Journal of Transport Geography 111 (2023) 103638

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Inequality in leisure mobility: An analysis of activity space segregation spectra in the Stockholm conurbation

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ARTICLE INFO

Keywords:
Mobility
Leisure
Inequality
Mobile phone data
Multilevel model
LISA
Intra-class correlation
Root mean square error

ABSTRACT

Leisure mobility forms an important part of people's spatial activity and mobility spectrum. This study aims to analyse the inequality dimensions of spatial mobility of individuals who seek to move to recreational and leisure destinations (often 'green' and 'blue') on designated days. The study traces – through the use of spatially dependent multilevel models – the mobility patterns of people from the greater Stockholm area, using individual pseudonymised mobile phone data and other publicly accessible data. We find significant socio-demographic inequalities in the observed residents' spatial leisure choices, where less affluent groups display especially low variation in mobility when comparing between weekdays, weekends, vacation season and work-periods.

1. Spatial mobility analysis: Introduction

Human spatial mobility shows not only great spatiotemporal variation, but also much heterogeneity in terms of travel motives, modes, and destinations. Travel behaviour is often seen as a derived demand that is determined by a broad spectrum of distinct spatial activities, such as work, shopping, family visits, or leisure trips (Schlich et al., 2004; Zhang Y. et al., 2021; Zhang S. et al., 2021; Zhou et al., 2022), geographically connected through spatial mobility (Neutens et al., 2010; Ahmed and Stopher, 2014; Schläpfer et al., 2021). The complex space of opportunities and observed movements of individuals or groups can be represented in a time-geographic *space-time cube*, as was suggested by Hägerstrand (1970), which in transportation planning is also known as 'activity-based travel analysis' (see e.g., Recker and Kitamura, 1985; Kitamura, 1988; Burnett and Hanson, 1979; Clarke et al., 1981; Koppelman and Pas, 1983).

The 3-dimensional space-time individual mobility behaviour may vary greatly among different people, depending on contextual conditions (e.g., urban morphology or transport infrastructure, availability of transport alternations, length of travel distance), and on individual travellers' characteristics (income, age, gender, profession, social status, etc.) (see e.g., Vickerman, 2003; Stern and Richardson, 2005; Poppelreuter and Donaghy, 2005). Moves originating from various residential neighbourhoods may thus exhibit great heterogeneity between individuals or socio-economic groups, as well as between travel motives in society (Donaghy et al., 2004; Gehrke and Wang, 2020; Mao and Chen, 2021). Consequently, actual socio-economic inequality is essentially projected in the observed pluriform mobility spectrum of the space-time economy characterised by a multi-domain socio-geographic segregation (Nessi, 2017; Cailly, 2014; OECD, 2018; Nieuwenhuis et al., 2020; Tammaru et al., 2021; Östh et al., 2018b). Segregation in time and space is often referred to as activity space segregation, where individuals' exposure to other groups of individuals or to different physical environment has been studied using travel diary or travel survey data (see for instance Wong and Shaw, 2011; Wang et al., 2012) or combinations of register data and GSM-mobility data (Östh et al., 2018b; Järv et al., 2021a, 2021b). This also holds for leisure mobility, although leisure related activity spaces are understudied.

Leisure mobility refers to discretionary space-time travel behaviour of individuals that is not generated by work, school, education, health care, sports or daily shopping commitments or motives (see e.g., Golledge and Stimson, 1987; Holden, 2016; Nessi, 2017; Ohnmacht et al.,

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https://doi.org/10.1016/j.jtrangeo.2023.103638
Received 14 July 2022; Received in revised form 7 June 2023; Accepted 20 June 2023
Available online 18 July 2023

2009). It is a specific form of spatial choice behaviour where – in contrast to, for example, commuting or educational trips – leisure travellers have generally a high degree of discretionary choice flexibility in the mobility spectrum of spatial choice opportunities (Thill and Horowitz, 2010). Leisure mobility may manifest itself in different forms, ranging from, for instance, walking in a park to visiting a pop festival. It is a specific type of activity-based travel behaviour, dependent on individual and group leisure motives (Goodwin, 1981, Diener et al., 2003; Stauffacher et al., 2005; Zhao et al., 2013; Lee S. et al., 2017; Lee R.J. et al., 2017; Qiao et al., 2021), where free time and free choice are characteristic features that allow people to expand their physical choice spectrum and to increase their leisure time satisfaction. Thus, leisure mobility is a way to bridge the tension between the utility of local amenities in two different places, a phenomenon that is based on a free spatial choice of citizens and that is often referred as voting by feet.

In the literature on freedom in geographical mobility the notion of '*feet voting*' is a well-known concept (see e.g., Tiebout, 1956). In general, this phenomenon refers to intercommunal spatial search and choice behaviour of residents leading to a structural move (such as migration) to a more preferred place (see e.g., Faggian et al., 2011; Zhang et al., 2018; Zhao et al., 2019; Gan et al., 2020; Zhang Y. et al., 2021, Zhang S. et al., 2021). Leisure mobility, on the contrary, is an ad hoc and short-term temporary mobility to another place that offers specific benefits that cannot be enjoyed in the place of residence (or origin) (Schlich et al., 2004; Holden and Norland, 2005; Halleux and Lambotte, 2006; Nessi, 2017). Leisure travel is essentially a flexible form of *temporary* 'feet voting' (Dowding et al., 1994). And therefore, leisure travellers have greater independence in choosing their activity trips (mode, distance, time, destination, route, duration). This enables identifying and analysing individual or group inequality in spatial drivers and effects on spatial leisure mobility. This research challenge, i.e., the quest for measuring socio-demographic inequality in a multi-faceted spatial spectrum of leisure behaviour, forms the inspiration source of the current paper.

The present study seeks to examine the inequality variations in the spatial mobility patterns of individuals, in particular differences in behaviour between weekdays and weekends, as well as between a holiday period (e.g., in the summer season) and a regular work period (e.g., in the spring season). An example can be found in a study on Estonia, where an analysis of observed mobility showed that people tend to leave the capital city of Tallinn in summer, with a significant variation across ethnic origins (Mooses et al., 2016). We would expect similar behaviour in the greater Stockholm area, with residents opting to leave temporarily their place or using surrounding non-urban locations.

The empirical focus in this study is on the variation in spatial leisure behaviour across people with different socio-economic backgrounds in the greater Stockholm area of Sweden, a country with a wealth of natural areas, forests and lakes, so that a significant part of leisure mobility may be related to "green/blue visits". To trace inequality differences in the Swedes' leisure patterns, we employ pseudonymised mobile phone data obtained from one of the major mobile network providers on the geographic mobility patterns of individuals. In this way, and given the almost full market penetration of cell phones in Sweden, we are able to capture the representative spatial leisure mobility of the population aged 10 years and above. In order to trace the effects of localisation, socio-demographic feature, and leisure destination choices, we also include contextual data describing the nature of the destinations (mainly from OpenStreetMap data) and their socio-economic composition (aggregated by origin or neighbourhood of residence from the population register) related to the leisure mobility trajectories. In our econometric approach, we employ a spatial multi-level (ML) model approach using a nested data structure including spatial dependence (autocorrelation) analysis, while finally we employ Root Mean Square Error (RMSE) to assess the nature and size of deviations in the empirical results.

The study is organised as follows. After this introductory section, we offer in Section 2 a selective overview of relevant literature on leisure mobility analysis, which leads to the formulation of three research hypotheses. Section 3 is then devoted to a description of the big database employed in our research. Next, in Section 4 we provide the methodological (modelling) framework for our analysis, followed in Section 5 by a description and interpretation of our findings. Section 6 draws some conclusions on inequality in leisure mobility.

2. Selected literature

There is an abundance of literature on spatial leisure choices. Observed mobility data have been employed in various empirical studies to find heterogeneous spatial leisure behaviour during holidays (see, e.g., Newman and Kenworthy, 1989; Méyère et al., 2006; Plateau, 2008; Mooses et al., 2016). The research in this field has indeed shown that leisure mobility may comprise a broad collection of discretionary spatial travel patterns, ranging from visiting natural parks to long-distance cultural tourism destinations (Burnett and Hanson, 1979; Banister and Button, 1993; Fotheringham and Trew, 1993; Pronovost, 2014). Leisure travel choices reflect, therefore, the diverse spatial preference and opportunity mechanisms of leisure consumers; hence, their observed spatial mobility provides a spatial spectrum of diversity (and inequality) in spatial choices (Dumontier and Pan Ke Shon, 1999; Viard et al., 2002; Schönfelder and Axhausen, 2003; Stauffacher et al., 2005; Potier and Terrier, 2007; Grefmeyer, 2007; Cornut and Madre, 2017; Lucas, 2012; Miranda-Moreno et al., 2012; Nessi, 2017). The variety present in the leisure mobility spectrum exhibits a great heterogeneity in observed behaviour, so that a pluriform spatial inequality tends to arise (Castles, 2010; Rosa and Scheuerman, 2010; Masso et al. 2019). For example, although a regular Saturday may be regarded as a leisure day, the differentiation in spatial leisure patterns on such a day is formidable, depending on the socio-economic, demographic, sociological, and geographic background conditions of people. The bulk of leisure behaviour is concentrated around the weekends, holiday and vacation periods, so that the most pronounced differences in leisure patterns likely display weekly and seasonal fluctuations, while other moderator variables such as urban morphology, city parks, entertainment centres, natural parks and lakes also play a role in the individuals' decision-making process.

Leisure mobility has also frequently been addressed in transportation analysis. Over the past decades, there has been an increasing number of transportation studies on the geography of leisure mobility from a socio-economic perspective (Ohnmacht et al., 2009). For example, a predictive simulation model of leisure mobility (see van Middelkoop et al., 2004) showed the tourist trip decision base per household, considering available time and money budgets; the results of that model could be extrapolated into segregation and inequality patterns of leisure. Hesam Hafezi et al. (2022) looked at the mobility of non-workers (without a particular focus on leisure); their literature overview suggests that discretionary mobility is more sensitive to changes in policies and costs of travel (or in time-geographic terms, to travel constraints). In another study, Aultman-Hall and Ullman (2020) analysed long-distance travel and pointed towards an increase in quality of life with more access to long-distance travel, whereas Järv et al. (2014) in their literature review pointed out contradictions in the existing literature in terms of whether weekend mobility is more dispersed as opposed to weekday mobility. It is also noteworthy that Mooses et al. (2016) showed differences between the ethnic majority and the minority in terms of holiday-related mobility, using as their information source mobile phone data in Estonia, while Kukk et al. (2018), using data from time-use surveys and in-depth interviews, showed similarities in leisure time activities in Estonia among ethnic groups, although the locations and times of these activities appear to differ. This observation makes ethnic segregation also of interest in the present paper. Clearly, social issues like equitable access to transport are often the source of heated debates, while equality in spatial leisure mobility is a less investigated topic. Although there is a

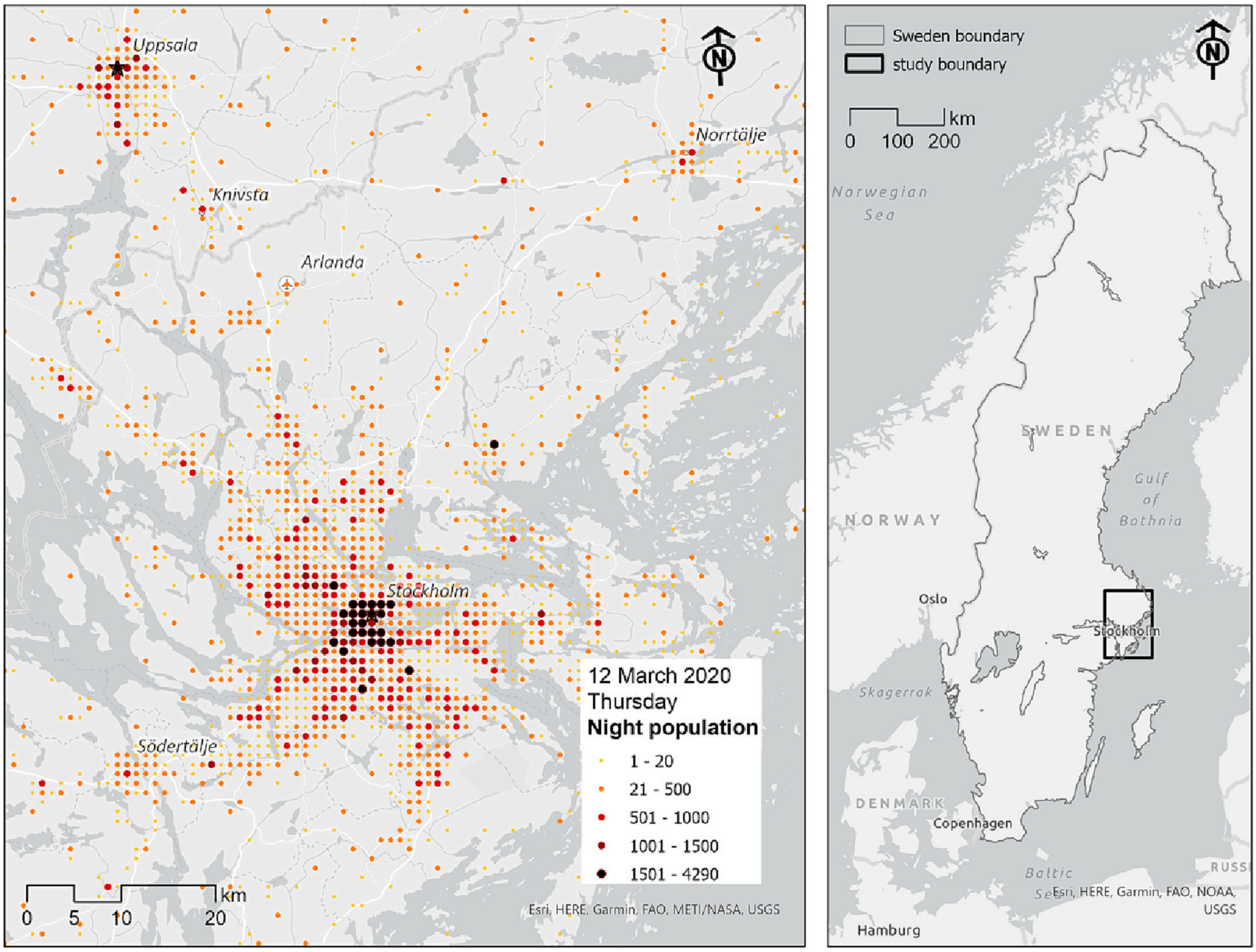

Fig. 1. Study area (right) marked on the map of Sweden with a rectangle, and zoomed in (left) to show the night population (number of phones per km^2).

wealth of general literature on equity and transportation (see e.g., McFadden, 1978; O'Kelly, 1994; Meyer, 1980; Poppelreuter, 2016; Litman, 2002; Ramjerdi, 2006; Bae and Mayeres, 2005; Martens and Di Ciommo, 2017), a thorough evidence-based analysis of inequality in leisure travel is largely lacking in the existing literature. And therefore, a solid data-analytical examination seems to be pertinent to fill this gap in the research.

Our research serves to provide empirical evidence on distinct types of individuals or groups in Sweden (in particular, residents from the greater Stockholm area) who can adjust their spatial leisure decisions and behaviour in accordance with the available choice options and preferences, in particular with regard to leisure destination choice. Destination choice can be defined as diverse through two channels: first the quantity i.e. per capita number of destinations and quality i.e. diversity in terms of natural amenities (blue and green). Furthermore, also the degree of flexibility of leisure consumers in keeping or changing their operational mobility choice spectrum can be assessed, against the background of the specific day of the week or distinct seasons. Following previous research, we assume that wealthy and highly educated people have the opportunity to exhibit more diverse destination mobility by adjusting it to their spatiotemporal preferences (in essence, their feet-voting), whereas poorer, less educated and visible minorities are more restricted in terms of mobility diversity and destination choices (in other words, there is less variance in their mobility behaviour over different times of the year). Given our research objectives and in light of the literature overview above, we seek to test the following hypotheses:

- Preferences regarding leisure time are revealed by mobility behaviour in a space-time activity spectrum. Our assumption is that, given the available opportunity spectrum, people travel towards more diverse destinations, especially natural and green/blue amenities. Therefore, given the opportunity, we assume that people will temporarily "feet-vote".
- In a hypothetical equitable space, equally diverse destination mobility between work and leisure will emerge across socioeconomic groups (at origin). However, because leisure mobility is discretionary and highly sensitive to available opportunities, leisure mobility will exacerbate inequality in summertime and at weekends.
- Mobile phone data can be used to relate to previous findings and contradictions in the literature on socioeconomic dimension of mobility, especially leisure mobility, focusing on inequality between wealthy/high educated and poor/less educated and visible minority populations.

These hypotheses frame our research endeavour and will be empirically tested in the remaining part of this study.

3. The data

The analysis of the distributional aspects of spatial leisure mobility calls for fine-grained data. In this study, we use an extensive dataset derived from the Uppsala University-based mobile phone database MIND (Toger et al., 2021). MIND contains longitudinal, geocoded data related to the mobility of between 1 and 2 million pseudonymised phones in Sweden. For this study we used only Swedish mobile phones (selected by their MCC = 240). In accordance with our research hypotheses, we test to what extent the mobility patterns change during leisure times, and, more specifically, whether and how mobility patterns are affected by socioeconomic characteristics and contextual factors.

Due to ethical guidelines in Sweden, we had to limit the duration of mobility observations to a maximum of 24 h. To compare mobility behaviour over longer time periods, we spatially aggregated our results from mobility observations to square grid units of 1 km^2. These units were next enriched with data describing local socio-demographics, job accessibility, population density, and access to green and blue amenities. The resulting 'big data' challenge calls for a data limitation to specific dates. The four selected dates include 18 July 2019 (Thursday), 20 July 2019 (Saturday), 12 March 2020 (Thursday) and 14 March 2020 (Saturday). These dates are chosen to represent in an unbiased way the space-time spectrum before the COVID-19 pandemic outbreak in Sweden, and can therefore function as a reference data platform for future sensitivity studies on pandemic-related effects on leisure mobility in an urban context in Sweden. Selection of Thursdays and Saturdays follows Toger et al. (2020) on selecting representative dates in mobile phone data.

The focus on an urban or metropolitan setting in our study can be justified for several reasons. First, in the pre-pandemic period (both during vacations and during weekends) the larger urban areas in Sweden, such as the Stockholm and Göteborg conurbations, always attracted many visitors. Secondly, in these areas the density of mobile phone antennae and the density and the spatial distribution of amenities and relevant land-use variables enable us to study the recreational and leisure choices with more accuracy than what would be possible in other parts of the country (Ogulenko et al., 2022). Thirdly, the Stockholm metropolitan area is residentially highly segregated, which enables relating socio-demographic variables in a district of origin to aggregate mobility in 1km^2 units. In our database, we consider mobility data from individuals who reside in the greater Stockholm area, including the peri-rural areas between the main urban settlements in the region including Uppsala, Norrtälje and Södertälje (ranging in population size from 40,000 to >200,000 inhabitants in the municipalities concerned). We study thus the mobile phone traffic of individuals who most likely are residents in the study region concerned. Residential information is here understood as having an estimated place of 'rest' within the designated area depicted in Fig. 1, between the night hours 03:00 and 07:00. Since we are unaware of the individual identity of phone users, the residence is not necessarily the home: it may be in the form of a hotel room, recreational vehicle, or even the bunk of a lorry, but it nevertheless enables us to time-cross-sectionally capture the spatial behaviour at each date of each cell phone owner.

In the greater Stockholm conurbation, there are 1759 square units of 1km^2 size, in which the residence of phones was observed for all four dates mentioned above. With the selection restrictions listed above (i.e., only including data from phones with a residence in a unit that has a population during all dates, and which are located within the larger Stockholm region), we have aggregated the mobility statistics for approx. 280,000 unique mobile phones. For each phone the following mobility related data were collected:

- ***Phone mobility***. These data comprise the relevant spatial information:
  - o *OD-distance*: the observed distance between the estimated location of residence (Origin) at night and the location in which the phone was present in daytime (Destination). The Origin is calculated as the median duration weighted position between 03:00 and 07:00 for each relevant date, using the coordinates of the antennae to which the phone was connected during these hours. The destination is measured using a similar approach, but only for the hours between 10:00–12:00 and 13:00–15:00. The destination hours have been selected to exclude lunch hours, but to include hours that commonly are associated with work, school, or service. For each 1km^2 unit, the median observed OD distance (Cartesian distance between km^2 unit midpoints) for all phones that originated from a position within this unit are saved and used as a representation of the local day-specific mobility value. This OD distance variable will be used as the dependent variable in the regression analyses to be performed later.
  - o *Destination to population (desttopop)*. In order to capture parts of the complexity of the OD mobility patterns, we created a variable that links the number of unique destinations with the local *resident* (phones) population. The variable assumes a value between 0 and 1, where higher values indicate a greater dispersion of destinations. The variable is sensitive to the origin population count, where only km x km units with at least a flow$\geq$ 20 individuals are used.
- ***Socio-demographic data.*** Using population register data from the PLACE database (an Uppsala University based geocoded, longitudinal full population register database developed by the Swedish Bureau of Statistics), we are able to map out neighbourhoods from a socio-demographic perspective. Departing from the midpoint of the 1 km square (i.e. from the middle of each square with 500 m to the top, bottom, right, and left side of each unit), we use the EquiPop aggregation (see Östh and Türk, 2020; Östh et al., 2016) to estimate the population composition among the k = 100 nearest individuals from each midpoint (rendering a share value between 0 and 1). The choice of a k-nearest approach is motivated partly by the availability of geocoded population data enabling the creation of bespoke neighbourhoods, but also partly because the available administrative population data varies substantially in geographical size and population count. Using k = 100 means that we capture the demographic structure of the core parts of the units in dense central parts of the greater Stockholm area, and more or less the full population in the less populated areas in the urban outskirts. The benefit (compared with a radius-based approach) is that the sample-size related variance is the same for each spatial unit, and is not affected by population density. Variables indicating population and job density can thus be included in our analyses.
- ***Socio-demographic data.*** These variables are related to spatial socio-economic equity issues at the individual level:
  - o *Visible Minority*. The share of Visible minorities, identified as individuals being at risk of discrimination or segregation due to their migration origin (including population from Africa, Asia excluding Russia, and Latin America).
  - o *Low Education*. The share of adult individuals (age > 19) who have had compulsory education (usually 9-years of education, but this variable is age- and country of origin- dependent).
  - o *Higher Education*. The share of adult individuals (age > 19) having a university degree (or other post upper-secondary education).
  - o *Poverty*. Using the EU definition of relative poverty (having a disposable income less than or equal to 60% of the median disposable income), the variable value identifies the share of the population falling into the relative poverty category.
  - o *Wealth*. Inverse to the poverty measure, the variable identifies the share of individuals having at least 140% of the median disposable income.
  - o *Old age*. Share of individuals aged 70 years or older. The variable is selected to identify areas with varying shares of non-commuting populations.
  - o *Employed*. Share of adult individuals (age > 19) who are registered as employed.
  - o *Unemployed*. Share of adult individuals (age > 19) who are registered as unemployed. The employed and unemployed populations do not sum up to 100%, since non-employed individuals who are not actively searching for a job are excluded.
  - o *Distance to jobs*. The metric, Cartesian distance needed to reach the 100 nearest jobs (coordinates for all jobs are available in the database) from the 1 km × 1 km midpoint. Distance^2 to reach jobs

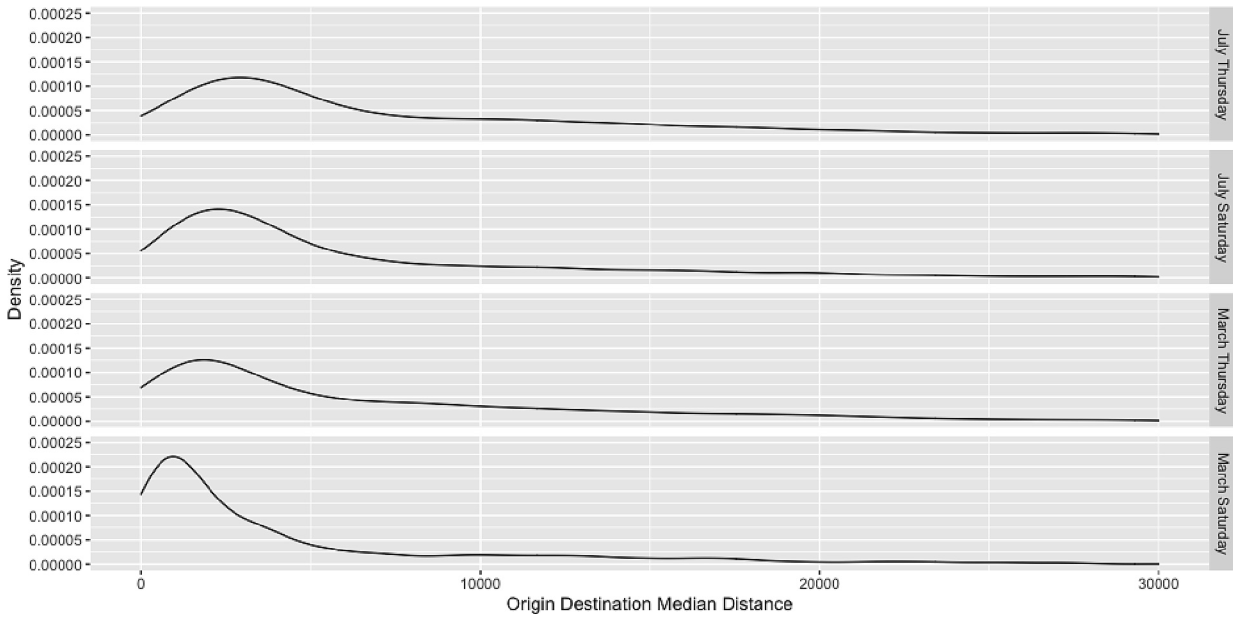

Fig. 2. Origin-destination median distance (values represent meters) – density (raw data) patterns shown for each of the included dates.

is also used in the analysis. We use both regular and squared distances to jobs to capture the spatial organisation of jobs and subsequent commuting patterns that are the result of strong job concentrations in the core and in commercial and industrial zones in the suburbs.

o *Distance to k = 100 individuals.* The same technique is used as for distance to jobs.

- ***Contextual variables***. Using GIS data derived from OpenStreetMap.org and Lantmäteriet (Land Survey Agency), we created two areal-domination variables that indicate the share of surrounding areas that are dominated by either water or greenery. Shapefiles containing information about land-use and water (freshwater and sea) are transformed to raster data, and subsequently subjected to focal statistics operations. The result is a raster file that at any point has a value that is representing the share of greenery or water within a 500 m radius. The km x km midpoints are thereafter associated with the underlying raster values using an extract-values-to-point procedure (Spatial Analyst in ArGIS Pro, Esri Inc., 2021), allowing us to enrich the unit midpoint with contextual data. These environmental data comprise:

o *Green share.* Including all kinds of environment that provides green surroundings, we have included forest and parks in the data-analytic computations. The values range between 0 and 1 and represent the share of greenery within a 500 m radius from the midpoint of the km x km unit (i.e. most of the unit). We have excluded, home gardens, farmland and fields from the variable greenery since the areas have restricted access, but included green areas that is publicly available.

o *Blue share.* Using the same 500 m radius approach, the share of freshwater and sea within the specified area is used as a variable value. The computation excludes marshland and similar areas.

4. Methodological framing

In this section, we present our modelling strategy. The panel structure of the data requires a regression framework that makes use of repeated observations in neighbourhoods (the scale of the analysis). In this context, multilevel models (ML) are commonly used to study clustered data at various scales (Snijders and Bosker, 2011; Teke-Lloyd et al., 2022). While MLs are often used to deal with the hierarchical structure of the information, where observations are nested under groups, they are also suitable for estimations based on panel data. In the latter case, time is the first-level variable, while observations at the neighbourhood level define the second level. Alternative modelling frameworks such as OLS with clustered standard errors are also possible. However, when the clusters are few (below 20), an ML model provides superior estimates (Hair Jr and Fávero, 2019). Similarly, while both Fixed Effects and Random Effects models are designed to account for clustering in data sets, MLs can incorporate both fixed and random effects simultaneously and are able to handle complex data structures better (Bell et al., 2019).

We now specify our generic ML model for differentiated leisure mobility as follows:

$$y_{ti} = \beta_{ti} x_{ti} + u_i + e_{it} \tag{1}$$

where y_{ti} is the median distance travelled from neighbourhood i on occasion t; x_{ti} denotes covariates; u_i are neighbourhood level random effects; and e_{it} is an error term.

The ML model, as defined in (1), accounts for the nested structure of the data (in this case by period), but ignores the spatial structure of the data. This becomes clearly a significant problem when we look at local measures of spatial autocorrelation (LISA; Anselin, 1995). Fig. 3 (top) left demonstrates a strong spatial dependence of the dependent variable (median distance travelled). In order to address this issue, we follow Pierewan and Tampubolon (2014) and add spatially autocorrelated residuals to (1) as follows:

$$y_{ti} = \beta_{ti} x_{ti} + u_i + e_{ti} \tag{2}$$

and

$$e_{ti} = \rho \sum_{i=1}^{k} w_{ij} e_{ti} + \varepsilon_{ti},$$

where e_{it} are spatially autocorrelated residuals; ρ is a spatial dependence parameter; w_{ij} is a spatial contiguity weight matrix; and ε_{it} are random errors.

In the full model, we estimate (2) (a spatial multilevel model) with the full set of covariates. We will also run (2) without any covariates to estimate a variance model (or empty model), which allows us to decompose the total variance into within-and between-period variances. Next, the residuals from the spatial multilevel model are used to map the Root Mean Square Error (RMSE) in order to assess the magnitude of

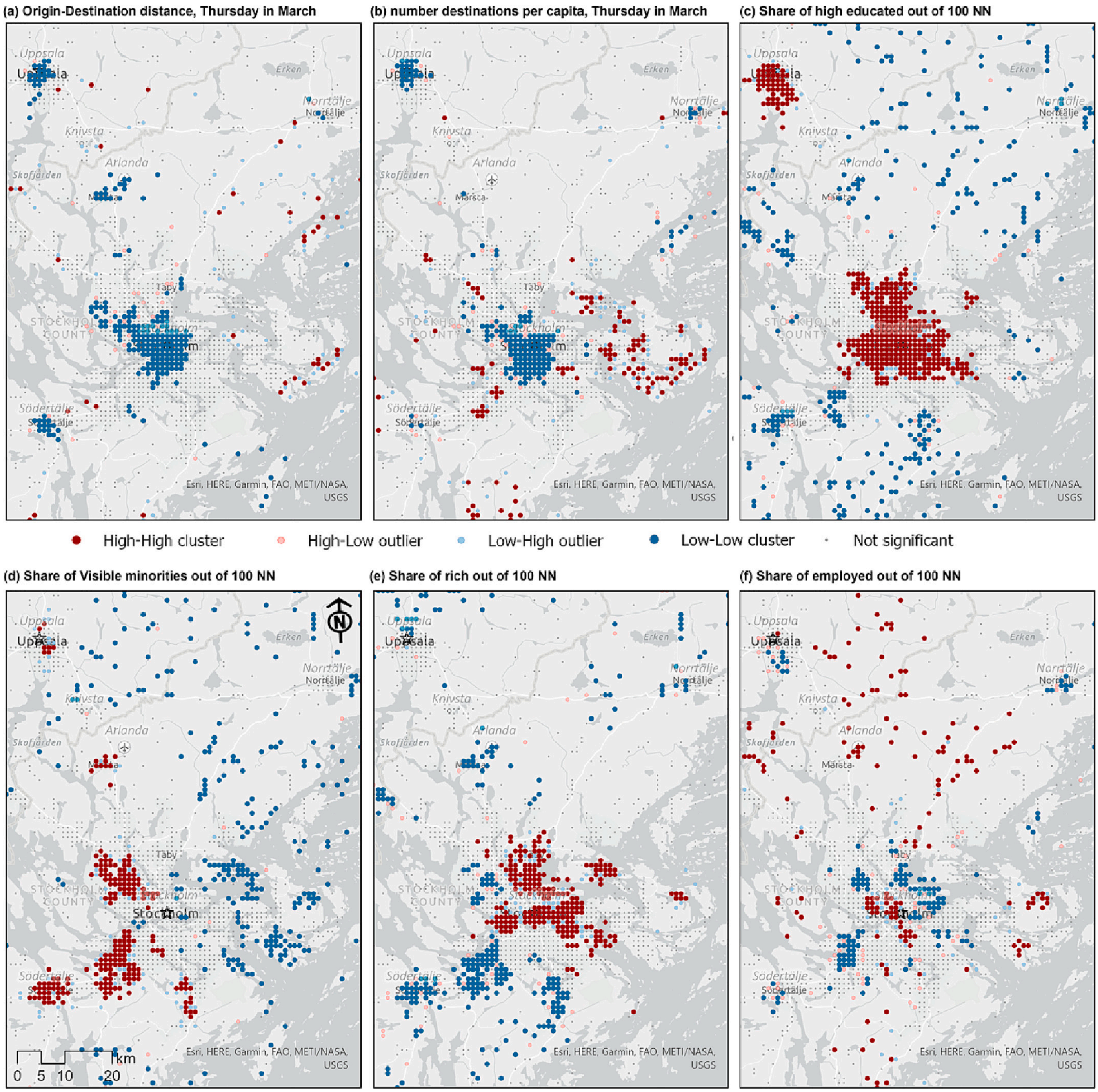

Fig. 3. Hot-spot/cold-spot maps, clusters of variables (LISA Morans' I) using the k nearest neighbours (KNN) neighbourhood of 100 nearest neighbours – hot-spots in red, cold-spots in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Legend: (a) Origin-Destination distance (during Thursday in March). The map shows areas (in blue) in which distances are shorter, and areas (in red) where the distances are long; grey sections show parts of the region where no distance-based clusters were observed; (b) Diversity of destinations by origin, namely: number of destinations from origin divided by population at the origin, during the Thursday in March; (c) Share of highly educated in the KNN, k = 100; (d) Visible minority share out of KNN, k = 100; (e) Share of rich in the KNN, k = 100 (f) Share of the working population out of KNN, k = 100.

deviations. We identify clusters in mobility both in the raw data and also from the empirical model by local Moran's I statistics. In particular, we use local spatial autocorrelation (LISA) statistics with a spatial contiguity weight matrix. In the next section, we systematically report and interpret our findings.

5. Empirical results

Our analysis addresses spatial inequality issues and, therefore, the question is: Are there any differences in mobility patterns between the dates under study, and what do the patterns tell us? The answer is shown in Fig. 2, where the patterns indicate that most destinations are located close to the origin, and that destinations are less favoured/visited as the distance increases. That being said, it is clear that the distributions vary substantially between different days. The longest overall OD-distances are observed for the July dates, and the Thursday in particular. This makes sense, if we consider the greater freedom and leisure orientation in July which is the main vacation period in Sweden, and if we consider that Thursdays (compared with Saturdays) have higher numbers of commuters. The March period clearly shows that most of the mobility is

Table 1
Regression results (from the 25th percentile by the number of people at origins and up).

Variables	Empty Model-Spatial	Full Model	Full Model-Interaction	VIF
JulySaturday (ref: July Thursday)		−52.013***	−133.362***	1.48
		(11.379)	(22.629)	
MarchThursday		109.289***	385.714***	1.48
		(11.357)	(21.653)	
MarchSaturday		6.817	123.278***	1.50
		(12.104)	(21.235)	
Destination to population		25,834.707***	26,037.176***	1.36
		(37.085)	(45.089)	
JulySaturday #c. Destination to population (ref: JulyThursday)			172.770***	
			(39.181)	
MarchThursday #c. Destination to population			−562.836***	
			(37.436)	
MarchSaturday #c. Destination to population			−234.894***	
			(38.467)	
Wealth		−105.039	−121.086	2.06
		(389.724)	(391.264)	
Higher Education		151.392	165.106	2.05
		(255.189)	(256.223)	
Visible Minority		8883.959***	8884.681***	2.71
		(334.233)	(335.564)	
Distance to jobs		0.202***	0.200***	8.94
		(0.043)	(0.044)	
Distance to jobs Sq.		−0.000***	−0.000***	6.27
		(0.000)	(0.000)	
Distance to k = 100 individuals		1.026***	1.025***	3.06
		(0.052)	(0.052)	
Green share		4407.274***	4410.301***	1.24
		(17.709)	(16.940)	
Blue share		4276.161***	4274.692***	1.05
		(30.519)	(29.183)	
Poverty		−3492.506***	−3460.565***	2.85
		(498.772)	(500.736)	
Old age		644.871**	662.036**	1.81
		(322.327)	(323.592)	
Unemployed		6618.132***	6580.550***	1.37
		(691.746)	(694.516)	
Employed		2311.026***	2332.359***	1.96
		(381.654)	(383.139)	
ρ	0.942***	0.997***	0.996***	
	(0.005)	(0.000)	(0.000)	
Var(Level1)	4.440	2.230	2.210	
Var(Level2)	1.220	1.190	1.250	
Constant	8390.654***	−9882.557***	−10,004.627***	
	(169.864)	(259.430)	(260.809)	
Log Likelihood	−60,380,739	−46,353,406	−46,154,989	
Pro>Chibar2	0.000	0.000	0.000	
Observations	6076	6076	6076	
Mean VIF				2.30
Number of groups	1666	1666	1666	

Estimated β values are reported.
Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

work/school oriented, while the Saturday mobility in March is limited, which means that recreation is more likely taking place at home or in the immediate vicinity.

In Fig. 3 a selection of the variables is mapped out in order to show the spatial patterns of different populations and mobilities.

So far, we have merely presented the generic patterns of heterogeneities in OD mobility, but what can we say from a geographical perspective? In Fig. 3a, a map of the median OD-distances in the study region is depicted for the working Thursday in March (top left). The map is produced using a local Moran's I estimation (or LISA; see Anselin, 1995), designed to find clusters of areas with different OD-distance mobility spectra. The result clearly shows that the shorter distances are clustered in the urban core areas, while longer distances are almost exclusively associated with the peri-urban or suburban parts of the region. The grey areas, mostly rural or suburban, indicate areas with either scattered settlements (making clusters difficult to form) or mixed mobility distances in larger parts of the suburban landscape.

The results in Fig. 2 and Fig. 3 reveal that there are substantial temporal and geographical variations. But what can be said about socioeconomic inequality issues? We will employ successively different regression techniques in order to capture the spatial and temporal dimensions of mobility among different groups. First, we employ a multilevel (ML) regression framework, where we study the effects of the included regressors and the magnitude of within and between km^2 unit level variation over the four days. In the empty model (Empty Model-Spatial), no regressors were included, and the main purpose of the approach is to identify the ICC (Intra Class Correlation) for variations between and within days in terms of mobility. The results render 78% variation in the first level (variance at the first level divided by the total variance in Table 1 first column), indicating that almost 78% of the variation is related to variation over time, and the remainder is attributable to within date mobilities. This means that without any information on local socioeconomic characteristics and destination attributes, we find that 78% of inequality in mobilities are attributable to differing mobility behaviour in workdays, weekends, work months and leisure months.

In the second model (Full Model), the ICC at the first level decreases to 65%, suggesting that the selected regressors are explaining a substantial part of the localised factors (13% precisely). It also means that 13% of the overall inequality in mobilities is explained by differing origin socioeconomic characteristics and destination diversity. At closer inspection, the coefficients indicate that, in contrast to the OD-distance on the studied Thursday in July, there are relatively small but expected day-effects. There is a slight decrease in distance on both Saturdays, but the greatest positive effect is observed for the Thursday in March, where commuting/schooling likely account for the lion's share of the prolonged distance. Among the socio-demographic variables (ranging between 0 and 1), the effect of increasing shares of wealth and higher education is insignificant and small, but poverty is associated with significant and substantial reduction of the OD-distances. Significant and substantial increases of OD-distances are observed for areas with an increasing number of working individuals, and the distances increase even further for areas with larger shares of unemployed and visible minorities.

Work is, of course, associated with an increase in commuting, but the positive correlation between unemployment and visible minorities needs further discussion. There are multiple causes behind this relationship, but the main factor is geography. Geographically speaking, the greater Stockholm region is relatively monocentric, with high housing costs near to the core and lower costs in the periphery. Areas with concentrations of visible minorities are located in the suburbs relatively far from the urban core; due to housing cost-related sorting, it is likely that the long distances travelled are associated with areas which have greater shares of visible minorities and unemployed (more often being unable to afford a residence in the more affluent, central areas). Also, areas with greater shares of individuals in the age group 70+ (variable *Old age*) are predicted to have longer commutes, and here also the geography is of relevance, since the rural parts of the greater Stockholm region have a larger number of the elderly compared with the more central parts. The variables *Distance to k = 100 individuals* and the *Distance to jobs & Distance to jobs squared* are all derived from the socio-

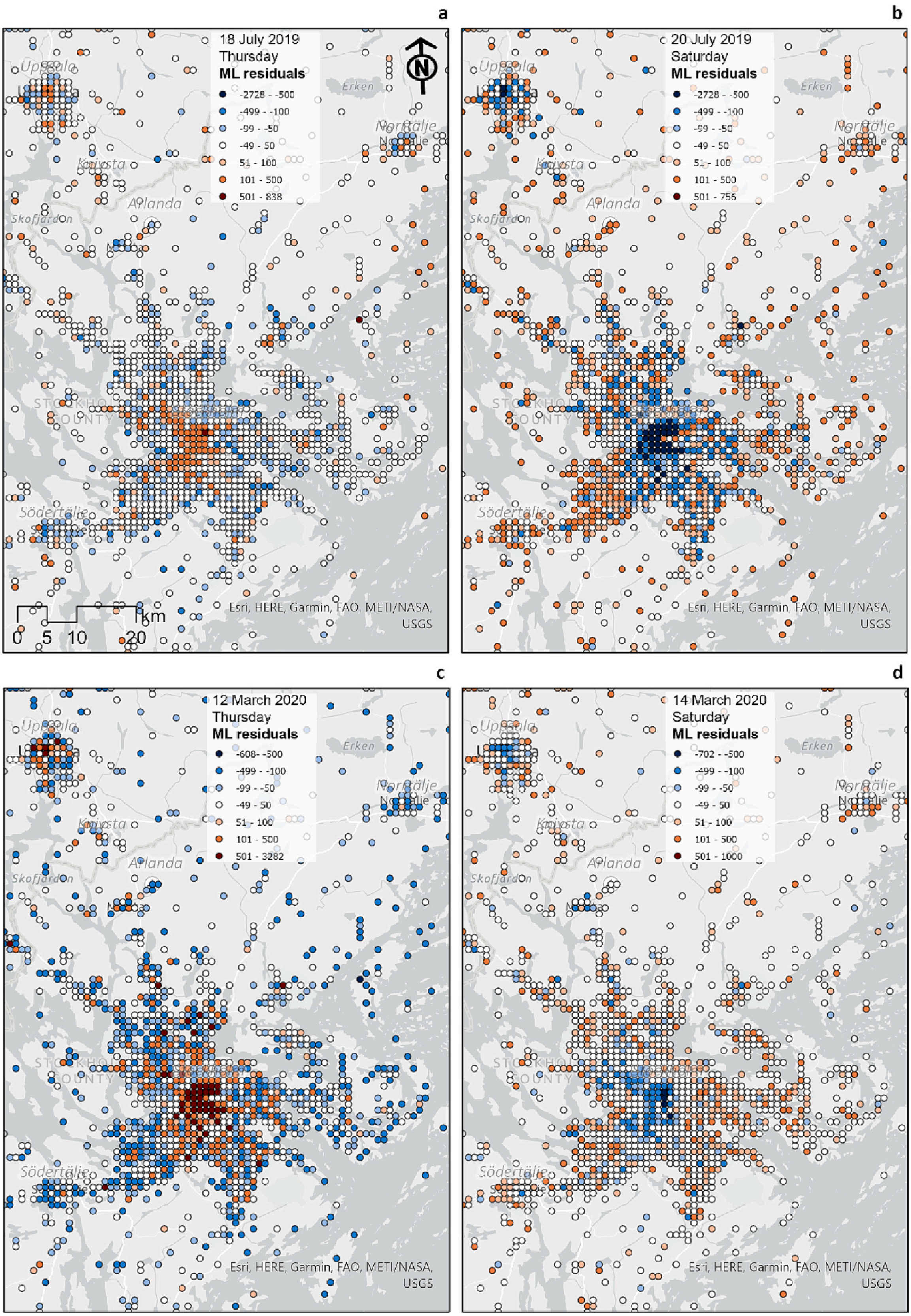

Fig. 4. Full Multi Level model residuals mapped for each date: (a) date1 Thursday, 2019-July-18; (b) date2 Saturday, 2019-July-20; (c) date3 Thursday, 2020-March-12; (d) date4 Saturday, 2020-March-14. Brown colours indicate that the residuals are positive (i.e. estimated distances are greater than observed) and blue colours indicate that the residuals are negative (i.e. estimated distances are shorter than observed). The coloration patterns show that inner and wealthy areas have shorter observed distances than expected during weekdays, and longer (recreational) distances during the weekend, while the opposite patterns are observable for less affluent and more suburban parts of the city. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

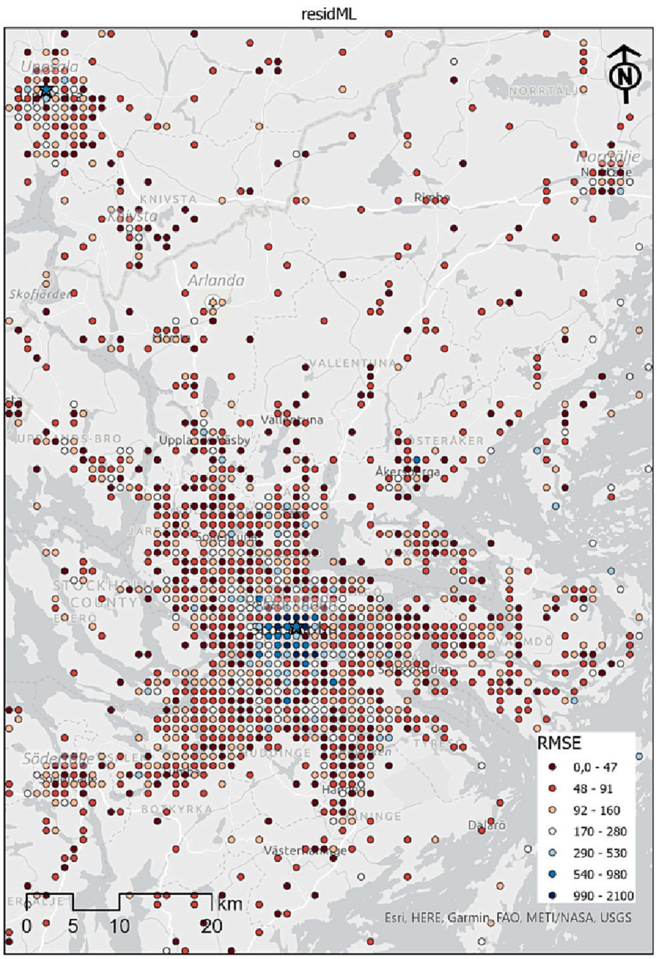

Fig. 5. RMSE values of ML model residuals across all dates.

demographic studies; they report the distance from each midpoint to reach 100 people and 100 jobs (note that the coefficients are related to metres to reach $k = 100$). As such, the variables are proxies for urban density and are instrumental in placing OD-distances in an urban functionality/urban form framework.

Overall, the measures indicate that the longer the distance needed to reach 100 jobs or people, the longer the OD-distances become (most likely, population density is linked to the availability of public transport). However, for job distances the negative squared distance coefficient suggests that at longer distances to reach k, the observed OD-distance is reduced (similar effects are not found for a distance to 100 individuals; also alternative specifications for both job distance and population distances have been evaluated). These results suggest that there is a limit to the attraction of jobs. If we study the share of green and blue in the destinations for the OD-trips, we can also see that destinations with greater shares of blue and green amenities (i.e. nature) require longer commuting distances.

Finally, the variable *Destination to population* captures the complexity and the range of alternatives, in terms of alternative destinations from any origin. The coefficient is strongly and significantly positive, suggesting that there is a clear link in the spatial mobility spectrum between longer travel distances and the number of alternative destinations.

In the final model (Full Model-interaction), the magnitude and direction of all variables remain as in the Full model. However, by introducing an interaction effect between *Destination to population* and date, we see a clear pattern indicating that there is a lower number of destinations (i.e., more focused commuting patterns) on Thursday and in March compared with Saturday and July. This suggests that recreational days and seasons offer more options when it comes opportunity to choose destinations. In subsequent sections, we analyse to what extent the relationship between distance and *Destination to population* varies in areas with different socio-demographic and geographical compositions. The last column of Table 1 includes variance inflation factor (VIF) for the full model. As it can be seen, the model is not subject to multicollinearity. The high inflation rate for job distance (among 100 nearest jobs) is the result of the quadratic term. An in all models, the spatial autoregressive parameter ρ (rho) is positive and significant. This is in line with LISA maps and supports our choice of a spatial multilevel model.

If we save and plot the residuals for each of the four dates in the Full model, we clearly see that there are spatial patterns that point to variations in mobility opportunities between locations. In Fig. 4, the range from blue (negative residuals) to red (positive residuals) colours swap between core areas and suburbs on a Thursday/Saturday basis, where map (a) represents Thursday in July, (b) Saturday in July, (c) Thursday in March, and, finally, (d) Saturday in March. The colour change is consistent with underestimation of distances in suburbs on weekdays, and the overestimation of distances in core areas. During the weekend, the opposite is the case, where the core areas are more mobile than expected. If we revisit the socio-demographic patterns depicted in Fig. 3, it is clear that weekend (recreational) mobility is greater than estimated in more affluent areas – and vice versa for the less affluent ones.

If we aggregate the full multi-level model residuals on km^2 unit level for each of the days using an RMSE (Root Mean Square Error) approach, we can assess the magnitude of deviations, which gives us an opportunity to find those areas that display the greatest variation in mobility over time. In Fig. 5, the RMSE values are depicted for the region, and the result clearly shows that the greatest deviation from predicted behaviour can be detected in the core, as well as in the more affluent parts of the urban landscape.

The map provides an informative visualization of the patterns. However, if we want to relate the predicted patterns to socio-demographic groups, in order to establish that there is less variation in the mobility pattern among some groups compared with others, we need to post-estimate some of the predicted values. In Fig. 6 we show predicted mobilities by date and socio-economic variables from the spatial ML model (Eq. 2). We have predicted mobilities from our model specification and plotted marginal effects in Fig. 6. We are also able to examine whether mobilities at a given socio-economic level are significantly different between days in July and March. The first graph shows the predicted mobility levels on the Thursday and Saturday in both July and March. As expected, median mobility is lower in July (around 10% compared with March), while on Saturdays it is lower than on Thursdays. It is plausible to assume that in an equitable mobility regime, individuals would be able to decrease or increase their mobilities according to their preferences ('feet-voting') which are – in this case – mainly driven by the time of the year (working dates vs holidays). Moreover, given the fact that with rising urbanisation, the spatial distance between people and also various activities have been increasing (Glaeser et al., 2002), spatial mobility has become crucial, both for participating in leisure activities and also to maintain social networks (Urry, 2002; Levitas et al., 2007; Östh et al., 2018a). From our estimates, we find that, when neighbourhood level economic factors are controlled in the model, minority concentration becomes a poor predictor of leisure mobility, so that irrespective of the segregation level, the same mobility patterns are generated for each date. This finding contradicts to the findings of Mooses et al. (2016) where they show a significant variation across ethnic origins in Estonia. On the other hand, neighbourhoods with high concentrations of relatively rich population display a higher variance in mobility between the four dates, while we estimate almost no variation in mobility in neighbourhoods with the least concentration of the rich. Similarly, in neighbourhoods with a high share of highly educated people, the population freely adjusts its mobility behaviour by date in the same order as rich neighbourhoods. Therefore, we may

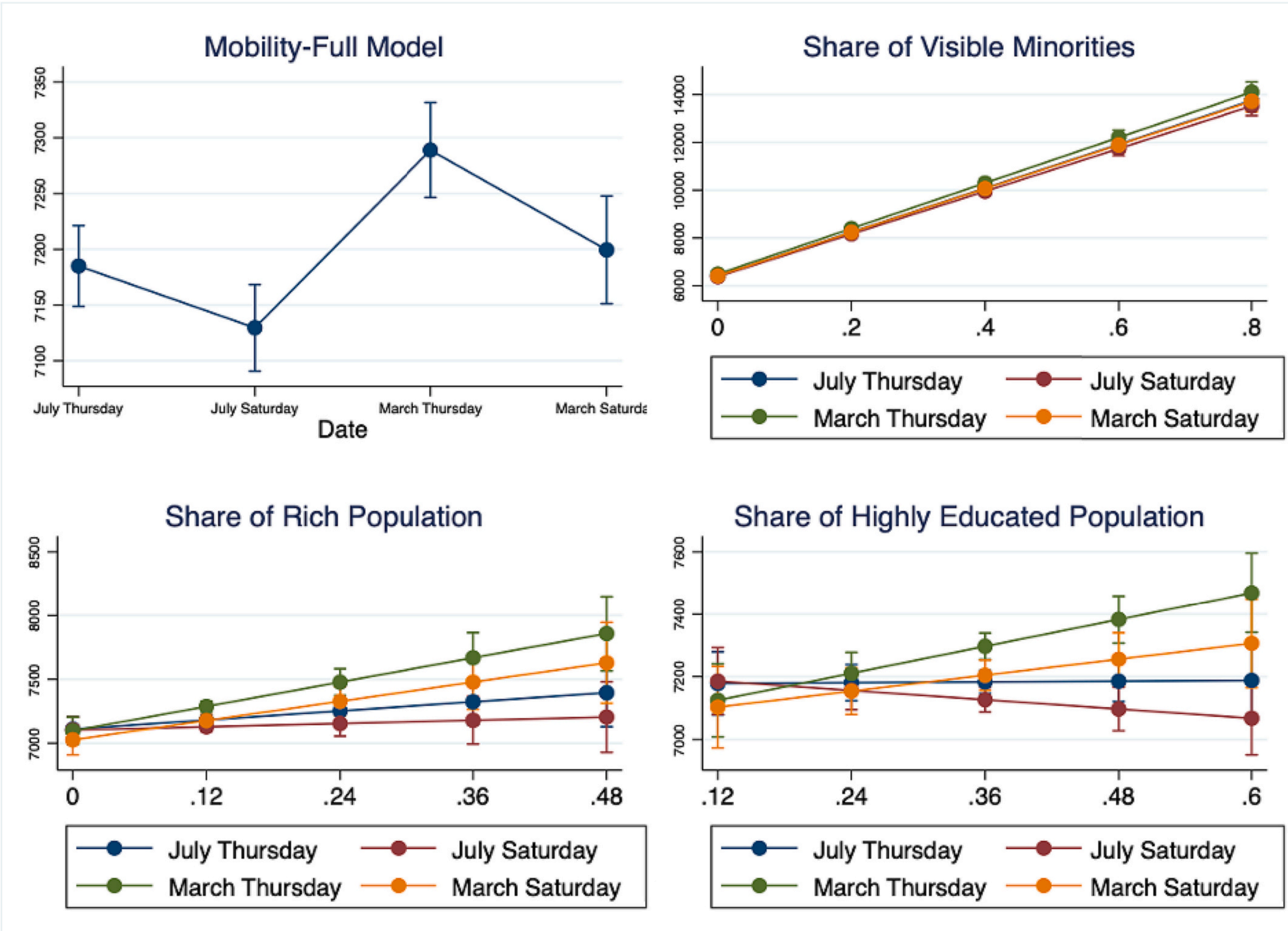

Fig. 6. Predicted mobilities from the spatial multi-level model by date and socio-economic factors. Values on Y-axis represent meters, and values on X-axis represents shares of population.

postulate that inequality in leisure mobility mainly results from economic factors rather than from minority vs native disparities. However, it is should be noted that, since visible minorities commute longer distances, irrespective of the time of the year, this points out a different kind of inequality which may be understood in the context of to spatial mismatch theories.

In conclusion, we find on the basis of empirical modelling approaches that:

- Our first hypothesis on temporary feet-voting towards more diverse destinations, especially natural and green/blue amenities, is confirmed.
- In line with our second hypothesis, leisure mobility displays increased inequality in diversity of mobility when comparing the working day in March with all other three dates (see, for instance, Fig. 6, Top left, Mobility – Full Model)
- Finally, the differences in income and education correlate with more diverse destination mobility during leisure time (see Fig. 6, bottom row), but the visible minority background seems to have no significant effect on mobility variance when controlling for income and education (see Fig. 6, top right).

6. Conclusion

Equity considerations have been extensively investigated in the transportation literature, in particular regarding specific target groups, such as the elderly, children, and minority groups (see, e.g., Mollenkopf et al., 2005; Odgaard et al., 2005; Rosenbloom, 2010; Di Ciommo et al., 2018; Di Ciommo and Shiftan, 2017). Such distributional effects are not only characterised by specific socio-economic groups, but are also place-specific (both origin and destination) (see also Kang et al., 2004; Sun et al., 2011; Lamsfus et al., 2015; Alyavina et al., 2020; Dueñas et al., 2021). In our study we have addressed, in particular, the empirical heterogeneity in spatial patterns of leisure mobility in the greater Stockholm area in Sweden. Using cell phone data and a broad range of background data (in particular, OSM data), we mapped the leisure mobility over a series of distinct dates for a large sample of Stockholm citizens. The results are really interesting and uncover noteworthy spatial leisure spectra, depending on the day of the week and the season.

It is particularly striking that relatively poor and low education areas show less variation in mobility over time; there is apparently a case of unequal opportunity for temporary 'feet-voting' during leisure time in the Stockholm area depending on socio-economic background. However, a specific minority background did not show variability in mobility between working and leisure time periods, contrary to our expectations. A novel finding in our study is also that leisure 'feet-voting' is spatially and socio-economically differentiated.

In addition, our results suggest that vulnerable groups tend to be more oriented towards a narrower choice of destinations, so that their leisure destination spectra are also more restricted in scope. It turns out that the socio-economic 'fortune' of people and their range of leisure choices are closely correlated, so that we may conclude that leisure patterns and socio-economic inequality profiles are interdependent.

We note that our analysis has addressed spatial leisure mobility in the period just before the COVID-19 outbreak. This was done deliberately in order to have a clean testing of our research hypotheses, without any disturbance by other intervening background factors. Other studies (e.g., Toger et al., 2021; Järv et al., 2021a, 2021b) hint that mobility during weekends and holidays during the pandemic may exacerbate inequality even more. It would, of course, be an interesting question to examine how much the COVID-19 pandemic has affected leisure-related mobility and its distribution over socio-economic groups. This research challenge will be taken on board as the next stage of our investigation. Finally, we note that the activity-mobility spectrum analysis initiated by Hägerstrand (1970) continues to be a rich source of innovative travel research.

A notable limitation of this study is a lack of socioeconomic information about the individual phone users. Socioeconomic data was joined ecologically with the underlying assumption that a phone represents the socioeconomic features of the neighbourhood where it was during night-time (assumed night rest location). This introduces a degree of imprecision in our estimates while protecting the privacy of phone users. Most of the Swedish population goes on holidays in July, this was the reason for assumption that July represents the typical leisure mobility. Of course, this choice will neglect the mobility of individuals who work in this time (for example in leisure industry).

CRediT authorship contribution statement

Marina Toger: Conceptualization, Funding acquisition, Data curation, Project administration, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Umut Türk:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **John Östh:** Conceptualization, Funding acquisition, Formal analysis, Methodology, Software, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Karima Kourtit:** Conceptualization, Project administration, Writing – original draft, Writing – review & editing. **Peter Nijkamp:** Conceptualization, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare no competing interest.

Data availability

The authors do not have permission to share data.

Acknowledgements

We thank the mobile phone data provider for the data. Marina Toger and John Östh acknowledge the FORMAS project "På rätt väg?" #2018-00255; and the European Union H2020 project INCULTUM with grant number 101004552. John Östh acknowledges support from the HORIZON-WIDERA-2021-ACCESS-02 project UR-DATA with grant number 101059994. Karima Kourtit and Peter Nijkamp acknowledge the grant from the Romanian Ministry of Research, Innovation and Digitization, CNCS - UEFISCDI, project number PN-III-P4-PCCE-2021-1878, within PNCDI III, project – Institutions, Digitalization and Regional Development in the EU. The authors also acknowledge the grant from the Axel och Margaret Ax:son Johnsons Stiftelse, Sweden – project “Urban-Environmental Presumptions of Public Life” 2018.

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