved in areas with an increase in walkable spaces.

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ABSTRACT

Current planning strategies promoting suburbanisation, land use zoning and low built-up density areas tend to increase the environmental footprint of cities. In the last decades, international and local government plans are increasingly targeted at making urban areas more sustainable. Urban structure has been proved to be an important factor guiding urban smart growth policies that promote sustainable urban environments and improve neighbourhood social cohesion. This paper draws on a series of unique historical datasets obtained from Ordnance Survey, covering the largest British urban areas over the last 15 years (2001–2016) to develop a set of twelve indicators and a composite Sustainable Urban Development Index to quantitatively measure and assess key built environment features and their relative change compared to other areas at each point in time based on regular 1 km^2 grids. The results show that there is a relative increase in urban structure sustainability of areas in and around city centres and identify that the primary built environment feature driving these improvements was an increase in walkable spaces.

1. Introduction

In 2018, urban areas accommodated more than half of global population (Brelsford, Martin, Hand, & Bettencourt , 2018). The 2018 population projections forecasted that urban areas will concentrate more than two thirds of the global population by 2050 (United Nations, 2018). This worldwide trend of urbanisation is expected to trigger economic growth and development as well as changes in the spatial organisation of population and land use (Batty, 2008). However, the rapid urban expansion of cities across the globe is also expected to put populations and natural environment under pressure. Additionally, the unfolding COVID-19 pandemic may influence future housing choices away from city centres to less dense areas. Current planning strategies promoting suburbanisation, land use zoning and low built-up density areas tend to increase the environmental footprint of cities (Jones and Kammen, 2014). In the last decades, international and local government plans are increasingly targeted at making urban areas more sustainable (Mohammed, Alshuwaikhat, & Adenle , 2016). Hence, urban smart growth policies, fostering compact and mixed land use development, walkable neighbourhoods and ensuring the availability of public transport and open spaces, have emerged as key strategies to create sustainable urban environments and improve neighbourhood social cohesion (Artmann, Kohler, Meinel, Gan, & Ioja, 2019).

The urbanisation process can take the form of compact or sparsely populated developments. Debates around the benefits and disadvantages of compact city forms have been ongoing since 1970s (Hamidi and

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Ewing, 2014). On the one hand, neighbourhoods with high density are often associated with low social interaction of local residents (Brueckner and Largey 2008) and suburban expansion is linked to increased productivity and wellbeing of populations in urban areas (Kotkin, 2016). On the other hand, proponents of compact cities argue that dense neighbourhoods increase the interaction and productivity of businesses due to the agglomeration economies (Ahfeldt and Pietrostefani, 2017), while cities characterised by low suburban density (i.e. urban sprawl) lead to greater private car usage (Glaeser and Kahn, 2004). Thus, sprawling areas have been blamed as a wasteful form of urban development due to longer commuting journeys (Batty, Besussi, & Chin, 2003); increased congestion (Bento. Cropper, Mobarak, & Vinha , 2005), obesity (Ewing et al., 2003) and air and water pollution (Anderson, Kanaroglou, & Miller, 1996). Nevertheless, the spatial organisation and form of built environment and their evolution over time are key to understand their impacts on people and the natural environment. To this end, urban morphology has emerged as a distinctive field of study seeking to quantify the physical form of cities and its evolution over time (Kropf, 2018).

Statistical indicators extracted from built environment characteristics represent a useful tool for measuring the internal structure of urban areas (Galster et al., 2001). Compactness, green space availability and walkability are key features of the built environment. The importance of these urban features has been highlighted due to their benefits to economic productivity, individual well-being and sense of community creation. The relevance of measuring the structure of built environment features has been long argued (Jacobs, 1961). Concepts such as urban sprawl and compactness, access to green space and walkability of cities have emerged as important factors influencing public health and reducing the cost of public services (Carruthers and Ulfarsson, 2003; Lopez, 2004).

More recently, quantitative approaches using geospatial vector data have been used to develop indicators capturing urban morphological structures such as built-up and green space density (Venerandi, Quattrone, & Capra, 2018), street networks (Boeing, 2018), building shape (Fleischmann, 2019) and land use diversity (Reis, Silva, & Pinho, 2016). Open Street Map (OSM) comprises a novel source of vector geospatial data. OSM data is freely available and provide global coverage (Haklay and Weber, 2008), but over a restricted timeframe (i.e. not more than 10 years) limiting their applicability to track changes in the built environment over time. Also, the data coverage and quality are not consistent across cities as it depends on user inputs. Satellite imagery is also becoming increasingly used to develop indicators of built environment characteristics (Heiden et al., 2012) and study hard-to-access and scarce-data settlements, such as slums (Kuffer, Pfeffer, & Sliuzas, 2016). Yet, while endeavours exist, feature extraction from satellite imagery to capture features of the built environment remains a challenging task and is usually limited to land cover, rather than land use (such as residential *versus* commercial buildings).

Compactness, green space and walkability stand out from the literature as key built environment features. These features are related to the way urban areas expand, impact on individuals' health and promote vibrant communities. ***Compactness*** is a measure that has been widely used to study urban sprawl (Galster et al., 2001). High built-up density and presence of residential and commercial developments (Burton, 2002) is a key contributing factor towards the urban smart growth (Mohammed et al., 2016), as it helps reducing the cost of public services and consequently reducing the overall environmental footprint of cities. ***Urban green space*** has also been shown to play a key role in improving individuals' health, wellbeing and decreasing the risk of mortality (Mitchell and Popham, 2007). Yet, the spatial distribution of green space tends to be very unequal. In the United States, more affluent areas tend to have larger presence of private green space compared to more deprived areas (Barbosa et al., 2007). In the United Kingdom, urban forest is more abundant in peripheral areas than in central locations (Stubbings, Peskett, Rowe, & Arribas-Bel , 2019). ***Walkable*** neighbourhoods is another important feature of sustainable cities (Artmann et al., 2019), as they offer positive benefits to public health by providing activity-friendly environments (Owen et al., 2007) and creating more vibrant streets (Hess et al., 1999). Larger sidewalks can help in social interaction within neighbourhoods and creation of a "sense of community" (Talen, 1999).

Monitoring the sustainability of urban areas has been recently encouraged (United Nations General Assembly, 2015, 2017; ISO, 2018) to facilitate comparisons across places and countries, and to enable reproducibility and share good practices between countries. A range of conceptual and methodological frameworks have been proposed to capture composite Sustainable Urban Indicators (OECD and JRC, 2008; Shen, Jorge Ochoa, Shah, & Zhang, 2011; Blackwood, Gilmour, Isaacs, Kurka, & Falconer, 2014; Science for Environment Policy, 2018). More recently, progress has been made on quantifying morphological features of urban areas and applications. This work has developed composite indicators focusing on Sustainable Urban Indicators, providing useful insights for urban areas development. However, gaps exist in three domains. First, composite indices have been developed to capture the built environment (Koch and Krellenberg, 2018; Higgs, Badland, Simons, Knibbs, & Giles-Corti, 2019; Giles-Corti, Lowe, & Arundel, 2020); yet, they do not consider the temporal dynamics of built environment features, which can enable valuable urban comparison over time and measure the pace of urban change. Second, the spatial granularity of data is often coarse (Boori, Netzband, Choudhary, & Voženílek , 2015); or, the study area is limited to a particular city (Nazarnia, Schwick, & Jaeger, 2016; Gullón et al., 2017; Assumma et al., 2021) which again hampers robust spatial comparability. Finally, the importance of measuring urban structures as a key to sustainable development in cities has been highlighted in UK-based studies (Dempsey, Brown, & Bramley, 2012). Yet, patterns of change in urban structures have not been examined, arguably because of the absence of a temporally and spatially consistent data.

To address these gaps, we propose a set of simple yet robust summary indicators to capture relative change in the urban structure of the 12 largest British urban areas over the last 15 years, 2001–2016. Drawing on a series of unique historical datasets obtained from Ordnance Survey, the national mapping agency of Great Britain, and we specifically aim to:

1. Develop a set of twelve indicators at 1 km^2 grid level to measure three dimensions of urban structure: Compactness, Green space availability, and Walkability;
2. Build composite indices to combine individual indicators by domain – Compactness, Green space availability, and Walkability – and create an overall Sustainable Urban Development Index of British neighbourhoods;
3. Establish the relative change of urban built structure at each point in time from 2001 to 2016.

The Sustainable Urban Development Index and its domain rankings provide a methodological framework to quantitatively measure and assess key built environment features and their relative change compared to other areas at each point in time based on regular 1 km^2 grids. Such an approach can help understanding relative changes in the characteristics of urban built structure between and within urban areas at each point in time (Tunstall, 2016). It can help identify inequalities in the built environment within cities which are masked by city-level indicators (Giles-Corti et al., 2020). The proposed framework can be used to assess past urban planning interventions that have shaped the local built environment and resident populations and help inform future planning strategies. Ultimately it can contribute to advance our understanding of cities and guide urban planning interventions creating healthy and sustainable cities with equitable access to services and infrastructure (Giles-Corti et al., 2016).

The rest of the paper is organised as follows: Section 2 describes the data and the methodological approach to create the proposed indices to measure neighbourhood-level urban structure as well as the data used in this study. Results are presented in Section 3 before we discuss the key findings in Section 4. Finally, Section 5 provides some concluding remarks and identifies potential avenues for future research.

2. Materials and methods

2.1. Data and study area

We used four temporal samples (2001, 2006, 2011 and 2016) to cover 15 years of urban transformation extracting data from the Ordnance Survey (OS) database for the 12 largest urban areas in Great Britain: Bristol, Edinburgh, Glasgow, Leeds, Liverpool, London, Manchester, Newcastle upon Tyne, Nottingham, Sheffield, Southampton and Birmingham. According to 2011 Census, these areas cover 80% of the Great Britain population. We employed the Functional Urban Areas (FUAs) layer produced by OECD (OECD, 2013) to define urban area extents. FUAs provide a common definition of metropolitan areas as ‘functional economic units’ across 29 OECD countries. These areas are dependent on population density and travel-to-work flows and offer a more accurate representation of functional labour market activity than administrative boundaries (Casado-Díaz, Martínez-Bernabéu, & Rowe, 2017; Rowe, Casado-Díaz, & Martínez-Bernabéu, 2017).

We used data from three OS product sources:

1. OS AddressPoint database - that provides information on residential and commercial addresses for 2001, 2006 and 2011;
2. OS AddressBase - that provides information on residential and commercial addresses for 2016; and
3. OS MasterMap Topography Layer - that provides information on polygons capturing building footprints, green space, roads and paths.

Point data from OS AddressPoint and OS AddressBase are classified into residential and commercial addresses that are registered in the Royal Mail’s Postcode Address File (PAF) and were used to calculate the density of residential and commercial adresses. That is the number of addresses in each 1 km^2 grid square. Polygon data were obtained from OS MasterMap Topography Layer and were used to calculate the density of each built environment feature (i.e. buildings, green space etc.). That is the area covered by each feature in each 1 km^2 grid square. Fig. 1 highlights the complexity of the raw data used in a small area of two grids. In each grid, there is a high volume of information such as different classes point (residential and commercial) and polygon (buildings, open spaces and roads/paths) data. Hence, in order to extract actionable information, the raw data can be summarised at 1 km^2 grids as it will be discussed in the following Section 2.2.

The data are based on 6,767 1 km^2 grid squares covering all 12 FUAs in our sample. Our focus is on examining urban structure, thus we used grids that correspond to areas with resident population. Similar to Patias, Rowe, and Cavazzi (2020) we considered grids with more than 15 people per 1 km^2 grid square, excluding unpopulated areas. Neighbourhoods -in the COVID-19 era- have been brought at the centre of discussions of urban planning. Proposals such as of 15-minute neighbourhoods suggest access to most of the essential amenities within short walk or ride. That is around 15 min of walk which is equivalent to about 1 km distance. We therefore selected 1 km^2 grids for our analysis which can be considered an approximation of a neighbourhood and we refer to them as neighbourhoods. We also used grids because they are not dependent on administrative boundaries. They are comparable over time and across space (i.e. areas varying in size and shape at various geographical scales, including cities, regions or countries). The importance of gridded data has been highlighted in a wide range of studies including population counts (C. T. Lloyd, Sorichetta, & Tatem, 2017), census variables (C. D. Lloyd, Catney, Williamson, & Bearman , 2017), socioeconomic change (Patias et al., 2020) and land use patterns (Galster et al., 2001) as an appropriate and flexible geographical unit to assess the effects of the MAUP and create customisable geographies. Additionally, the Office for National Statistics in the UK is planning to produce population estimates on 1 km^2 grids for the upcoming census in 2021 acknowledging and facilitating the use of grids to harmonise datasets at various scales and time periods (Office for National Statistics, 2018).

2.2. Overall methodology

The methodological framework developed in this study includes four stages as presented in Fig. 2. Stage 1 involved the calculation of 12 individual indicators of urban structure at 1 km^2 grid level using OS data. These indicators were used to capture three distinctive domains in Stage 2 and they were standardised and weighted within each domain in Stage 3. In the final Stage 4, we used the three domain-specific ranks to calculate an overall Sustainable Urban Development Index (SUDI).

2.3. Stage 1: Grid-level indicators calculation

The first stage includes the computing process from raw geospatial data to creating 12 statistical summary indicators at 1 km^2 grids. The raw data are split into point and polygon data. In both cases we aimed to

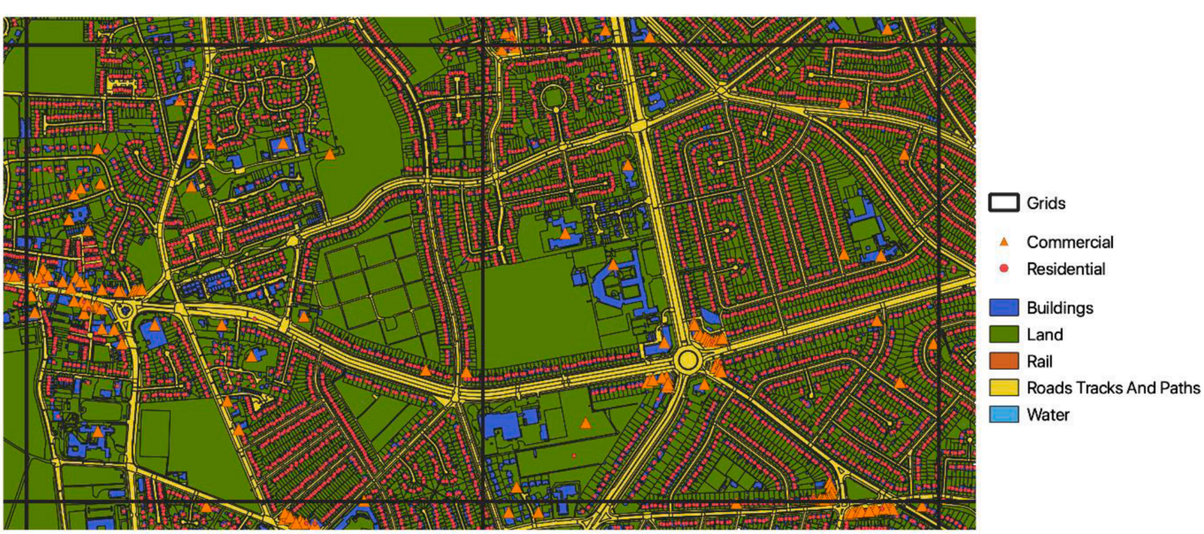

Fig. 1. Raw point and polygon data. © Crown copyright and database rights 2021 Ordnance Survey.

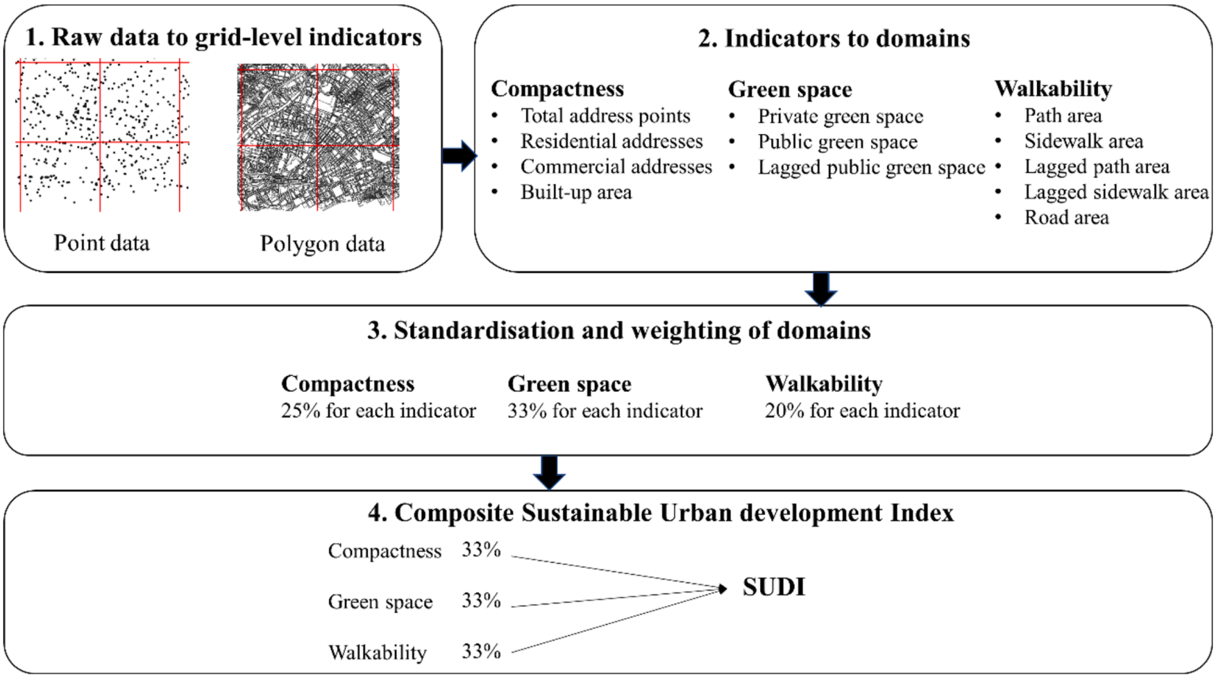

Fig. 2. The diagram shows the overall methodology which consists of four stages, from raw data to the final output. The weights of each indicator to the creation of the corresponding Domain Index and the weights used for each of the three domains to the Composite Sustainable Urban Development Index (i.e. 33%). The figure contains Ordnance Survey data.

summarise the data by capturing their density in each grid square.

For point data, we firstly divided them according to land use classification, specifically into residential and commercial points. For each of these two groups and the total number of points (i.e. the sum of residential and commercial points), we calculated the number of points by grid square. These numbers express the density of address points by grid square and class (i.e. residential, commercial and total). This process was performed for each of the years in our study (i.e. 2001, 2006, 2011 and 2016).

For polygon data, in addition to applying the same steps as for the point data, we created an urban environment feature class field. The six classes are: (1) buildings; (2) public green spaces; (3) private green spaces; (4) paths; (5) sidewalks; and (6) roads. Then, for each of the feature classes, we calculated the density of each urban environment feature, which is the area covered by each feature in a 1 km^2 grid square.

We analysed changes in the set of 12 indicators over time. Our analysis captures the relative change of urban built structure at each point in time from 2001 to 2016 and it required consistent data over two different product specifications (OS AddressPoint 1999–2015 and OS AddressBase 2011-current). A key challenge was the integration of data from OS AddressPoint 1999–2015 and OS AddressBase 2011-current. The AddressPoint product only identifies residential and commercial address points, while the AddressBase product provides a detailed breakdown for commercial addresses, offering a very detailed classification of land use types (e.g. grocery shops, clothing, etc.). Thus, we opted to achieve consistency of the data products used over time compared to more detailed land use classification provided in most recent AddressBase dataset. We amalgamated the point data based on the two-class definition used in the AddressPoint product (i.e. residential and commercial).

2.4. Stage 2: Indicators and domain selection

To capture *Compactness*, four indicators were created by measuring: (1) the number of total address points; (2) the number of residential points; (3) the number of commercial points; and (4) the built-up area in m^2 within each 1 km^2 grid square. The first indicator captures the density of address points. This can reveal the overall density (i.e. number of points by grid square) of businesses and residential units within an area which is a key factor of measuring urban sprawl (Galster et al., 2001). The second and third indicators measure the abundance of residential and commercial properties. These two indicators act as decomposed variables to account for the balance between land uses and are linked to the idea of mixed land uses which promote human social interaction and represents a main advantage of the new urbanism perspective (Talen, 1999). The fourth indicator captures the area in m^2 occupied by buildings in each 1 km^2 grid square. This indicator, in conjunction with the density of address points, can provide insights into high built-up density areas which contribute towards urban smart growth (Mohammed et al., 2016), by reducing the time people have to travel to access essential daily services. Another important consideration is to include the population density of each grid. However, some of the variables we include in the compactness domain -particularly built-up density and density of address points- already capture population density and are positively correlated. S9 in the Supplemental material presents a correlogram between population density and the domains included in our study.

To capture *Green space availability*, we computed three indicators: (1) area in m^2 occupied by public green spaces; (2) area in m^2 occupied by private green spaces; and (3) lagged area in m^2 occupied by public green spaces. These three indicators were selected given the growing recognition that urban green spaces can have a positive impact on physical and psychological well-being, as well as the general public health of urban residents (Wolch, Byrne, & Newell, 2014). When selecting indicators, we accounted for both private and public green spaces to capture the overall presence of open spaces in each grid square. This is because the spatial distribution of green spaces can be unequal, where more affluent areas tend to have larger presence of private green spaces compared to more deprived areas (Barbosa et al., 2007). We also calculated the average area of public green spaces of the adjacent grids as a proxy for neighbouring green space availability captured by our geographically lagged measure of green space, reflecting that most people are willing to travel a short distance to access a public green space (Maat and de Vries, 2006). To identify adjacent cells, we considered the Queen's contiguity method which accounts as neighbouring all cells that share a point-length border (Lloyd, 2010). This method takes into account the equal size of grids – other methods such as Rook contiguity or inverse distance have been proved to perform poorly by a series of goodness-of-fit regression tests (Getis and Aldstadt, 2004).

To measure W*alkability*, we computed five indicators: (1) area in m^2 occupied by roads; (2) area in m^2 occupied by sidewalks; (3) area in m^2 occupied by paths; (4) lagged area in m^2 occupied by sidewalks; and (5) lagged area in m^2 occupied by paths. The selected features were based on the rationale that grids with large areas covered by roads leave less space for activity-friendly environments (Owen et al., 2007). On the other hand, areas with large areas covered by paths and sidewalks, amplify the creation of more vibrant streets (Hess et al., 1999), which in turn enables more social interaction in local neighbourhoods (Talen, 1999).

The way current studies methodologically approach walkability measures varies. Recent studies often incorporate one or more variables regarding population, land use and street network characteristics (Dovey and Pafka, 2019). A collection of studies has focused on using population and land use characteristics, such as population density and mixed land use, to measure local walkability (Leslie et al., 2007). Other studies have used street network characteristics, such as street connectivity (Boeing, 2018), destination accessibility (Witten, ,Pearce, & Day, 2011), total road and sidewalks length (Kotharkar, Bahadure, & Sarda, 2014) and area covered by sidewalks and roads (Galanis and Eliou, 2011) as proxies of walkability. While arguably these measures should be integrated to capture different domains of walkability in a more holistic manner, data availability imposes constraints on what can be done in practice. There is a trade-off between detail in data and temporal availability, here we seek to balance these issues to provide insights into the dynamic nature of the built environment which is often considered as a static feature of places. To measure walkability, we considered the area covered by the road network properties as the preferred approach, due to data for two main reasons: first, because of a lack of data on land use mix and road network for matching years in our study period; and second, due to the focus of this study to highlight the area available for pedestrian use (i.e. area occupied by paths, sidewalks and roads in each grid). We made a distinction between paths and sidewalks, as paths are areas dedicated solely for pedestrian use and are usually found in city centres or in parks. Like for the green space domain, we also considered the values of adjacent grids for paths and sidewalks as a proxy of how walkable an area is. In the Walkability domain, the path and sidewalk indicators are considered as positive measures (i.e. the higher the area covered by paths and sidewalks the more walkable the neighbourhood), while roads as negative (i.e. the higher the area covered by roads the less walkable the neighbourhood). This means that the higher the area occupied by roads, the lower the overall domain Walkability score. On the other hand, the higher the area occupied by paths, the higher the overall domain Walkability score.

2.5. Stage 3: Standardisation and weights

All indicators were standardised by year and have been given equal weights for calculating the domain scores (see Fig. 2). The standardisation process helps comparing all indicators with one another at a particular point in time. We standardised (i.e. using z-scores) the indicators within each domain to a common scale with a mean of zero and a standard deviation of one (OECD and JRC, 2008). Then we chose to use equal weights in each indicator for each domain in the absence of theoretical justification for using different weights. However, as discussed in the Supplemental Material our results do not differ much when using different sets of weights, where most of grids move up or down by one decile in the composite index ranking (S2 and S3 in the Supplemental Material present a sensitivity analysis by using different indicators and weights across domains). Finally, we ranked each grid square based on their corresponding domain score based on data for all 12 areas in our sample. The ranking was a two-level process. Firstly, we ranked the grids for each domain and then we ranked all three domains in the Sustainable Urban Development Index, as discussed in the following section (2.6). The higher the rank, the better the performance of the grids in each domain.

2.6. Stage 4: Sustainable urban development index

Individual domain scores were combined to generate an overall Sustainable Urban Development Index (SUDI). First, grids with no data for a domain indicator are ranked last in the respective domain. For example, an extreme case could involve grids that have only Green space features. In this case, they would be ranked very high in the Green space domain but last in the Compactness and Walkability domains. Thus, the Sustainable Urban Development Index (SUDI) will reflect the overall rank of these grids. The ranks -R- are defined as $R = 1/N$ which indicates best performing grid square; and, $R = N/N$ (i.e. $R = 1$) which indicates the worst performing grid square; N is the total number of grids in the 12 urban areas in our sample.

Second, we standardised the domain scores by ranking them to a range from 0 (worst performing) to 1 (best performing), so they have a common distribution. Then, we scaled the ranking of each domain score (Compactness, Green space and Walkability) R to lie within the range of [0,1].

Then, we combined the individual domain scores to generate the SUDI. This is achieved by transforming the domain ranks to a specified exponential distribution (see Equation (1)). In this way, we ensured each domain score is comparable (with similar distributions) and selected an appropriate method to combine the indicators not leading to high values in one domain but 'cancelling out' low values on another. We calculated the transformed domain score X (e.g. Compactness, Green space, Walkability) using:

$$X = -23\ln\left(1 - R\left(1 - exp^{-100/23}\right)\right) \tag{1}$$

where: 'ln' denotes the natural logarithm, and 'exp' the exponential transformation.

The three domains were weighted to create the overall SUDI. Identifying appropriate weights is a challenging task and there is a large literature suggesting various approaches, including factor analysis, data envelopment analysis and unobserved components models (OECD and JRC, 2008). Following the methodology used by a recently created Composite Index based on UK data and adopted by local government agencies –Access to Healthy Assets and Hazards-AHAH (Green, Daras, Davies, Barr, & Singleton, 2018; Daras, Green, Davies, Barr, & Singleton, 2019), we employed an equal weighting scheme as there is no theoretical justification or empirical evidence to place more importance on one domain over others. Thus, the SUDI derived after adding together all domain scores (post standardisation), by giving each domain an equal weight. As highlighted above, the results are not sensitive to using different sets of weights. Small changes are observed of grids moving only one decile in the composite index ranking as presented in S3 in the Supplemental Material.

2.7. Analytical strategy

Our analytical strategy incorporates both the spatial and temporal change of the SUDI index. First, we analysed the temporal pattern of SUDI index for the 12 FUAs included in this study. Second, we sought to identify areas experiencing large changes in SUDI between 2001 and 2016. We used these two analytical stages to establish the relative change of urban built structure at each point in time from 2001 to 2016. To measure temporal changes in urban structure, we analysed relative changes in the SUDI over a 15-year period. Specifically, we examined relative changes in the SUDI ranking at each time point 2001, 2006, 2011 and 2016.

To analyse the temporal pattern of the SUDI, we classified the grids into deciles based on their SUDI ranking. The 1st decile includes the 10% best performing grids, while the 10th decile includes the 10% worst performing grids. We then calculated the distribution of grids that belong to each decile of SUDI by FUA and year. The same was done for each domain. With this analytical process, we identified areas with high concentration of the best or worse performing neighbourhoods (for each year) as well as differences between FUAs. Hence, we can get a better understanding on the distribution of SUDI index across space and over time.

To identify areas experiencing large relative changes in SUDI at each point in time between 2001 and 2016, we followed a two-step process to create a temporal typology of SUDI change. First, we calculated the absolute difference in the deciles for each grid square (for both SUDI and the three domains) in the overall period 2001–2016 and each sub-period (i.e. 2001–2006, 2006–2011 and 2011–2016). The difference was calculated by subtracting the decile ranking position in t (i.e. 2006, 2011 and 2016) and t-n (i.e. 2001, 2006 and 2011). For the resulting ranking difference, positive scores indicate an increase in ranking, whereas negative scores indicate a decrease. The second step was to analyse the 10% of grids reporting the most change – both increasing and decreasing. We focused on large changes; that is, grids experiencing unusual changes moving over 3 deciles in a ranking composed of 538 grids. S5 in the Supplemental Material provides a diagram illustrating the process of selecting these grids. We identified 304 of which recorded a large increase of more than 3 deciles in the SUDI ranking, and 234 which registered a large decline of more than 3 deciles. We performed k-means clustering analysis to generate a classification of grids following similar trajectories of change. We evaluated cluster solutions by performing 1,000 iterations to achieve more distinct clusters and an elbow curve analysis based on the distance between clusters. A four-cluster was chosen as the optimal based on the evidence from the evaluation of these outcomes. Separate analyses were conducted for grids recording increases and grids recording decreases.

3. Results

3.1. Spatial and temporal structure of changes in urban fabric

Fig. 3 shows the distribution of neighbourhoods (grids) across SUDI deciles by FUA over 2001–2016. FUAs have been ranked from top left to bottom right based on the number of best performing neighbourhoods (i.e. 1st decile) in 2016. The horizontal line indicates the average distribution for each decile (i.e. 10% as we have used deciles) and how each FUA deviates from this line. Our results reveal marked differences across the 12 FUAs in our sample. Out of all, 12–18% of neighbourhoods in Edinburgh, London and Newcastle scored in the best performing decile in 2016, while only 3–7% of neighbourhoods ranked in the best performing decile in Leeds, Southampton and Birmingham. When looking at the worst performing decile, British cities tended to be more similar than when analysing the best performing decile, yet variations exist. Around 13% of neighbourhoods are consistently at the worst performing decile in Manchester, but it accounts only for 3% in Newcastle.

The overall score however conceals significant variability across subdomains. Hence, decomposing the SUDI to its constituent domains reveals considerable variation in their respective contribution (S6 in the Supplemental Material presents line plots for each of the domains). Assessing individual domains shows that the primary urban feature

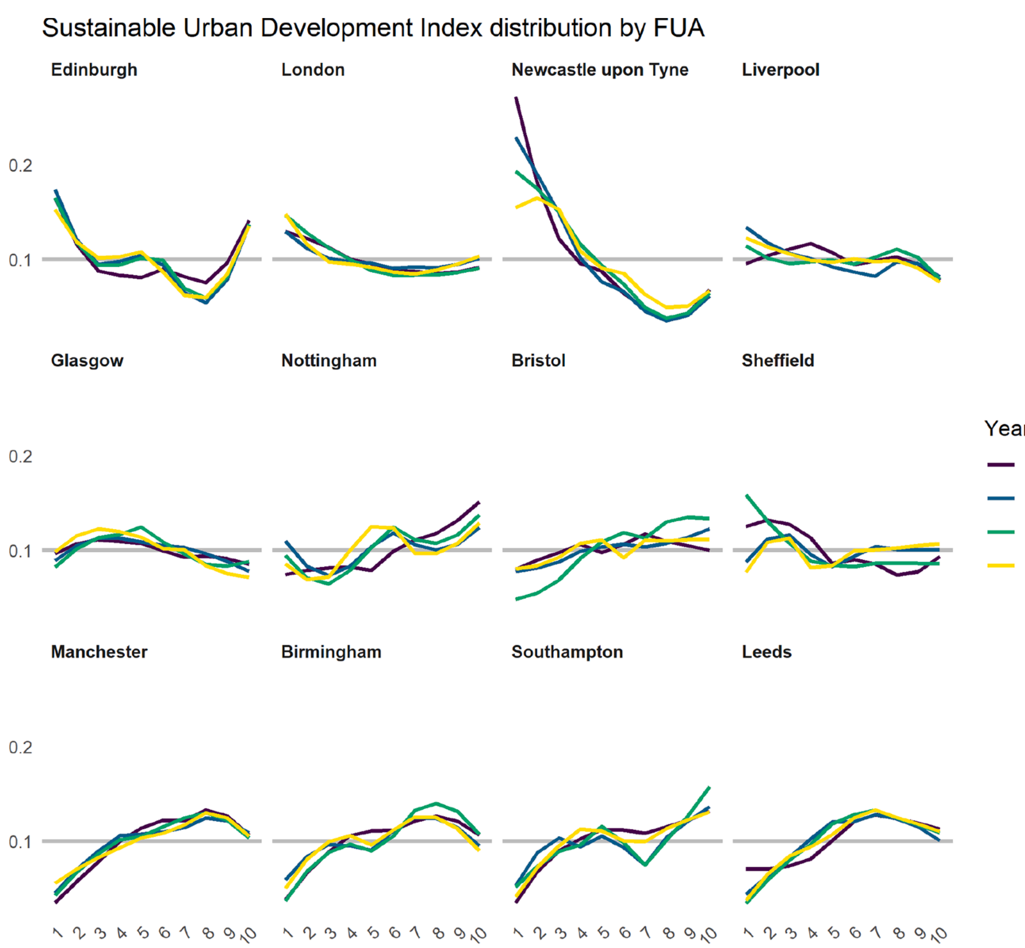

Fig. 3. Line plots of the distribution of grids that belong to each decile of the Sustainable Urban Development Index by FUA and year.

contributing to high SUDI scores in Edinburgh, London and Newcastle differs. Green space drives high SUDI scores in Edinburgh, Compactness in London and Walkability in Newcastle. Similarly, lack of Walkability contributes to a low SUDI score in Leeds, while low Compactness and Green space contributes to low in SUDI scores in Southampton and Birmingham, respectively.

Fig. 3 also reveals remarkable stability in the overall sustainability of neighbourhood as captured by the SUDI. Very little changes in the SUDI distribution are recorded across most FUAs. Focusing on the worst performing neighbourhoods, little changes is observed across most FUAs, except for Nottingham (that recorded a decrease in the share of neighbourhoods in the worst performing decile by 4%) and Southampton (that reported an increase in the share of neighbourhoods in the worst performing decile by 3%).

The situation differs when examining changes in the share of best performing neighbourhoods over time. Unusually large changes are observed for the highest SUDI decile neighbourhoods in Newcastle and Sheffield; that is, from 28% in 2001 to about 14% in 2016 in Newcastle, and from 13% in 2001 to 5% in 2016 in Sheffield. For other FUAs, the changes can be classified into four categories: (1) FUAs that do not change -Birmingham, Bristol, Glasgow and Southampton; (2) FUAs that slightly decreased the share of their neighbourhoods in the best performing decile by around 2–4% -Edinburgh and Leeds; (3) FUAs that considerably decreased the share of their neighbourhoods in the best performing decile by around 8–14% -Newcastle and Sheffield; and (4) FUAs that increased the share of their neighbourhoods in the best performing decile by around 2–4% -Liverpool, Manchester, London and Nottingham. These variations across FUAs reflect differences in the scale and timing of urban restructuring across Britain during the first part of the 21st century.

While differences across British urban areas exist, there seems to be a consistent local spatial pattern. Fig. 4 shows the spatial distribution of SUDI deciles across FUAs in the sample in 2016. It reveals that neighbourhoods in the best performing deciles tend to be in the urban cores of cities, while worst performing deciles in the periphery. Looking at the previous years, we see a gradual increase in the ranking of neighbourhoods in or around city centres (see S7 in the Supplemental Material). Arguably these patterns reflect the geography of implementation of city urban regeneration strategies in British metropolitan areas which have largely focused on revitalising city centres (Hamnett, 2003).

3.2. Long-term trajectories of change of SUDI ranking

To examine the timing and extent of changes in local urban structure across FUAs, we created a typology to capture the relative long-term trajectory of neighbourhood change (i.e. from 2001 to 2016). We performed k-means cluster analysis and identified eight distinct classes of neighbourhood change as discussed in section 2.7. The input data was the absolute difference in the deciles for each neighbourhood (for both SUDI and the three domains) in the overall period 2001–2016 and each sub-period (i.e. 2001–2006, 2006–2011 and 2011–2016. Separate analyses were run for neighbourhoods displaying a decreasing SUDI decile rank change and for neighbourhoods reporting an increasing SUDI decile ranking change.

Fig. 5 shows the resulting clusters (columns) of neighbourhoods moving up and down in the SUDI ranking in separate panels for the overall index and each domain (rows). The top panel shows the changes over the entirety of the period in analysis (2001–16) and the three sub-panels for each of the three sub-periods, 2001–06, 2006–11 and 2011–16 (note that the total change is not the sum of the individual domains for a given year). Cell numbers represent the median decline change in the relevant ranking indicator (rows). Positive values indicate an increase in ranking, while negative values indicate a decrease in ranking (i.e. higher ranking in 2016 compared to 2001 results in a positive number). The first row in each period panel shows the change in

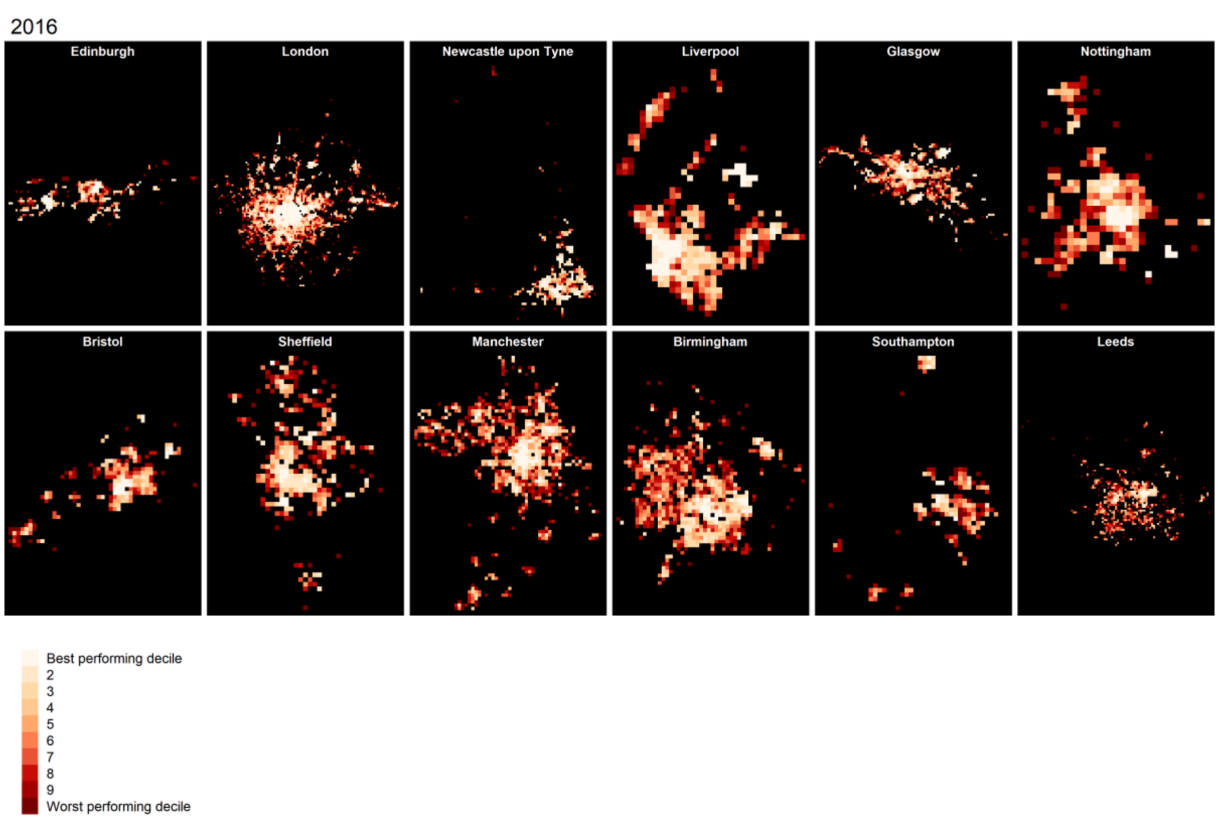

Fig. 4. Maps showing the spatial distribution of SUDI index ranking in 2016. Interactive maps showing the distribution of SUDI deciles can be found in [https://patnik.github.io/sustainable-urban-development-index/].

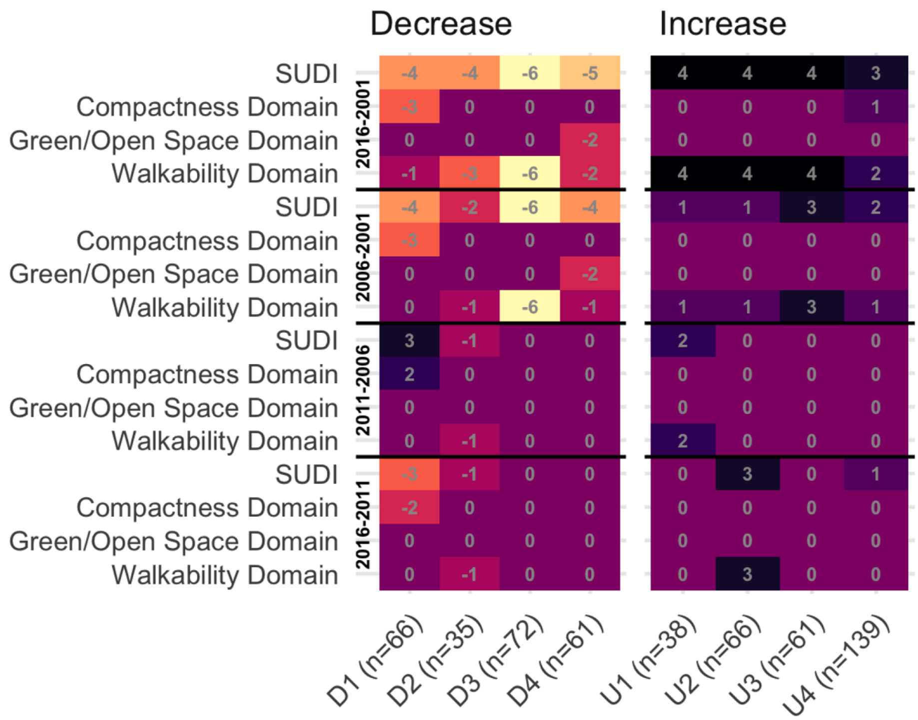

Fig. 5. Median value of decile change in ranking domain by cluster and trend (increase or decrease). The left panel (Decrease) shows clusters moving down in the SUDI ranking. The right panel (Increase) shows clusters for grids moving up in the SUDI ranking. Lighter colours indicate large decreases in the deciles. Darker colours indicate large increases in the deciles.

the overall SUDI ranking, and second to fourth rows display the change in each constituent domain index. For example, a change in the SUDI of 4 would indicate increase from decile 6 in 2001 to decile 2 in 2016.

The identified cluster classification captures distinctive trajectories of relative change. Clusters containing neighbourhoods experiencing a decrease in SUDI decile ranking reveal changes driven by distinctive set of urban features.

- *Cluster D1* encompasses neighbourhoods with a decline of a median equals to 4 in the overall SUDI ranking between 2001 and 2016 driven by a decline in the Compactness index. Urban Compactness seems to have declined during 2001–2006 and 2011–2016 but counterbalanced by rises in the intervening period 2006–2011. Neighbourhoods in this cluster are mainly found in London. Thus, an increase in Compactness domain in the intervening period 2006–2011 coincides with an intense period of urban development in London, resulting from a range of large-scale infrastructure projects undertaken in preparation for the Olympic Games of 2012.
- *Cluster D2* contains neighbourhoods experiencing a decline in the overall SUDI ranking mainly triggered by small drops in the Walkability domain. Drops of 1 decile change occurred in the three sub-periods in analysis but translated in a greater compounded decline of 4 declines in the overall SUDI ranking over the entire 2001–16 period.
- *Cluster D3* comprises neighbourhoods registering the largest declines in the SUDI ranking with a median of 6 deciles driven by reductions in the Walkability domain in 2001–2006.
- *Cluster D4* includes neighbourhoods recording declines in SUDI ranking triggered by reductions in the Green space and Walkability domains particularly in 2001–2006. Cluster D1, D3 and D4 consists of similar number of neighbourhoods. Cluster D2 is of smaller size.

Fig. 5 also displays clusters with neighbourhoods experiencing increases in SUDI ranking decile principally driven by an improvement in Walkability domain but with a differentiated temporal signature. Most clusters capture changes that are related to a single sub-period; that is, 2006–2011 for U1, 2011–2016 for U2, and 2001–2006 for U3. Cluster U4 captures changes in the sub-periods 2001–2006 and 2011–2016. These clusters also differ on their cluster membership size. Fewer neighbourhoods have increased their ranking due to Walkability domain change in 2006–2011 as captured by Cluster U1 and more in the sub-periods 2001–2006 and 2011–2016 as captured by Cluster U4.

There is a clear distinction in spatial arrangement of the neighbourhoods moving up or down in the SUDI index ranking. Neighbourhoods moving up are found mainly in the urban core, while neighbourhoods moving down in the periphery of FUAs. Neighbourhoods in clusters D1 and U1 are predominantly found in London. Neighbourhoods in Cluster U1 tend to be predominantly urban areas, while neighbourhoods in Cluster D1 are prevalently in the periphery. Interactive maps that allow the user to zoom in areas of interest can be found here [https://patnik.github.io/sustainable-urban-development-index/]. S8 of the Supplemental material examines two well-known areas to validate our cluster classification.

4. Discussion

This study developed a composite index for summarising a list of indicators relating to urban structure in Great Britain. It started by calculating 12 individual indicators of urban structure at 1 km^2 grid level that are used to calculate distinctive domain ranks (i.e. Compactness, Green space and Walkability). The domain specific ranks were used to calculate an overall Sustainable Urban Development Index. The resulting index captures the sustainability of the urban structure and the relative change across areas at each point in time based on consistent 1 km^2 grids.

Our study contributes to the literature through the development of multidimensional measures of urban structure. Previous research focused on studying urban structure capturing individual domains separately, ignoring the importance of temporal dynamics of changes, or use coarse geographic levels (Basaraner and Cetinkaya, 2017).

Sustainable Urban Development indicators can also be extended beyond Compactness, Green space and Walkability to Housing, Education and Air quality. However, in the UK these data were not available over the period of study. As such, our proposed methodological framework aimed to facilitate the development of consistent indicators to enable urban comparison across cities, countries at different time points. In our methodological framework, multiple dimensions of the built environment are measured and analysed to identify underlying connections between different built environment features and relative changes over time. Moreover, by capturing multiple time periods at 1 km^2 grid level is proven useful to extract spatiotemporal signatures of urban structure. Although urban blocks provide a more organic delineation of space in cities, hence potentially adapting better to the underlying nature of the urban fabric, there are important advantages of using grids over more detailed urban blocks. Grids provide a geographically consistent geographical framework that can be used for temporal comparisons. Urban blocks are less robust in this sense as changes in one block would significantly alter the relevant indicators. Moreover, grids facilitate integration with other datasets such as satellite images and official national statistics based on varying spatial scales (Office for National Statistics, 2018). Finally, urban blocks could in some cases be riskier for data disclosure, particularly in low-density areas, something that grids allow to overcome. By addressing the above gaps, we provided a methodological framework which can capture the built environment configuration of local urban structures and can guide urban planning interventions to make neighbourhoods more sustainable.

We identified relative changes in the urban structure within FUAs displaying similar trajectories of built environment change. We showed that the proportion of neighbourhoods in the worst performing decile between 2001 and 2016 remained stable in most FUAs. This stability may reflect no real change in these 'worst performing' neighbourhoods but can also be result of overall improvement across the SUDI distribution. In contrast, the change in the share of neighbourhoods in the best performing decile between 2001 and 2016 varied across British FUAs. We identified four groups of FUAs: (1) FUAs recording no change; (2) FUAs displaying small decreases in their share of neighbourhoods in the best performing deciles; (3) FUAs displaying large decreases in their share of neighbourhoods in the best performing decile; and, (4) FUAs displaying increases their share of neighbourhoods in the best performing decile. We identified a uniform increase in the ranking of neighbourhoods in and around city centres, likely a result of public expenditure on redeveloping urban centres or areas of interests, such as waterfronts (Butler, 2007; Thorning, Balch, & Essex, 2019). This can be attributed to the focus of local government on redeveloping urban centres given their perceived importance and contribution to economic productivity (Cottineau, Finance, Hatna, Arcaute, & Batty, 2018); and, on places of public interest (such as blue or green spaces) due to their importance on social wellbeing, interaction and inclusion (Wood, Hooper, Foster, & Bull, 2017).

We proposed a methodology for identifying signatures of relative changes in SUDI at each point in time between 2001 and 2016 in its constituent domains and sub-periods. We identified eight distinct signatures of neighbourhoods to capturing the underpinning nature of the local trajectories of built environment change. We identified four signatures capturing neighbourhoods which experienced relative increase in the SUDI ranking with a distinctive temporal signature of change. The primary built environment feature driving these improvements was an increase in walkable spaces. We also identified four signatures capturing neighbourhoods which experienced a relative decrease in SUDI ranking. These signatures were differentiated by changes in different domains of the built environment. These are Compactness for D1, Walkability for D2 and D3 and a combination of Green space and Walkability for D4.

The proposed method for highlighting the attributing factors of relative change in urban structure over time, can contribute to the growing demand of quantitative tools in urban planning (Nieuwenhuijsen et al., 2017). It can help on identifying successful interventions that can act as -best practice- examples to be applied in areas lacking urban sustainability. By developing appropriate urban planning interventions, decision makers can help promoting the sustainability of cities in many aspects such as reducing inequalities, promoting sustained, inclusive and sustainable economic growth, fostering resilience and protecting the environment (United Nations General Assembly, 2017).

Existing literature notes that the construction of composite indices entails many methodological assumptions that are made by the researchers (OECD and JRC, 2008). In this study, we are open and forthcoming regarding our methodological framework and results by accounting for different decisions that might affect our results with sensitivity analyses (see Supplemental material S1, S2, S3 and S4). One of the limitations of the study is that we put more emphasis on identifying areas that score higher in the SUDI (i.e. using the exponential transformation). This decision means that the SUDI has a limited capacity to capture changes in the built environment for areas with low SUDI scores as they may reflect no real changes but also be the result of an overall improvement along the SUDI distribution, although such situation is highly unlikely. Yet, our method allows to look at changes in the relative ranking in SUDI for areas with high or low SUDI scores, as well as identifying successful interventions that can act as -best practice- examples to be applied in areas lacking urban sustainability. We considered that identifying disadvantaged areas in terms of their built environment qualities relative to other areas at each point in time was important from an urban planning perspective, regardless of whether they experienced a change, or other areas in the country experienced changes. Arguably if an area has not changed and therefore its position in a ranking domain is worse, because of improvements in other areas, that is valuable information that would be relevant to influence local urban planning strategies (Tunstall, 2016). S1 in the Supplemental Material presents a sensitivity analysis by using a pooled dataset (ie. across all years) standardisation. The results are quite robust to changes in the way data are standardised which in turn means that our approach captures both relative changes in grids ranking as well as real world changes in the built environment.

5. Conclusions

This study is a first attempt to provide an analytical framework that captures the relative change of urban built structure at each point in time from 2001 to 2016 in Great Britain. By employing Ordnance Survey's data for the 12 most populous FUAs from 2001 to 2016, we developed a set of indicators capturing three domains (Compactness, Green Space and Walkability) and a composite index at 1 km^2 grid level. Our analytical framework provides a robust tool that can efficiently reveal relative changes in urban structure. Using the Sustainable Urban Development Index and its domain rankings, we can understand differences in the characteristics of urban structure between and within urban areas at each point in time between 2001 and 2016. By establishing the relative increase/decrease in the SUDI ranking, past urban planning interventions can be assessed to inform future planning strategies.

The proposed methodology provides a useful tool to extract information of the urban structure of cities. It captures the main component of relative temporal change in SUDI index, by decomposing to its domains and sub-periods. It can identify key long-term relative change, the timing of these changes and main underpinning source (i.e. urban compactness, green space and walkable spaces). Our methodology can be used as to generate empirical evidence of effective urban planning interventions to guide future urban planning policies at the local level.

Data availability is an important component of this study. Although we make use of the highest resolution data available in Great Britain, our methodological framework could also be applied using freely and continuously improving data such as Open Street Map (OSM) and satellite imagery to get useful insights from other countries as well as the global scale. However, challenges regarding the data will need to be addressed to enable temporal analysis and comparability. While OSM provides an open data source around the world with high levels of completeness for street networks and building footprints (Barrington-Leigh and Millard-Ball, 2017), there is still limited completeness in other built environment features such as pathways (Mobasheri, Zipf, & Francis, 2018). OSM also offers limited temporal coverage looking 10 years in the past where only around 29% of England was covered in 2010 (Haklay, 2010). Finally, satellite imagery also presents challenges. Building a temporally consistent cloud-free imagery composite is very challenging, particularly in countries close to the poles or wet climate, like the UK. This would, for instance, require geometry correction, and cloud detection and correction, which are large-scale undertakings that space agencies and companies are starting to develop (Al-Wassai and Kalyankar, 2013; Lin, Lin, Lee, & Chen, 2015).

Future research could develop this framework further by investigating the relationship and causality between socioeconomic and urban structure change. Such evidence can be helpful understanding the ways urban planning public policy interventions may impact the resident population composition of neighbourhoods and target the development of more inclusive urban habitats. The proposed framework lays out the way to examine future scenarios by forecasting future change in urban structure features, to identify relevant policy areas for reducing inequalities across and within urban areas. This could be expanded further by incorporating domains such as Housing, Education and Air quality to capture more aspects of urban spaces (Koch and Krellenberg, 2018; Giles-Corti et al., 2020). Finally, future research could also investigate the use of higher spatial resolution grids and incorporate information on urban block level to advance our understanding of built environment inequality within urban areas using different geographic levels.

CRediT authorship contribution statement

Nikos Patias: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Francisco Rowe:** Conceptualization, Methodology, Supervision, Writing - review & editing. **Stefano Cavazzi:** Conceptualization, Supervision, Writing - review & editing. **Dani Arribas-Bel:** Supervision, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104148.

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