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Dynamic-IMD (D-IMD): Introducing activity spaces to deprivation measurement in London, Birmingham and Liverpool

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ABSTRACT

Indicators of deprivation intersect a variety of disciplinary contexts. In this article, we build a multi-space measure of deprivation by introducing urban mobilities derived from location footprints of nearly three million mobile phone users. Traditionally, experiences of deprivation have been estimated through a lens fixed to residential spaces, which overlooks the likelihood individuals experience deprivation beyond that implied by where they live. By quantifying how exposure to deprivation varies by human movement patterns across three English cities, we construct a Dynamic Index of Multiple Deprivation (D-IMD). Analysis of this measure highlights how deprivation exposure converges to a more homogenous middle ground, which implies the deprivation gap lessens as individuals across the socio-economic spectrum coalesce in spaces that exhibit similar environmental conditions. Using a hypothetical example, our D-IMD measure identifies 185 neighbourhoods that would enter England's eligibility criteria for funding opportunity intended to alleviate socio-economic inequality and hardship. These practical implications are extensible to international contexts that mobilise deprivation indices in similar ways to English institutions.

1. Introduction

Multi-space deprivation measurement is a critical function towards understanding the conditions of marginalisation and spatially concentrated inequality (Norman, 2010). Insights into the deprivation of urban spaces provide evidence-based motivation for service commissioning to those most marginalised and disadvantaged across cities globally (Allik et al., 2016; Bell et al., 2007; Exeter et al., 2017; Havard et al., 2008). Those most deprived groups suffer a disproportionate burden of health and economic risk, yet are also less likely to be empowered to act upon this, and access resources required to remediate against disadvantage. Without accurate tooling to identify those most deprived at areal-level, cities risk facing demand for more reactive, cost-intensive service provisioning, as opposed to more idealised preventative remediation measures (Bhalla & Lapeyre, 1999). The capture of disadvantage and social deprivation provides fundamental evidence for identifying areas to which resources can be optimally allocated for improving deliveries of policy interventions designed for remediating against urban inequality.

The accurate measurement of deprivation carries cross-disciplinary relevance by informing diverse research avenues, determining policy impacts, and ensuring resources are allocated optimally towards marginalised areas with the highest level of need (Exeter et al., 2017; Phillips et al., 2016). Underpinned by census data, deprivation indices typically combine weighted sets of variables believed to represent the multi-dimensional character of deprivation into a single index score (Norman, 2016). While different national indices of deprivation vary according to the set of included variables and how various items are weighted (Bell et al., 2007; Cabrera-Barona et al., 2016; Havard et al., 2008; Maier et al., 2012; Panczak et al., 2012; Pearce et al., 2006; Pornet et al., 2012; Ward et al., 2019), they commonly include measures of unemployment, material wealth, socio-economic position and housing conditions across census tracts (Allik et al., 2016; Norman, 2016). By combining these measures, deprivation indices typically offer a static snapshot of how neighbourhoods rank among others relative to the conditions of deprivation experienced elsewhere.

In this article, we develop a dynamic deprivation measure that captures the varying degrees of deprivation experiences through individuals' time-space dynamics. Enabled by large-scale, highly granular urban mobility traces, this dynamic measure provides a more nuanced picture of deprivation reflecting the different daily life patterns of people beyond their area of residence. Conditional on obtaining two ingredients, neighbourhood-level deprivation measures *and* mobility

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traces, our applied method has global applicability to various different urban contexts, and offers the opportunity to yield a fresh perspective of deprivation experiences in cities across the world. Moreover, in building a dynamic measure, we present an extension to deprivation measurement that is traditionally undertaken from the sole dimension of space. Deprivation indicators typically explore deprivation from a static, fixed-location perspective inspired from Townsend's (1987) classical definition of relative deprivation, "...a state of observable and demonstrable disadvantage relative to the local community, wider society or nation to which an individual, family or group belongs." These measures assume experiences of deprivation are highly containerised within particular neighbourhoods (Norman, 2016; Ward et al., 2019) (e.g., census tracts (Farber et al., 2012)), and typically estimate relative deprivation through a lens fixed to residential space.

More recently, a rallying theme across urban segregation research argues exposure to varying degrees of deprivation occurs across different socio-geographical contexts (Netto et al., 2015). Deprivation in residential space reflects one aspect of hardship, but ignores the reality individuals may be exposed to deprivation beyond the residential unit of aggregation. Our proposed measure includes both spatiality *and* temporality in framing the conditions of relative deprivation people are exposed to. This approach is motivated by the framework of time geography which describes human activities as anchored to particular places for a certain duration of time (Hagerstraand, 1970). Moreover we operationalize the concept of *activity spaces* (Farber et al., 2015; Osth et al., 2018; Silm & Ahas, 2014b; Toomet et al., 2015; Xu et al., 2019), that differences in how daily activity spaces of visited locations provide a basis to understand exposure to varying conditions of deprivation, which we use to reveal differential patterns among neighbourhoods across the urban fabric. While traditional measures isolate deprivation experiences by the area of residence, our dynamic measure introduces activity spaces to account for exposure and interaction between different areas. Using urban mobility traces, we reveal changes between how residents of one area experience varying levels of socioeconomic (dis) advantage as they interact with different areas of the city when compared to their residential space. We believe such a perspective is more compelling in contemporary societies with growing freedom of travels as people are less bounded to the neighbourhoods around their home (Zhang et al., 2019).

We further argue this new perspective offered by a dynamically-enabled measure of deprivation carries significant impact on multiple research avenues across different urban contexts. Firstly, we contribute to new global knowledge on deprivation measurement by introducing an approach that carries applicability to cities globally, conditional on obtaining two essential ingredients: neighbourhood-level deprivation measures *and* large-scale mobility traces. Our applied method and findings offer a fresh perspective for identifying deprivation that aligns with a rallying theme in urban segregation research that argues both *spatiality* and *temporality* frame experiences of deprivation in contemporary society. With this trend emergent across cities globally, we argue our contribution is perfectly placed to incorporate activity spaces into the measurement of deprivation. Secondly, we find interesting relationships between our dynamic measure of deprivation and the underlying urban landscape, which carries implications for providing alternative ways for addressing deprivation in urban renewal projects. Finally, as traditional deprivation measures have been highly influential on policy decisions and public resource allocation across cities globally (Ajebon and Norman, 2016; Bell et al., 2007; Cabrera-Barona et al., 2016; Harris & Longley, 2002; Havard et al., 2008; Landi et al., 2018; Mitchell & Norman, 2012; Norman, 2016; Pearce et al., 2006; Ward et al., 2019) our approach also carries several practical policy implications. We illustrate this with a hypothetical thought experiment which shows potential changes of eligibility for public expenditure in 185 neighbourhoods across our three English cities. While we demonstrate this in reference to a concrete example based on England's neighbourhood-level deprivation data, we note how similar exercises and reinterpretations of deprived spaces might be enabled with a similar exercise across cities globally.

2. Literature review

2.1. Indicators of deprivation

Area-based deprivation indices, typically constructed from census data, have been highly influential to understanding and describing whether the deprivation of places have an independent effect on well-being beyond that of individual socioeconomic circumstances (Allik et al., 2016). In turn, deprivation measures are often used to allocate public resources to areas identified as suffering disproportionate hardship, alongside determining the impact of policy interventions intended for remediation (Phillips et al., 2016).

As mentioned, all national deprivation indices are defined based on fixed spatial divisions that containerise deprivation within particular neighbourhoods. The differences among the indices are in the input variables, geographical scale and method of combining them to a single index score. Commonly considered input variables include unemployment, material wealth such as car ownership or income, and socioeconomic position, particularly factors like education and housing conditions (Allik et al., 2016; Norman, 2016). Deprivation measures have been proposed in a number of different countries, with the set of input variables chosen according to different national priorities and contextual variation. While England's Index of Multiple Deprivation (IMD) (McLennan et al., 2019) is the most matured, efforts to develop deprivation indices have emerged across many different countries, including: Scotland (Allik et al., 2016), France (Havard et al., 2008), Canada (Bell et al., 2007) and New Zealand (Exeter et al., 2017). Endeavours have also focused on innovating different techniques and datasets to construct deprivation indices, including multi-criteria and principal component analysis (Cabrera-Barona et al., 2015; Lalloue et al., 2013), alongside the use of commercial big data to compliment their construction (Wami et al., 2019). Finally, a cohort of works focus on optimising the scale of aggregation used by reporting units, and how this impacts deprivation indices when the same data are grouped at different spatial resolutions (Stewart et al., 2018).

More recently, a focus on how household deprivation is amplified by the deprivation in wider, surrounding areas has emerged in the literature (Burke & Jones, 2019; Green et al., 2018). Decreased accessibility to certain resources and environmental features have been linked to lower qualities of life for poorer residents who, for example, might face financial constraint with respect to transport access (Le Zhang & Pryce, 2020). These works share the motivation of our work that deprivation and inequality extend beyond an individual's residential environment, and attempt to measure deprivation considering their access to urban resources (e.g., transport, health, schools) or functional areas (e.g., recreational/business areas). While these works extend the measure to go beyond the fixed areas of residence, our work takes a step further by reflecting the actual activity spaces of the people.

2.2. Motivating activity spaces

Increasing individual mobilities within contemporary society has led researchers to recognise hardship extends beyond where individuals live, and applies to where people experience isolation from, or exposure to, the day-to-day life spaces of other groups (Zhang et al., 2019). This line of enquiry includes the spatialities *and* temporalities inherent in daily mobility that frame the conditions by which material wealth, socio-economic position and housing conditions between people from different residential neighbourhoods take place (Netto et al., 2015).

To capture the degree of exposure within the interaction channels of different groups, studies typically adopt the concept of *activity spaces*. At the individual-level, an activity space is the set of visited locations traversed as a result of day-to-day activities (Golledge & Stimson, 1997).

Differences in how daily activity spaces are shaped provide a basis to understand exposure of different groups to various conditions. Such a view extends from the concept of *homophily*, that individuals sharing similar traits will tend to associate, which regresses to a state of segregation when certain types of contact are prevented among socially different actors (Brun & Chauvire, 1983; Netto et al., 2015). The longer an individual meaningfully interacts within locations characterised by social, environmental or economic conditions different to their residential environment, the less they experience segregation (Park & Kwan, 2018). Thus, activity spaces can be examined to reveal patterns of use across the urban fabric. Systematic differences in activity spaces between social groups infer different day-to-day territories, which lessen the likelihood of interaction. Affluent individuals, for example, might choose to use well-designed, enclosed sites or privatised exclusive facilities (like sports clubs), which isolate the socially advantaged from the disadvantaged (Zhang et al., 2019). Low material well-being among low income groups limits participation to large numbers of out-of-home activities, which drives the process of marginalisation (Toomet et al., 2015).

2.3. *Activity space-based segregation research*

While activity space-based approaches have yet to be introduced directly to neighbourhood-level deprivation measurement, a rich cohort of studies have explored urban segregation through this lens. These studies seek to examine the full spectrum of inequality, thereby addressing the so-called Uncertain Geographic Context Problem (UGCoP) (Kwan, 2012). The UGCoP posits that associations between neighbourhood units and individual behaviours may be misspecified due to errors resulting from the individual's true spatial and temporal context remaining unknown. While the UGCoP is seemingly related to geography's modifiable areal unit problem (MAUP), it differentiates because it is not due to using different zonal schemes but instead due to using arbitrary areal units for area-based variables that lack knowledge of precise spatio-temporal configuration of social factors influencing individual behaviours. Therefore, the UGCoP poses serious inferential challenge and is a fundamental methodological problem. Mitigating the UGCoP has seen urban segregation research moving beyond the residential realm which anchored much previous research in this area, but ambiguity remains in how activity spaces are conceptualised. Typically these studies operate on a continuum between *people*- and *place*-based measures of segregation (Shen, 2019).

Place-based measures focus explicit attention on the geographical properties of daily activity spaces. Studies estimate the spatial extent of day-to-day trajectories using techniques such as standard deviational ellipses (Schönfelder & Axhausen, 2003) and minimum convex hulls that connect all visited locations of the individual by straight lines (Buliung & Kanaroglou, 2006). This direction assumes places within the polygon boundaries are inclusive of the individual's activity space, therefore likely including large swathes of unvisited locations. For example, in Beijing, China, Wang et al. (2012) and Zhang et al. (2019) visualised activity spaces of residents inside and outside privileged enclaves and across different housing types, respectively, finding statistical differences between how different social groups access urban spaces. Problematically, both studies fail to take account for actual social interactions in their activity space analysis, although their contribution cannot be discounted too far owing to the difficulty in attaining such information. Moreover both use travel behaviour survey data which is typically time-consuming and costly to reproduce. Elsewhere, Zenk et al. (2011) found types of occupation were significant predictors of an individual's activity space size in Detroit, United States. Yet their contribution was limited by potential seasonality biases of the data collection period that coincided with the coldest weather and fewest hours of daylight. These conditions unconducive to outdoor physical activity could have led to failure in identifying credible relationships between land use and activity spaces. Krivo et al. (2013) classified activity spaces of different ethnic groups into advantaged and disadvantaged, evaluating the degree of exposure between the out-of-home routines of different groups. Critically, the authors recognise research in this area should examine the *consequences* of spatial inequality in neighbourhood access with varying socio-economic characteristics in order to build comprehensive understandings of social isolation. More generally, a well-known conceptual problem of describing activity spaces using geometric representations is they often erroneously include an extensive number of unvisited locations (Wong & Shaw, 2011). Moreover, Shen (2019) argues these works often measure place-based segregation from static perspectives that simplify the temporal dynamism of mobility patterns, with Farber et al. (2015) adding this line of enquiry often fails to generalise findings into replicable or transferable measures of exposure.

People-based measures offer an alternative approach, measuring exposure through intersection of individual geographic contexts (derived at finer spatio-temporal resolutions) with static census-based measures (Farber et al., 2015). Proposed instruments typically involve exploration of space-time paths. Human activities are anchored to particular places for a certain duration of time, meaning space and time are inseparable (Hagerstraand, 1970). Under this time-geographic conceptualisation, Farber et al. (2013) develop indicators of 'social interaction potential' derived from overlaps between the space-time prisms of individual mobility traces, which reflect the feasible spatial and temporal zones individuals can participate within. However, their metric is insensitive to some details of individual-level space-time trajectories, capabilities and constraints. For example, their measure cannot be used to estimate probabilistically the likelihood of actual joint activity between individuals, but is more focused on the way urban form, transportation and commuter flows inhibit activity space participation. Park and Kwan (2018) use daily travel surveys to explore multicontextual segregation across various geographic and temporal contexts within people's daily lives. However, while their proposed segregation index does take into account various daily life contexts, it cannot capture segregation occurring at micro scale - within workplaces and buildings, however. While arguably these would be difficult to obtain, such "micro inequalities" have powerful effects on the reproduction of segregation within different spaces (Creese, 2017). Finally, Le Roux et al. (2017) examine similar data to map the hourly changing segregation experienced by individuals with different educational backgrounds. Yet, their conclusions are based on samples of daily trips during the weekday, ignoring weekend trips due to small sample sizes during this period. This limitation is significant because under conventional working patterns, weekends are critical points of social mixing.

Elsewhere, fine-grained social media data has been used to explore socio-spatial inequality (Shelton et al., 2015), and to infer isolation across neighbourhoods of different race and income characteristics in fifty North American cities (Wang et al., 2018). Most recently, mobile phone location data has been used to infer the degree of exposure between population groups. Xu et al. (2019), for example, couple location footprints documented by call detail records (CDR) with people's socioeconomic status to understand dynamics of spatio-temporal and social-network segregation in cities. A limitation of this study, and all studies that use similar data, is that the analysis is limited to active phone users, meaning certain demographic tiers (e.g. elderly individuals who tend to be less frequent mobile users) might be under-represented. This limitation is particularly pertinent in the case of Xu et al. (2019) because the dataset was collected in 2011, a time when online messaging will still in its infancy, which potentially distorts the distribution of their applied measure. CDR data has also been used to explore temporal variation of ethnic segregation in Tallinn between Estonian and Russian-speakers (Silm & Ahas, 2014b) and to understand co-presence between different ethno-linguistic groups (Toomet et al., 2015). Critically, both studies rely on the same sample of passive mobile positioning data derived from a single cellular operator, raising questions of generalisability to the whole population of Tallinn and in different urban contexts. Finally, in Sweden, Osth et al. (2018) combine daily mobility data with detailed socio-economic residential statistics, showing mobility alleviates segregation for certain individuals, but remains in others even when daily mobility is accounted for. Yet their data are limited to a single day, a Tuesday, which raises generalisability limitations of their research. Overall, despite the noted limitations which share commonality across many works in this area, examining urban mobility using mobile phones has shown to be highly promising across recent segregation studies (Dannemann et al., 2018; Jarv et al., 2018; Silm & Ahas, 2014b).

Across the past few years, the concept of activity spaces has become increasingly influential to investigations of urban segregation that extend beyond the traditional focus on residential environments. Under similar motivations to these previous works, in this paper we argue a research gap can be addressed by introducing activity spaces to the measurement of neighbourhood-level deprivation. Using urban mobility traces, we identify how residents of particular neighbourhoods experience varying degrees of exposure to different conditions of deprivation when compared to their residential environment. In doing so, we reveal differential patterns among neighbourhoods across the three cities when compared to the static, fixed-location perspective yielded from the IMD. While we illustrate our proposed measure with the example of urban segregation, we note this finding as one possible outcome from this work, as more generally this paper introduces a new framework for building a dynamically-enabled measure of deprivation. Therefore, we envisage our dynamic measure of deprivation to open other interesting use cases and questions that build understandings of social mixing and interaction within cities that include segregation, but also extend beyond.

3. Data

3.1. Index of Multiple Deprivation (IMD)

Our proposed, dynamically-enabled measure of deprivation, the D-IMD, is built upon the Index of Multiple Deprivation (IMD) (McLennan et al., 2019). We take the IMD 2019, the latest iteration of a national survey carried out by the UK Ministry of Housing, Communities and Local Government. IMD measures conditions of relative deprivation as a composite index, spanning seven weighted domains reflecting different facets of deprivation, including: income (22.5%); employment (22.5%); education, skills and training (13.5%); health and disability (13.5%); crime (9.3%); barriers to housing and services (9.3%); and the living environment (9.3%) (McLennan et al., 2019). IMD is measured for small area statistical unit known as Lower Layer Super Output Areas (LSOAs). LSOAs are administrative boundaries that reflect the principal neighbourhood geography that UK government census statistics are produced for. LSOA boundaries are designed to accommodate similar population size and social homogeneity, hosting an average of 1614 residents or 650 households in and around the UK (ONS, 2016). In our study, we observe an uneven number of LSOAs across the three cities, with there being 4835 LSOAs in London, 639 LSOAs in Birmingham and 298 LSOAs in Liverpool.

3.2. Human mobility traces

To understand the exposure of individuals to different conditions of deprivation across their daily activity spaces, we use anonymized mobility traces from nearly 2.8 million users. These are passively collected by radio access events of user mobile devices across the cities of London (2,357,760), Birmingham (282,195) and Liverpool (152,124). Radio access events refer to interactions between individual mobile phones with telecommunication networks, and their logs capture device handovers as a user attaches and detaches between antennas based upon the quality of the connection, normally choosing an antenna proximate to the device. Therefore, radio access events are collected passively, even where the mobile phone user is not actively receiving or transmitting data.

By tracking devices handovers as users attach and detach between different antennas, we estimate near continuous mobility traces of individuals across our three urban contexts. Our data distinguishes from those used in prior works that require manual user actions, which are far sparser in terms of spatio-temporal granularity (e.g. CDRs or geolocated social media check-ins (Noulas et al., 2012; Onnela et al., 2011; Shelton et al., 2015; Wang et al., 2018; Xu et al., 2019)). Only cell phone towers within each city's urban boundaries as defined by official Local Authority District definitions (ONS, 2019) were used in this analysis. In regards to the representativeness of the data, mobile phone internet use penetration is typically high across male and females, 80% and 78%, respectively, and while ownership rates are expected to decline with age, the share of people over the age of 55 who own a location-aware device is growing (Statistica, 2020). In the UK, while mobile phone penetration is ubiquitous across younger demographics, up to 87% of 55–64 year olds own a smartphone, with 65% among the 65+ group in 2020 (Statistica, 2020).

Our chosen cities represent the major population and cultural areas of England, reflecting the South (London), the Midlands (Birmingham), and Northern England (Liverpool). Moreover, they each reflect different tiers in the hierarchy of English cities, with London as the preeminent capital, Birmingham as England's second city, and Liverpool as a Northern powerhouse of commerce and industry. We collect data for these cities during the month of January 2020, which is provided by a major telecommunication operator in the United Kingdom. One limitation of this chosen month is potential seasonality biases in the data collection period. January coincides with the coldest weather in the UK, and these conditions maybe unconducive to outdoor physical activity, which may potentially limit individuals realising their true activity spaces.

The location of the devices is approximated from the spatial coverage area of the antennas, estimated through Voronoi tessellation. This means we create an antenna polygon for each antenna, which forms a mosaic of polygons across each city (see Fig. 4.1). Depending on the density of antenna deployment, the mobility traces estimated from which antenna polygon a user is located within (and connected with) can be as fine-grained as LSOA neighbourhood tracts,[1] but become increasingly coarse with sparser deployment across physical space.

4. Methods: building a dynamic measure of deprivation

We conceptualise Dynamic Index of Multiple Deprivation (D-IMD) scores as the average degree of exposure to the conditions that define a location's deprivation status, which also range from 0 to 100 like IMD scores. Intuitively, the D-IMD measure can be understood as the outcome of *dipping* a mobile device's location footprint among the composite deprivation conditions users are exposed to across their activity spaces. We define these scores for individual mobile phone users based on their movement across geographical space, which we then aggregate at two geographical scales, city-level and neighbourhood-level. The space-time trajectories unique to mobile users lead to different patterns of deprivation exposure for each individual as they leave their residential neighbourhoods.

We begin constructing a dynamic measure of deprivation based on urban mobility derived from the location footprints described earlier.

[1] Our collection of this data has been performed in light of growing concerns to big data ethics (Metcalf & Crawford, 2016), meaning we ensured the importance of assuring privacy guarantees when using home detection and trip identification. Concerning privacy, every device is assigned a pseudonymous device ID and no personally identifiable information such as name, age or address are included in the data, with our findings themselves presented at aggregated scales across whole cities or LSOA statistical units.

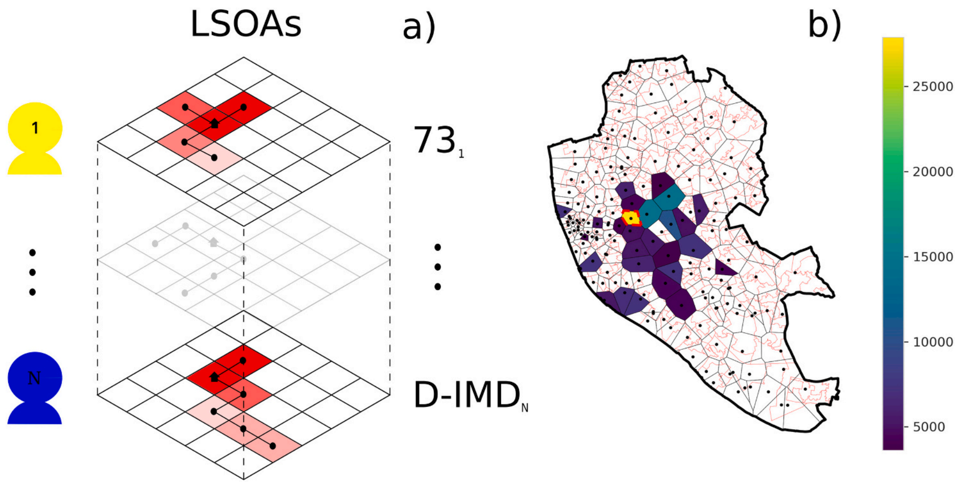

Fig. 4.1. A) Example aggregation of D-IMD scores for N users in a single LSOA neighbourhood across a hypothetical grid of LSOAs. Darkness of red proportional to time a user spends in a particular LSOA. Right-most number reflects average IMD score of a user's visited LSOAs, weighted by duration of time spent in these locations, which generates the user-level D-IMD score. B) Number of seconds spent within visited antennas for one hypothetical user in the city of Liverpool. *Note*: residential antenna marked by the dashed red border. Additional antenna masts represented by small black points with their corresponding Voronoi cell shown by black polygons. Lower Layer Super Output Area (LSOA) boundaries shown by the light red polygons. Mismatch between the antenna polygons and LSOA geographies illustrates the areal interpolation problem. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This first involves measuring the exposure each individual phone holder experiences to different degrees of deprivation based on the duration of time spent within particular areas (see Fig. 4.1).

We formulate this problem by presenting a collection of individual device holders for each city, whose location footprint can be represented by a sequence of visited areas, $[(t_1, IMD_1),(t_2, IMD_2),\ldots(t_a, IMD_a)]$, where t_a reflects the duration of time spent within the visited area a, and IMD_a represents the IMD value assigned to a. Such information allows us to create – at the individual level – a D-IMD score that measures the aggregate exposure users face to varying conditions of deprivation,

$$D\text{-}IMD_i = \frac{\sum_{a=1}^{n} t_a \cdot S\text{-}IMD_a}{\sum_{a=1}^{n} t_a} \tag{4.1}$$

where $D\text{-}IMD_i$, for individual i, is computed as an average over the deprivation conditions experienced within the number of different areas visited a, weighted by the duration of time spent there, t_a. Thus, $D\text{-}IMD_i$ computes aggregate exposure to deprivation experienced between the hours of 08:00 am to 23:59 pm, assuming this temporal window reflects the time period individuals might typically leave their residential environment to traverse their day-to-day activity spaces. While this chosen temporal window reflects the typical time duration individuals spend among their residential environment during the night, we concede some individuals might exhibit lifestyle patterns that require early morning commutes, around 04:00 am, for example. While true, we argue these are *not* the atypical working patterns for the vast majority of the UK labour force, meaning our chosen time window remains valid in spite of this concern. We support this decision choice with an empirical validation that suggests polarisation in socio-economic class is not distinct enough in our case study, and that individuals are generally stationary during extreme night hours. For all individuals during the night hour window between 23:00 pm and 08:00 am, we measure the ratio of instances where the spatial deviation of a person was greater than two kilometres, finding this to be less than 5% of individuals in our sample. This supports our argument that individuals are *generally* stationary during the night-time hours. In committing to this decision, we focus attention to our phenomena of interest, daily activity spaces, and prevent $D\text{-}IMD_i$ being over-weighted by the time t_a spent where individuals are likely to be at home overnight.

$D\text{-}IMD_i$ is computed for each user, and we perform two separate aggregations to develop our findings. Firstly we aggregate at city-level by simply averaging over all users. Then separately, we also aggregate to summarise the average exposure that users in each residential area experience across the month. This is calculated simply as,

$$D\text{-}IMD_a = \frac{1}{N_a} \sum_{i=1}^{n} D\text{-}IMD_{ia} \tag{4.2}$$

where $D\text{-}IMD_a$ is an average over the sum of individual $D\text{-}IMD_{ia}$ values in a by the number of phone holders whose residential location is designated as N_a.

There are two challenges in computing the above D-IMD measures. The first is the mismatch between the boundaries of antenna polygons and LSOAs: as described in Section 3.2, the visited areas are estimated from the antenna polygons whereas the IMD values are based on LSOAs. The second, the neighbourhood-level (i.e., LSOA) aggregation of individuals' D-IMD requires identifying the home area of the people. We below describe how we address each challenge.

4.1. Mapping between LSOA neighbourhoods and antenna polygons

In order to reconcile between the mismatch of antenna polygons and LSOA neighbourhood boundaries (see Fig. 4.1), we create a mapping between each antenna polygon and the IMD score of LSOA neighbourhoods. This means we assign each antenna polygon an IMD score, and by measuring which antennas individuals connect with across the month, we summarise the conditions of deprivation people encounter across their daily activity spaces. We frequently observe finer average granularity for antenna polygons (0.33 km^2) than LSOA neighbourhoods (0.37 km^2). In larger urban areas, the deployment of phone mast antennas is higher due to servicing of a denser population, meaning the size of an antenna's coverage is potentially smaller than the overlapping LSOA boundary. Conversely, coverage may span across multiple LSOAs in more remote neighbourhoods covered by fewer antennas, meaning the antenna polygons are far larger. To overcome this mismatch, an areal interpolation between the antenna polygon and LSOA boundary is designed to assign each antenna an IMD value, IMD_p, based upon a weighted average of the overlapping LSOA, where the weights are proportional to the area of overlap between the antenna coverage polygon and the corresponding LSOA boundary,

$$IMD_p = \frac{\sum_{j=1}^{n} area_{pLSOA_j} \cdot IMD_{LSOAj}}{\sum_{j=1}^{n} area_{pLSOA_j}} \tag{4.3}$$

where IMD_{LSOAj} represents the IMD value of LSOA j that overlaps antenna polygon p, and $area_{pLSOAj}$ is the area of overlap between p and LSOA j. Residents are assigned a IMD_p value based on their home antenna, and to build a dynamic measure, we extend this measurement to record other antennas that people connect with across their activity spaces between 08:00 am and 23:59 pm. As a validation exercise, we assess the extent of dispersion present in the LSOA IMD values that overlap the antenna polygons. A high standard deviation would infer the antenna polygons overlap LSOAs with highly diverse IMD values, meaning the IMD_p value is less reliable. As shown in Fig. 4.2, across the three cities, 80% of the standard deviations for each antenna polygon are less than ten for London, and fifteen for Birmingham and Liverpool, which we tolerate as an acceptable range of dispersion. Interpolating IMD scores from LSOA neighbourhoods to antenna polygons means we can estimate deprivation exposure based on which antennas individuals connect with. After computing this mapping, we can then aggregate over all individuals at city-level, but also at the antenna-level (i.e. Eq. (4.2)), which requires us to detect the homes of individuals described in the preceding paragraph. To transform D-IMD scores of individuals whose home is identified at a particular antenna polygon back to LSOA neighbourhoods we use a reverse of the transformation applied in Eq. (4.3). This means, for every LSOA neighbourhood, we have an area-level D-IMD score for which we can compare to the official IMD scores provided by the UK Ministry of Housing, Communities and Local Government.

4.2. Home detection

Building a neighbourhood-level indicator of dynamic deprivation requires identifying residents of each LSOA. While there are many methods for identifying residences from mobility traces, they commonly aim to isolate activity regularity during the evening and/or weekends (Bojic et al., 2015; Kung et al., 2014). A method for home antenna detection is developed using this intuition but that is specific to the data employed here. We infer home residential locations using a simple heuristic that identifies regularity in diurnal patterns. Across the month, devices remaining within the same antenna polygon between 00:00 am to 08:00 am across a two week period are resolved as a user's home location, while remaining devices failing to satisfy this criteria are discarded from the dataset. To ensure spatial accuracy, the radius of gyration is employed to estimate the spatial deviation of a device and filter out the days when the estimated radius is larger than 2 km. When mobile phone users are below the 2 km radius of gyration period for at least 14 days during the month, the home antenna is allocated to the given individual.

5. Results

In this section, we discuss the implications of our main findings in several directions. In the *first* sub-section we discuss how when taking into account a dynamically-enabled picture of deprivation, we observe highly differentiated patterns from the static picture shown by the IMD. This revealing is important because it shows cities can yield a fresh perspective on deprivation conditions when taking into account urban mobility. In the *second* sub-section, we aggregate our estimated D-IMD scores into neighbourhood statistical units and compare differences between the IMD and D-IMD at the neighbourhood level across the urban landscape. In this way, we learn whether convergence is observed throughout the whole city or is restricted to particular places, and further explore convergence across the socio-economic spectrum. Finally, in our *third* sub-section, we explore the magnitude of difference between the IMD and D-IMD scores at neighbourhood-level, in order to recover instances of strong departure between the two. This research direction is meaningful because it provides indication of whether inter-city differences occur between IMD and D-IMD scores, which is suggestive of whether there are deviations between the static and dynamically-enabled landscapes of deprivation. Drastic changes in the IMD and D-IMD scores could mean neighbourhoods now quality for government remediation resources that are allocated based upon these scores, which has implications to cities worldwide that use scores like the IMD to address socio-economic disparity. In culmination of these three findings, we demonstrate an enriched picture of deprivation that is uniquely enabled through use of location-aware devices, which have the

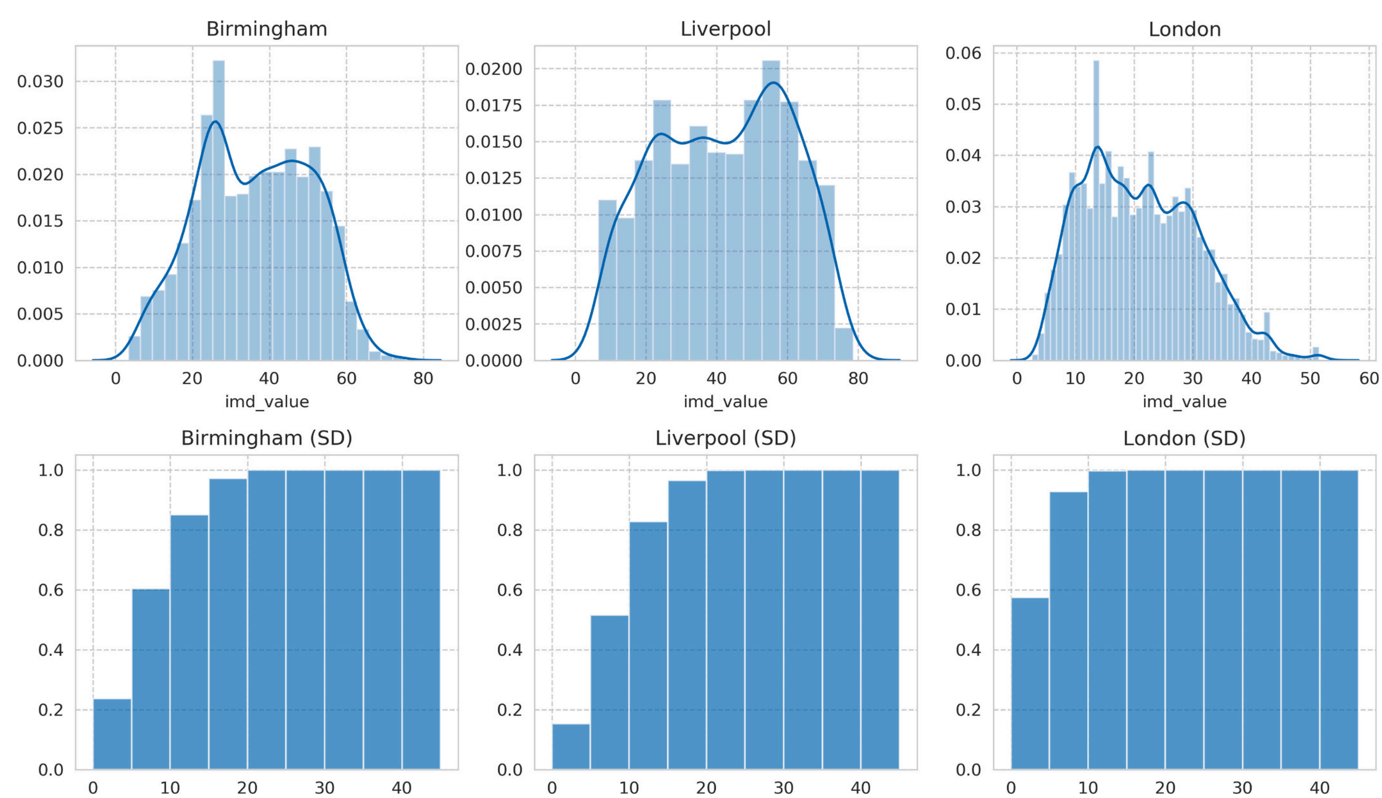

Fig. 4.2. First row shows the probability density of IMD_p across the three cities. Second row shows cumulative probability density histograms of standard deviations for LSOA IMD scores that overlap each antenna polygon.

potential to yield new, actionable insights to solve issues of urban disparity across cities globally.

5.1. Deprivation convergence

Our analysis opens by visualising the distribution of D-IMD scores for individual mobile phone users. The violet curves of Fig. 5.1 provide an overview of the D-IMD scores for users across our three urban contexts. We overlap this result with the original IMD scores of LSOA neighbourhoods among the three cities (visualised in green curves) in order to compare the distributions and assess deviation between the two.

Across the three cities, a consistent pattern of *deprivation convergence* emerges where the densities of individual D-IMD scores appear to be higher peaked with thinner tails compared to the density of original IMD neighbourhood scores. This higher kurtosis suggests that people coalesce in spaces that exhibit similar degrees of disadvantage when people leave their home, and day-to-day exposure to deprivation generally converges towards a more homogeneous middle ground. People who reside in less deprived areas spend time in relatively more deprived areas, and vice versa. This smoothed, continuous picture of dynamic deprivation invoked by the D-IMD measure stands in contrast to the discontinuous measure of deprivation that are typically identified from traditional lattice-based geographical units like the IMD.

While one could speculate the deprivation convergence is a statistical artifact of the weighted averaging across the IMD scores, we instead find the convergence to be based on collective mobility choices. For example, rather than convergence we recover some counter examples, i.e., deprivation divergence, across each city. Around 1.6%, 5.2% and 6.3% of individuals in London, Birmingham and Liverpool who are in the top 50% most deprived areas appear to show a D-IMD score of worse deprivation than the IMD score of their home area. For the other half, 10.3%, 2.6% and 1.3% of individuals in the top 50% least deprived areas of the three cities appear to show the opposite, a D-IMD score of less deprivation. We further elaborate upon possible outcomes other than deprivation convergence in the Discussion and concluding remarks section.

Of note to inter-city variation, London appears to show significantly less variance in the original IMD among the LSOAs than the other two cities. As deprivation convergence further takes place upon a relatively homogeneous urban IMD landscape, the D-IMD distribution also shows a much higher kurtosis than those of the two cities. We comment on this difference throughout the paper as it is reflected in the subsequent analyses.

5.2. Consistency across the urban and socioeconomic landscape

Having measured individual-level D-IMD scores, we now aggregate these scores upwards to the LSOA neighbourhood scale. The notion is to build a measure describing the average degree of deprivation individuals in particular LSOAs are exposed to as a result of their day-to-day movement across physical space. The measure allows us to directly compare the static impression of deprivation from the official government IMD source with our dynamic D-IMD variant. As described previously, using each individual's estimated home antenna location, we average every individual's D-IMD score within a particular antenna, and finally use a reverse mapping to translate these aggregate antenna values back to LSOA geographies.

As a result, it is possible to explore the variation between D-IMD and the original IMD of the LSOAs across the urban landscape. Fig. 5.2, which shows variation over the map of our three cities, demonstrates that deprivation convergence is generally observed throughout the whole city rather than being restricted to particular areas. Comparing the colour contrasts of the choropleth maps of the original IMD and D-IMD, we note that the colour contrast is milder for the D-IMD maps. The LSOAs that have darker colours in the original IMD map shows a lighter colour in general, indicating that the deprivation score of the most deprived areas decreases when taking account of their daily mobility, and vice versa.

We also measure the observed deprivation convergence along the socioeconomic spectrum. The variation between D-IMD and the original IMD is broken down by the socioeconomic groups inferred from the IMD decile assigned to each neighbourhood. An IMD decile is calculated by ranking the 32,844 LSOA neighbourhoods in England from most deprived to least deprived, dividing them into ten equal groups. Neighbourhoods in the first and second IMD deciles are, for example, among the top ten and 20% *most* deprived areas nationally, while the ninth and tenth deciles represent the top twenty and ten *least* deprived neighbourhoods, respectively.

Fig. 5.3 visualises the distribution of IMD and D-IMD scores across the IMD deciles along the horizontal axis for every LSOA across of the three urban contexts. The figure demonstrates consistency of the deprivation convergence across the socioeconomic spectrum in all three cities. On the most deprived end (decile 1 and 2), the deprivation score decreases drastically when we account for D-IMD. In London, for example, the D-IMD score medians in IMD deciles 1 and 2 are 10.23 and 6.32 units lower than the IMD score medians, respectively, which trend is reciprocated in Liverpool and Birmingham albeit with less magnitude. We observe continuity in this trend until decile 3 in Liverpool and Birmingham and decile 5 in London. Afterwards, the D-IMD medians gradually increase above the IMD medians.

Furthermore, Fig. 5.3 shows greater deviation at the extreme ends (compared to those who are closer to the overall median or average). The figure reveals a degree of asymmetry across the socioeconomic spectrum, as differences between the IMD and D-IMD scores are generally larger for the most affluent neighbourhoods (deciles 7 to 10). This suggests neighbourhoods in these deciles, more than the others, typically have a wider gap between residential and activity-space deprivation. For Liverpool and Birmingham in particular, we argue this degree of asymmetry results from the over-representation of more deprived neighbourhoods in these cities. This over-representation adds

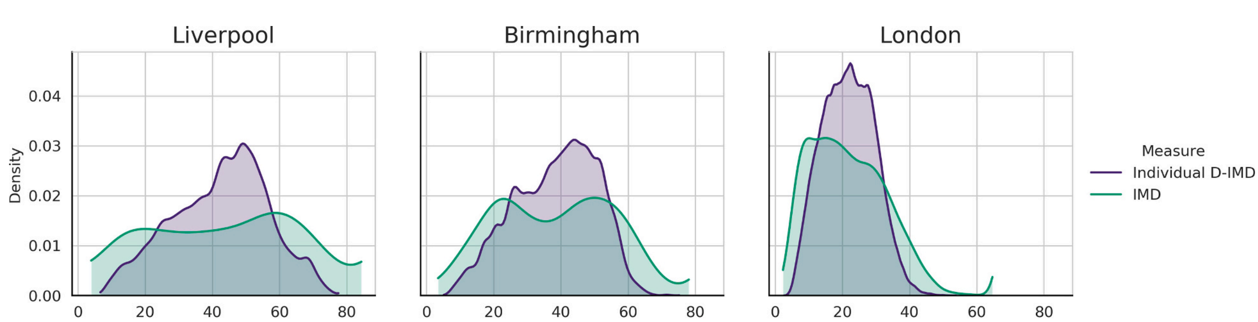

Fig. 5.1. Individual-level densities of D-IMD scores for mobile phone users across Liverpool, Birmingham and London, alongside IMD score densities for LSOA neighbourhoods. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

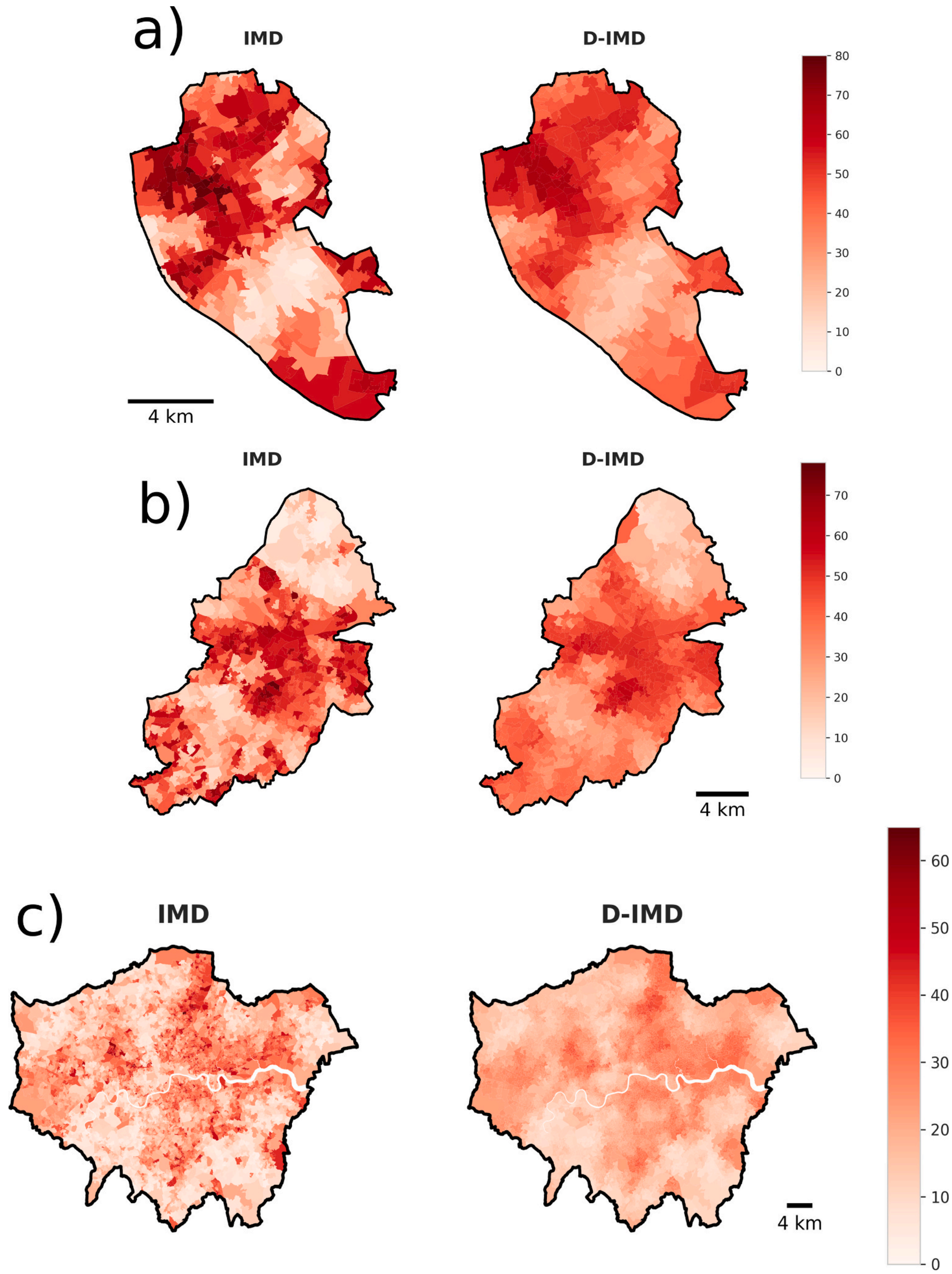

Fig. 5.2. IMD and D-IMD values across LSOA neighbourhoods in a) Liverpool, b) Birmingham and c) London. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

skewness, which means the urban landscape is characterised mostly by more deprived neighbourhoods, which is shown by the higher average IMD score from the horizontal dashed line in Fig. 5.3. This contributes towards the larger gulf between the IMD and D-IMD scores for the most affluent neighbourhoods.

As a corollary to these findings, we also explore differentiation between D-IMD scores and the average radius of gyration $rg(u)$ across users in each LSOA neighbourhood. The radius of gyration characterises the average spatial spread of users' visited locations. According to classical theories of "spatial mismatch" (Kain, 1968), one might expect deprived neighbourhoods to be poorly connected to work centres, and so require people to travel longer distances to arrive at workplaces. On the other hand, individuals from affluent neighbourhoods might also have access to various modes of transportation, including automobiles, which enables them a greater freedom of mobility to access less relatively deprived social and recreational environments.

Radius of gyration is calculated as $rg(u) = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(r_i - r_{cm})^2}$, where N is the set of antennas a user visits, r_i is the tuple of easting and northing coordinates, and r_{cm} is the centre of mass, or average coordinate pair of visited locations. Within each LSOA neighbourhood, $rg(u)$ measures user's typical distance travelled, and averaging across all users per neighbourhood yields a sense of the how many kilometres users traverse on average across our study period. We find evidence of weak-to-moderate negative correlation between neighbourhood-level average gyration and D-IMD scores in Liverpool (Pearson's correlation $r = -0.41$, P value < 0.005), London (Pearson's correlation $r = -0.26$, P value < 0.005) and Birmingham (Pearson's correlation $r = -0.25$, P value < 0.005). This infers individuals in neighbourhoods who face higher levels

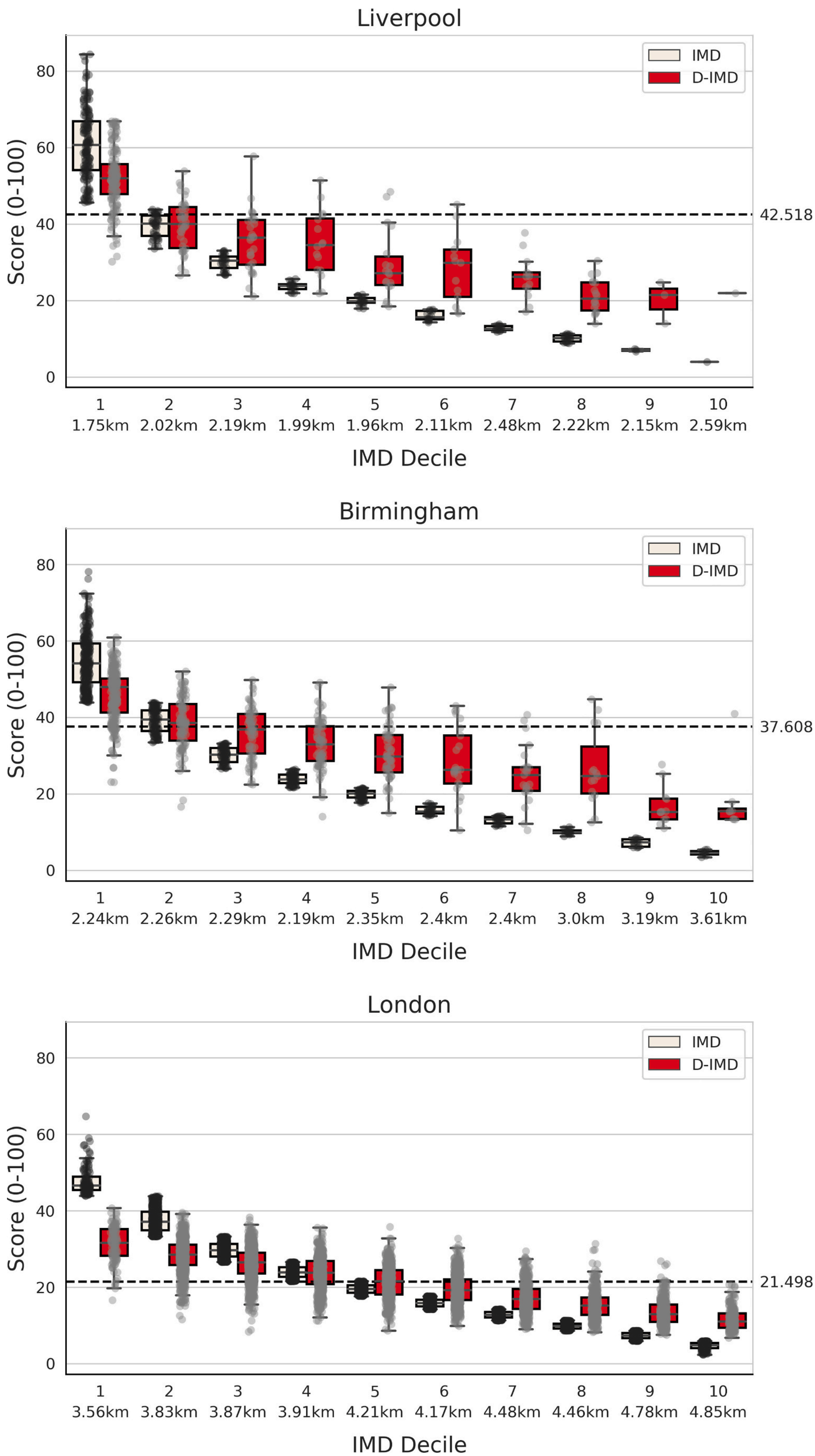

Fig. 5.3. Distribution of IMD and D-IMD values grouped by IMD decile. Avg. gyration per IMD decile shown below decile labels, 1–10. Observed IMD and D-IMD values for individual LSOA neighbourhoods shown by black and gray circles, respectively. Horizontal dashed line shows the average IMD score for each city.

of exposure to day-to-day deprivation typically have a smaller mobility radius.

As an extension, we also compare average gyration along IMD deciles, which reveals any potential systemic difference in the distances particular socioeconomic groups travel when partaking in their day-to-day activity spaces. The average gyration is shown under the IMD deciles along the horizontal axis labels of Fig. 5.3. Counter to the theory of "spatial mismatch" and confirming our previous finding, we find people in neighbourhoods at the lower end of the socioeconomic spectrum have the lowest average gyration and, mechanically, spatial spread of visited locations. Possibly in alignment with Tardiff's work (Tardiff, 1975) relating to the reported frequency of recreational travel to socio-economic status, we find the least deprived neighbourhoods also have the highest average gyration and, mechanically, spatial spread of visited locations. However, our findings do not differentiate between the purpose of travel, whether it differentiates between work, social or recreational activity. This creates difficulty in proving or disproving these existing theories that link socio-economics to travel activity.

5.3. *Magnitude of difference between IMD and D-IMD*

Overall, the IMD and D-IMD (Spearman rank correlation $\rho = 0.81$, P value < 0.001, 95% confidence interval (CI): 0.798–0.812) exhibit strong correlation, however some disparities between the two at LSOA neighbourhood-level reveal interesting patterns. In this section, we break down the magnitude of difference between the scores by LSOA neighbourhoods in order to recover instances of departure between the two.

Fig. 5.4 provides an overview of the direction and magnitude of difference between the IMD and D-IMD. The vertical axis represents the percentage of LSOAs that are binned into particular classes along the horizontal axis, with each class reflecting different ranges of difference between neighbourhood D-IMD and IMD scores ($D-IMD_i - IMD_i$). The differences are binned into classes using Jenks natural breaks

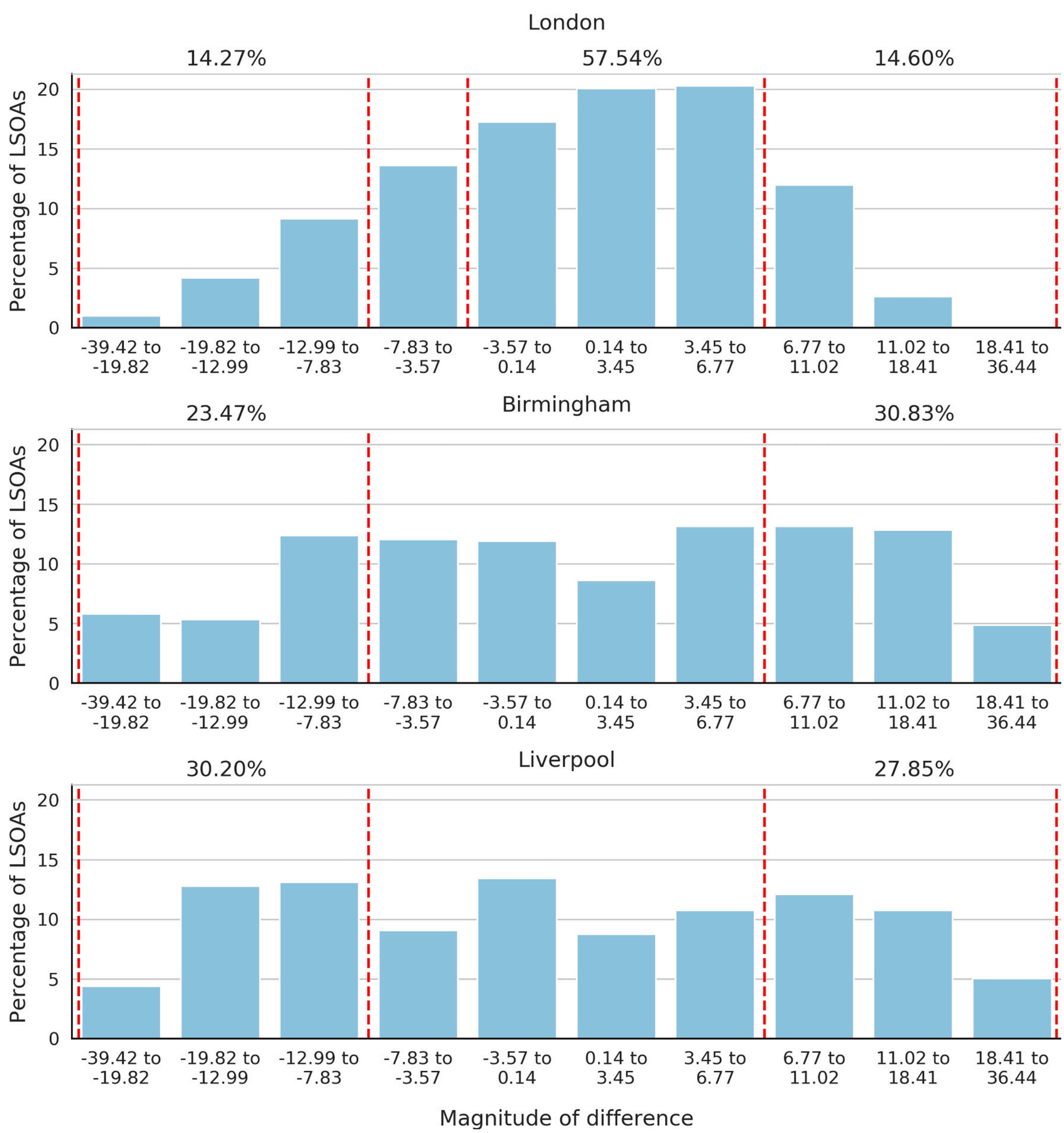

Fig. 5.4. Proportion of LSOA neighbourhoods with different magnitude of change between D-IMD and IMD ($D-IMD_i - IMD_i$) scores among the three cities. *Note*: the dashed vertical lines are used to identify the regions along the *x*-axis that are summed, with the summed values centred between the two lines for a desired region. For example, the first two dashed red lines in the top panel of the figure sum the left-most region of the figure as 14.27%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

classification (Jenks, 1967), a standard approach which optimises arrangement of values into bins by minimizing variance within classes and maximizing variance between them. A positive difference along the horizontal axis represents the percentage of LSOAs of which members, on average, involve movement and dwell time across other areas of higher levels of deprivation than their residential environment. A negative difference indicates the opposite. Lastly, we group several classes and sum their cumulative proportions, with these groups shown in Fig. 5.4 between the red vertical dashed bars.

The result reveals substantial inter-city differences between London and the other two. Whereas the majority of the LSOAs centre over relatively small magnitude of differences in London (57.54% of LSOAs share a magnitude of difference between −3.57 to 6.77), the cities of Liverpool and Birmingham appear far more uniformly distributed. The difference of London is expected, as commented early on, since the city shows a relatively homogeneous deprivation landscape. For example, variation in IMD scores show higher similarity in London (10.90) than in Liverpool (20.61) and Birmingham (16.95), which indicates less opportunities for people in London to be exposed to environments with more diverse deprivation conditions than the other two.

On the other hand, a significant portion of LSOAs exhibit large deviation of D-IMD in the other two cities. For instance, 30.83% and 27.85% of LSOAs in Birmingham and Liverpool, respectively, have D-IMD scores 6.77 units (or more) greater than its IMD score, while London's proportion of neighbourhoods within the same range are only 14.60%. On the other end, 23.47% and 30.20% of LSOAs in Birmingham and Liverpool, respectively, have a negative magnitude beyond −7.83, while London's proportion of neighbourhoods within the same range is only 14.27%.

The magnitude of difference between D-IMD and IMD scores could impact neighbourhoods in contrasting ways, depending on the deprivation status of the given neighbourhood. IMD scores are constructed to facilitate the easy identification of the most deprived LSOA neighbourhoods, which is achieved by using exponential transformations on the constituent domains that calculate the index. As a consequence, the LSOAs in the 10% most deprived decile have a exponentially transformed IMD score between 43.86 and 100, while the remaining 90% have scores across the narrower range of between 0 and 43.86 (McLennan et al., 2019). As the majority of LSOAs lie in the narrower range, even a small magnitude of difference of D-IMDs within this range imply that the LSOA ranking of deprivation could change drastically. Particularly, the magnitude of difference could have greater implications for the LSOAs of which deprivation score sit near the classification break point of 43.86, since many social aid programmes are designed to support the top 10% most deprived areas. We elaborate further on the policy implications of these findings in the Discussion and concluding remarks section.

We next extend the analysis by exploring the relationship between the magnitude of D-IMD deviation and the urban landscape. Specifically, we analyse whether the deviation of D-IMD is associated to the degree of heterogeneity in IMD scores of LSOAs in close spatial proximity, assuming people frequently visit locations nearby their homes. A strong association would imply deprivation conditions of nearby neighbourhoods could be an important factor driving change between the IMD and D-IMD. Nearby neighbourhoods might be environments of social mixing and interaction, and the IMD scores of these neighbourhoods will, therefore, determine the conditions of deprivation people are exposed to across their activity spaces.

Fig. 5.5 plots the LSOAs by taking their D-IMD score and original IMD scores as their coordinates, hence the LSOAs with large D-IMD deviation are located far from the diagonal line. Alongside this, we colour each LSOA point by the average difference between the LSOA's

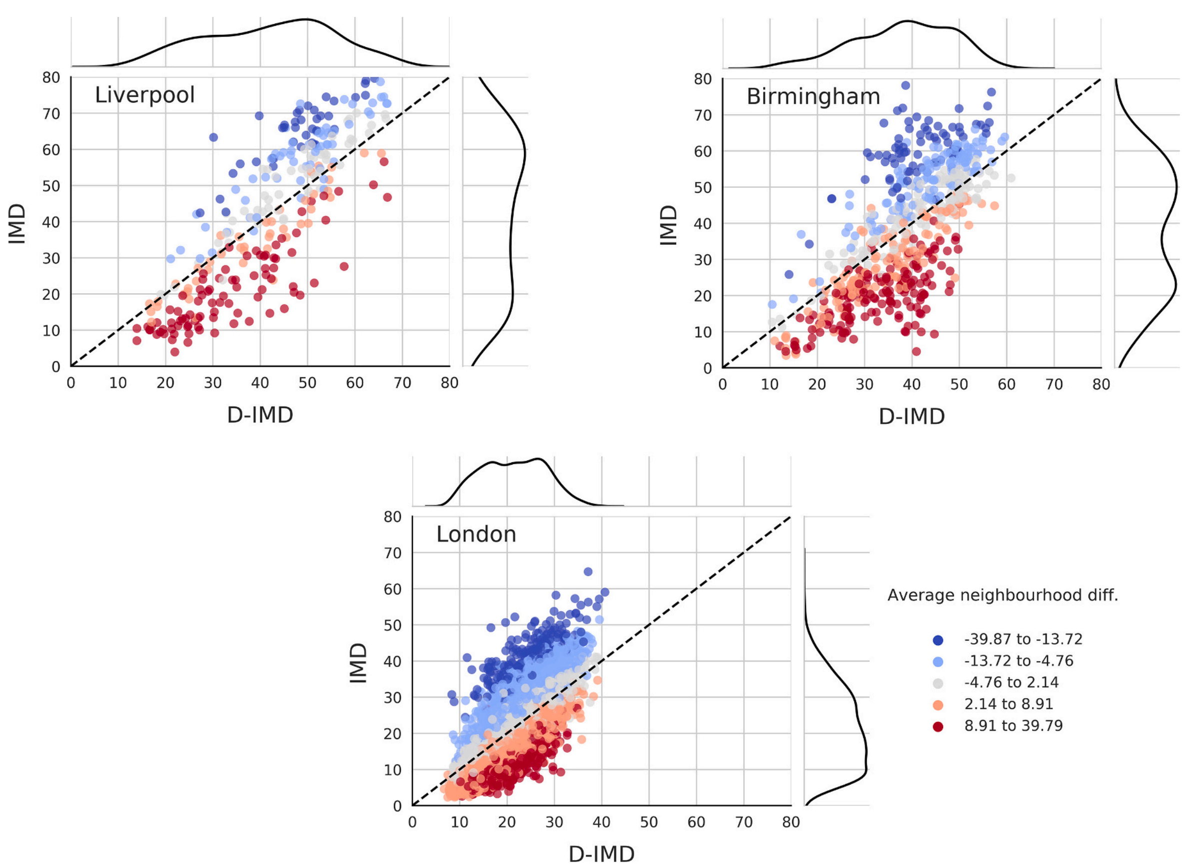

Fig. 5.5. Relationship between individual LSOA neighbourhood IMD and D-IMD scores. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

IMD score and IMD scores of other neighbourhoods within a spatial proximity of 4 km. The average is weighted by the distance to each neighbourhood within the four kilometre buffer, with those neighbourhoods located closer to the LSOA in question assigned a higher weighting. This is known as taking the *spatial lag* of a variable (Anselin, 2010) (see Appendix A). A darker blue colour infers the IMD scores of LSOAs within a four kilometre proximity are, on average, lower than the IMD score of the particular LSOA in question. Conversely, a darker red colour implies the IMD score of the LSOA's surrounding neighbours are higher than the IMD score of the particular LSOA. Styling each point by the spatial lag is useful as an indicative property of whether the difference between a particular LSOA neighbourhood and its neighbouring LSOAs might be related to change in its D-IMD score. This operates under the assumption individuals' activity spaces include work, social or recreational locations proximate to their residential environment, which spaces might expect people to spend time among (Hanson & Hanson, 1981).

We note a consistent pattern between the deviation from the diagonal line and the colouring across the three cities. In all cities, the LSOAs coloured a darker blue tend to appear above the diagonal line, meaning its D-IMD score is less than its paired IMD score. We expect that the neighbouring LSOAs with less deprivation to drive the D-IMD score to be lower under the assumption that day-to-day activity spaces of individuals occur in close proximity. Conversely, LSOAs coloured darker red most typically appear below the diagonal line, which implies their D-IMD score is higher than its paired IMD score. These LSOAs are the antipode of those coloured darker blue. All together, these results suggest that the degree of deprivation convergence might be linked to the deprivation conditions of nearby neighbourhoods in spatial proximity.

6. Discussion and concluding remarks

This study demonstrates a conceptual extension of the empirical characterisation of deprivation. As the study of deprivation intersects a variety of disciplinary contexts, this work carries strong research implications and practical significance to the design of policy response and decision-making across areas including social justice, segregation and urban economics.

Our finding of deprivation convergence provides an alternative view of the degree of social segregation, which is preferential among the other possible outcomes. We speculate that two other possible outcomes were, first, that the distribution of the D-IMD scores shows little difference from that of the original IMD distribution. Such a scenario would indicate that there is no deviation between deprivation exposure within individuals' residential spaces and all other socio-geographic spaces they encounter day-to-day. Second, the D-IMD distribution could have shown deprivation divergence with multiple peaks distant from each other if people tend to selectively choose areas to spend time among places in a more segregated manner; for example, people from less deprived areas only spending time in less deprived, and vice versa. Instead, the convergence observed in Fig. 5.1 indicates less isolation in the activity spaces than the residential spaces. This finding strengthens the related findings on mobility segregation made at a coarser-level previously (Järv et al., 2015; Silm & Ahas, 2014a). For example, through Call Detail Records (CDRs) Silm and Ahas (2014a) observe a temporal variation in the degree of segregation in the capital city of Estonia, arguing that the degree of segregation is lower when considering mobility data than when considering census data. Overall, our finding corroborates the argument with continuous mobility traces, and provides a more comprehensive view along a finer socioeconomic spectrum and geographical landscape.

One *could* argue the deprivation convergence we observe is an automatic result of systematic sampling, as the D-IMD score is created by sampling within the IMD value ranges at neighbourhood-level. We use three examples that elaborate on possible mobility patterns that would not lead to deprivation convergence. Firstly, if individuals exhibit homophily in their mobility destinations and frequent places with deprivation conditions similar to their residential environment, the D-IMD score distribution would have multiple peaks. For example, there could be three peaks including those in the range of the most deprived, those at the centre, and the least deprived. Secondly, if there was a general preference of less-deprived neighbourhoods, the D-IMD score distribution would be skewed towards lower values. Likewise, an opposite preference would skew the distribution towards higher values. In our case, we dismiss our findings as an automatic result, as we observe deprivation convergence to reject these three possible behavioural features: homophily, preference of the less deprived, and more deprived. However, we do clarify that deprivation convergence itself does not specify a particular behavioural feature. A mobility pattern governed purely by geographical distance may exhibit deprivation convergence *if* areas of diverse IMD scores are located in close proximity; on the other hand, a random mobility process could exhibit deprivation convergence as well.

Our finding of the association between deprivation convergence and the deprivation conditions of nearby neighbourhoods also provides insight on urban renewal or neighbourhood revitalization projects, such as the establishment of a mixed-use complex or the enhancement of community infrastructure (e.g., Scher, 2019). We find geography matters, as the diversity of conditions within nearby neighbourhoods carries strong bearing on how people are exposed to deprived environments. The finding can help urban renewal projects to better deal with complicated trade-offs between location and the distribution and nature of benefits across different communities. For example, the finding suggests that deprived communities that are surrounded by similarly deprived areas might need more investment, since the activity spaces are often limited within those areas. The finding also helps projects for social integration, and we suggest that a useful strategy could be to consider investing in “bridging” projects that are located geographically to provide integration between communities that are socioeconomically distant.

Another practical implication of this work concerns issues of social justice, and the allocation of funding towards instruments that safeguard England's vulnerable communities. At present, the IMD provides a critical function in determining the eligibility criteria for various funding streams. Several funding arrangements are contingent on individuals or neighbourhoods being classified within the top ten and 20% most deprived environments. Examples range from scholarship and bursary offers from universities and training colleges that provide students up to £3000 annually across three years (FSC, 2020; Loughborough University, 2020), to Sport England's Families Fund, a £40million award seeking to facilitate opportunities of healthy activeness for five to fifteen year old children (Sport England, 2020). In addition, English city and county councils fund energy efficiency measures such as loft and cavity wall insulation to deprived households identified through the IMD (Bristol City Council, 2019; Suffolk County Council, 2017). Historically, previous iterations of the IMD in 2010 have also been used to distribute £448million funding to local authorities for the Department for Communities and Local Government's (DCLG) Troubled Families Programme, while the 2000 Spending Review funding for all domestic regeneration programmes allocated £430million to regional development agencies based on the IMD 2000 (OSCI, 2011). While we reference only a small number of existing applications, this varied cross-section of uses highlights the diversity and importance of the IMD for directing policy resources.

In certain LSOA neighbourhoods, our findings indicate a strong magnitude of difference between the IMD and D-IMD scores, and we highlight one immediate practical application of the D-IMD to issues in social justice using a hypothetical example. We find many cases where neighbourhoods would become eligible for several funding arrangements when we classify the D-IMD scores under the same classification break points the IMD 2019 uses to classify IMD scores into different deciles. To reiterate, the IMD 2019 methodology splits IMD scores into ten deciles, reflecting the top 10%, 20% (and so forth) most deprived neighbourhoods. When we re-calculate deciles based on our computed D-IMD scores using the same break points the IMD uses, we found 185 neighbourhoods would enter the eligibility criteria for remediation resources under the typical requirement of a neighbourhood being classified within the top ten and 20% most deprived environments. By city, we found this broke down to 115 neighbourhoods in Birmingham, 36 in Liverpool and 34 in London that would be entitled to further funding support mechanisms. This hypothetical example highlights a clear, policy-related advancement in how resource allocation could be distributed to neighbourhoods that suffer hardship if interpretations of relative deprivation included activity-space perspectives.

Lastly, while our study focuses on English cities, we further note the extensibility of our conceptual framework to international contexts that use deprivation measures. These include countries that construct deprivation indices like Ecuador (Cabrera-Barona et al., 2016), Australia (SEIFA, 2018), Scotland (Allik et al., 2016), France (Havard et al., 2008), Canada (Bell et al., 2007), and New Zealand, whose IMD is directly inspired from its English counterpart (Exeter et al., 2017). This also includes countries like the United States, where growing internal pressures from public health bodies have explicitly cited the IMD in stressing the need for data describing social deprivation to assess needs-based resource allocation (Phillips et al., 2016). To varying degrees, these countries use deprivation indices to assess community needs, adjust clinical funding, inform research avenues and determine policy impact. Clearly, deprivation measures carry significant policy implications internationally. Therefore, this work provides a conceptual framework for a measure intended to supplement and provide a new perspective to the measurement of hardship for international bodies that leverage deprivation indices in similar ways to English institutions.

To balance this discussion however, we also caveat our analysis by noting the accuracy of the D-IMD measure is dependent on the scale and fidelity of our sampled number of mobile phone users across space. An evident limitation is that the findings are deduced from dense urban areas. Rural locations or less densely populated places where users are sparsely situated could increase the uncertainty of the calculated D-IMD measure when the number of sampled mobile phone users is low. For this reason we advise interested parties to consider the D-IMD is presently suitable only for calculating deprivation exposure among established urban centres. A secondary source of bias relates to a commonly raised problem in geography known as the *modifiable areal unit problem*, where inferences of individual, point-based activities are erroneously deduced from the neighbourhood to which those individuals belong (Pearce, 2000). This problem is amplified by our areal interpolation mapping of IMD scores from LSOA neighbourhoods to antenna polygons, and also the reverse mapping of D-IMD scores from antenna polygons back to LSOAs. We assume neighbourhood-level experiences of deprivation can be aggregated from the geographical area of overlap of antenna polygons that intersect the neighbourhood boundary, but this naively assumes the relationship between the attribute being interpolated is spatially homogenous. If the D-IMD measure is heterogeneous across the spatial area of antenna polygons, then assuming homogeneity when we interpolate between the antenna polygon and LSOA neighbourhood is likely to intensify the MAUP. In our case, we argue this problem was not so severe, because we analysed the D-IMD measure at both geographic scales and identified consistent trends at both levels, meaning the MAUP did not constrain our analysis too significantly.

Overall, the key academic contribution of this work introduced spatio-temporal variation to the measure of deprivation. The analysis unlocked a new picture describing multi-space deprivation exposure which was uniquely enabled through access to large-scale mobility traces. There are multiple directions for extension of the proposed concept. For example, a recent work by van Ham et al. (2020) shows workforce professionalization has increased the share of high-income workers whose locational preferences for social mixing are towards central areas of cities. One extension may be to explore differences in the D-IMD across socioeconomic groups in inner-city and outer-suburban areas across our three cities.

A further extension might be to explore whether the urban mobility patterns and their interaction with static deprivation measures follows any particular non-stochastic process, extending previous work in this area by introducing the interaction with deprivation (Gallotti et al., 2016; Gonzalez et al., 2008; Yan et al., 2013). One could argue the convergence we find might simply be obtained by simulating the trajectories as a random process. However, randomness in this instance does not imply a null result. A random process would actually imply an important behavioural feature, that the destination of individuals are independent of the perceived deprivation ascribed to a particular neighbourhood. Future research might seek to explore whether the convergence pattern observed follows a particular process that shares commonality or differences across the selected cities.

Another natural extension would be to expand the number of cities included in the analysis, which would allow a cross-city deduction of how variation in deprivation considerations within particular cities affects the results of the D-IMD calculation. The scale of our analysis could also be enlarged through linkage of mobility traces from other telecommunications providers, which England's Office for National Statistics (ONS) has previously achieved to estimate commuting flows using administrative census data (Williams & Weakley, 2017). This ONS example highlights such integration of telecommunications data exists within the bounds of feasibility. With these extensions in mind, we anticipate that introducing urban mobilities inferred from mobile phone traces into the measurement of deprivation could greatly enhance the accuracy, scope, and future analyses. Moreover, the results, data and code we publish alongside this article are intended to supplement existing measures of deprivation, and we argue the framework presented could be continuously benchmarked and improved as new location-aware technologies with similar spatio-temporal granularity become available.

CRediT authorship contribution statement

Sam Comber: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Souneil Park:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Daniel Arribas-Bel:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interest.

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Data availability

The D-IMD measure at LSOA neighbourhood level for the three cities constructed in this work are available online at the git repository: https://github.com/SamComber/DIMD.

Code availability

A computational notebook describing our findings is available online at the git repository: https://github.com/SamComber/DIMD.

Appendix A. Spatial lag of IMD neighbourhood scores

For each LSOA, we draw a four kilometre buffer from its centroid (central point) and record which other LSOAs fall into this buffer, which we enter into a spatial weights matrix, $\boldsymbol{W}$. This defines a neighbour structure where non-zero elements of $\boldsymbol{W}$ record the spatial connectivity between LSOA neighbourhoods, subject to exponential distance decay expressed as,

$$W_{ij} = \begin{cases} 1, & exp\left(-\left(d_{ij}^2\right)/d^2\right), \text{if } d_{ij} \leq 0 \\ 0, & \text{otherwise.} \end{cases} \tag{A.1}$$

where d_{ij} is the Euclidean distance between neighbouring LSOAs and d is the fixed distance bandwidth of four kilometres which ensures that every LSOA neighbourhood has at least one neighbour. Furthermore, this spatial weights matrix is row-standardized, meaning each row sums to unity $\sum W_{ij} = 1$. This means the matrix-vector multiplication of $\boldsymbol{W}$ and the vector of IMD score differences is a weighted average of neighbouring differences, with non-neighbours excluded as $w_{ij} = 0$.

Appendix B. Constructing 95% confidence intervals for LSOA-level D-IMD measure

To express the degree of uncertainty in our neighbourhood-level D-IMD scores, we build 95% confidence intervals using a resampling procedure. These intervals are supplied in the data release that accompanies this work. To construct the intervals, we use a disproportionate stratified random sampling technique, where we sample with replacement *D-IMD$_i$* scores from residents of antenna polygons that overlap each LSOA neighbourhood we build intervals for. Each antenna polygon reflects a different strata, and the probability of sampling residents from an antenna polygon is proportional to the geographical area of overlap between the polygon and the LSOA neighbourhood. If, for example, an LSOA overlaps two antenna polygons, and the area of overlap is 70% with one and 30% with the other, then we sample residents with replacement from their home antenna polygon with probability of 70% and 30%. We estimate the maximum number of residents to sample for each LSOA neighbourhood based on the overlapping antenna polygon which has the smallest sample size. Confidence intervals can then be constructed in the conventional manner of using the standard deviation of our sampled residents *D-IMD$_i$* scores at LSOA neighbourhood level, $D - IMD_{LSOA_i} \pm 1.96\frac{\sigma}{\sqrt{n}}$.

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