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From national recreation statistics and mobile data to local estimates of recreational activity in Finland

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Abstract: The concept of multi-local living is a current and growing phenomenon in Nordic countries and elsewhere. However, the changes that multi-local causes in the temporal recreational activity of areas have remained unknown because official population statistics are not capable of detecting the temporal mobility of the population and thus the changes in the recreational activity of areas. The aim of this article is to estimate local recreational activity in Finland using new databases and to study the changes in local recreational activity caused by multi-local living. The results reveal that multi-local living remarkably changes recreational activities during the year and highlights the need to identify spatio-temporal changes at local and regional levels. Mobile phone data seems to be valuable for the regional targeting and prioritisation of recreational activities because it can identify the changing temporal roles of the regions.

Keywords: Recreational activity, multi-local living, mobility, rural areas, Finland

1 Introduction

The concept of multi-locality is a current global phenomenon, which in its simplest definition means that a person or family has more than one residence or place to stay for a longer period of time (Wisbauer et al., 2013; Rannanpää et al., 2022). Multi-local living is distinct from daily commuting (circulation) and relocation (migration) (Greinke & Lange, 2022), however, and in the case of multi-local housing, it requires an overnight stay (Rannanpää et al., 2022). Multi-local processes related to second-home mobility occur in other Nordic countries besides Finland and in several countries in Europe, including Switzerland, Austria, Germany, and the UK (Overvåg & Berg, 2011; Di Marino, 2022). Half of the population of the Nordic countries are estimated to have access to a second home, and these homes are increasingly being used year-round (Rye & Berg, 2011; Slätmo & Kristensen, 2021). Multi-local living has recently increased, with COVID-19 having evolved into somewhat of a *catalyst* for the adoption and increasing use of digitalisation (Amankwah-Amoah et al., 2021). This has widened the concept of multi-local living from a form of leisure to a means of teleworking (Rannanpää et al., 2022).

Research evaluating the impacts of seasonal mobility on local recreational activity patterns is limited because it is difficult to quantify the recreational activity of diverse locations and dates. The temporal variability of the population due to second-home usage is largely ignored in policy and spatial planning in the Nordic countries (Slätmo & Kristensen, 2021) even though multi-locals also use local infrastructure and services as do permanent residents (Adamiak et al., 2017) and has potential for local and regional economic empowerment as tourism in general does (Antić et al., 2020). Permanent population statistics are unable to detect the recreational use of areas as they do not recognize the spatio-temporal variation of the population because people are dwelling in different areas than expected (Dittrich-Wesbuer et al., 2015). The popularity of multi-local living highlights the need for new spatial data in order to carry out ecosystem service accounting, project evaluations, land use planning, regional targeting and prioritisation of recreational activities, and quality improvements where people are (including in time, but not officially) (Merrill et al., 2020). Previous studies, such as Lankia et al. (2015), have based their analyses on surveys targeted at respondents' permanent home addresses, overlooking the

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phenomenon of multi-local living. This research addresses a gap in the literature. By incorporating the effects of multi-local living, our study offers an approach how to provide a more accurate depiction of recreation demand across different regions.

The aim of this article is to estimate local recreational activity, which is understood here as participation in outdoor activities, in Finland. We use new GIS (geographic information system) data sources and study the changes in local recreational activity caused by multi-local living by investigating how much multi-local living changes the spatial pattern of participation in outdoor recreational activities during the year and the factors that explain the monthly changes in the recreational activity of these areas. This article also investigates how mobile phone data and questionnaire-based data can be used to count recreational activity. Our study provides policy-relevant information on the impacts of multi-local living, which is essential for efficient and equitable planning and decision-making concerning recreational resources. This information addresses the challenges of providing equal recreation opportunities across different regions and informs the allocation of financial resources to meet the needs of various areas.

2 Multi-local living changes spatial pattern of recreational activities

The spatial and temporal dimensions of multi-local living vary significantly in areas, emerging in and affecting areas and regions differently. While the most important forms of multi-local living in urban areas are related to long-distance commuting and teleworking, in rural areas they are mostly associated with leisure (Voutilainen et al., 2021). An estimated 2.4 million out of the total of 5.5 million Finns regularly spend time in rural areas (Adamiak et al., 2017). Hence, instead of making permanent moves, individuals are increasingly opting to divide their time living seasonally between an urban permanent residence and a rural second home. This justifies the use of Finland as a case study to map temporal changes in recreational activities within the country. The rise of multi-local living alters both the spatial and temporal patterns of local recreation and outdoor activities, particularly in rural areas (Sievänen et al., 2007).

Many studies have shown that the motives for multi-local living relate to recreational activities. Spending time in the countryside may reflect an interest in subsistence activities, including hunting, fishing, and gathering wild and home-grown products, which have been connected to rural lifestyles (e.g., Pouta et al., 2006). In Pitkänen and Kokki's (2005) study, opportunities for fishing as well as picking berries and mushrooms were important motives for recreational home use. Recreational home users have been found to actively participate in many traditional outdoor activities that use the surrounding nature, such as berry and mushroom picking, fishing, and boating (Sievänen et al., 2007).

However, limited attention has been directed at including multi-local living and increased mobility of people when planning public services such as recreational activities. Existing national recreation statistics are biased in that they describe recreational activities in a multi-local society, and these statistics cannot be used to estimate recreation activities at the local level (e.g., Lankia et al., 2015). Therefore, new special data sources are needed to reflect the dynamic nature of a society characterised by multi-local living.

In recent years, mobile phone data have been increasingly used to measure recreational use of different areas. For example, phone data have been used to investigate spatio-temporal patterns of recreation within parks via data derived from exercise tracking apps (e.g., Creany et al., 2021) or geo-tagged posts on social media to estimate visitor use (e.g., Wilkins et al., 2020). However, these data sources represent only the small proportion of public that opt to use those specific social media outlets, and they lack adequate temporal and spatial resolution (Merrill et al., 2020) because they rely on the active participation of the visitor (Creany et al., 2021). More recently, studies that use commercially available human mobility datasets based on cell phone locations have become increasingly common. Those studies have estimated visitation to water recreation areas (Merrill et al., 2020) or the impacts of tropical weather (temperature, rainfall, and wind) and holidays on visitor numbers and stay time in urban protected areas (Jaung & Carrasco, 2021).

In this study we acknowledge the increased mobility of people and break the tradition of understanding recreation behaviour originating only from one home location. In the analysis we take advantage of mobile phone data for an entire country and incorporate multi-local living and mobility to estimate participation in recreational activities. This improves the future allocation of resources and planning of sustainable recreational activities.

3 Methodology: Estimating and examining patterns of recreational activity in Finland

This section describes the analytical steps undertaken to estimate local recreational activity (Figure 1). First, the estimation of local recreational activity is described in

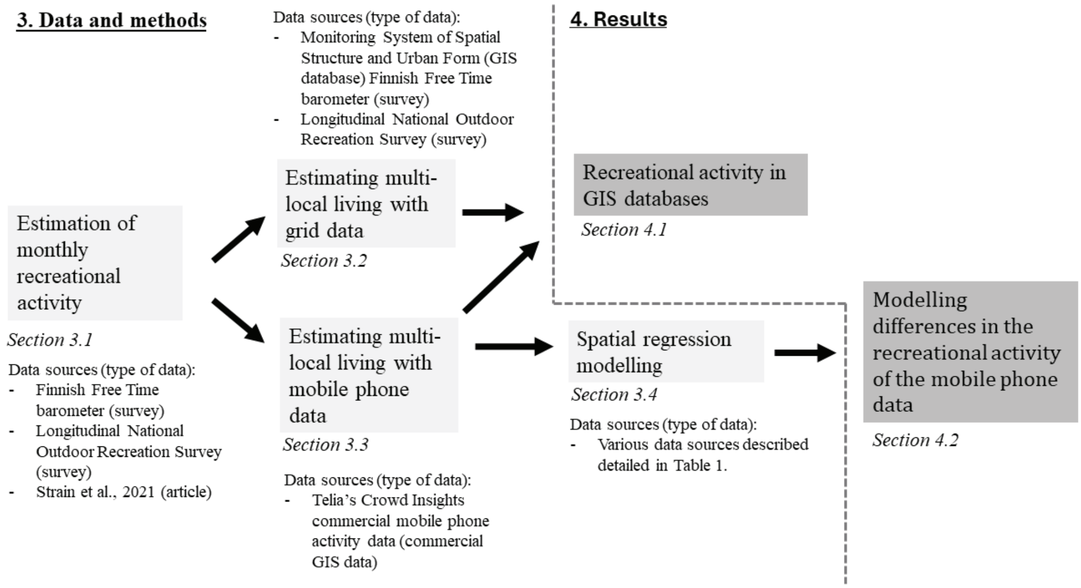

Figure 1: Flowchart of the research process.

detail (section 3.1), followed at a second step by a description of grid (section 3.2) and mobile phone data (section 3.3) to account for local recreation activity with spatial data. The grid and mobile phone data were used to calculate the statistics of the local recreational activity. In the third step (section 3.4), a spatial regression model is presented with the variables that explain the recreational activity during different months.

3.1 Estimating monthly recreational activity

The focus in examining the impacts of multi-local living on recreational activity is on second-home mobility because it comprises the largest multi-local population group in Finland (Rannanpää et al., 2022). The potential local recreational use of the area is calculated based on data from the National Inventory of Recreational Uses of Nature (LVVI, 2020), which received survey responses from nearly 8,700 Finns. The national inventory is utilised in research in the field, and it promotes the construction and management of outdoor recreation services. The participants in the survey were randomly extracted from Statistics Finland's (Tilastokeskus, 2023) population database concerning the population of Finland. These data were used to calculate the potential monthly close-to-residence recreation use in grid i ($RActivity_{ji}$) based on the following calculation:

$$RActivity_{ij} = Recreation_{ij} * Population_{ij} \qquad (1),$$

where the variable Recreation denotes the annual number of participations in outdoor recreational activity of the region k based on the definition in the LVVI survey. The average value for outdoor recreational activity (*Recreation*) was 182 times in 2020, of which 77% occurred within walking distance from home used in this study to account for activities (LVVI, 2020). Since no information is available about the monthly recreational activity, the annual recreational activity is used to estimate monthly activity. This estimation is based on recreational activity statistics from another monthly recreational activity study (Strain et al., 2021) and on the statistics of monthly use of second homes in Finland (Voutilainen et al., 2021), which were used to calculate monthly activity and further divide the volume of annual recreation activities into monthly ones. The calculation of the monthly population statistics in grid i ($Population_{ij}$) is described in sections 3.2 and 3.3. The original spatial units in the mobile phone data are described in Figure 1 along with urban-rural categories and division into regions. To facilitate a comparison between the different spatial units, the results of the grid data are summarized based on the grid used in the mobile phone data.

Due to the strong association between multi-local and urban-rural living styles, the results of the local variations in recreational activity are described using urban-rural typology (see Figure 2), which divides areas into seven categories: Three urban and four rural categories (Helminen et al., 2020). In the typology, urban categories contain inner urban areas, outer urban areas, and peri-urban

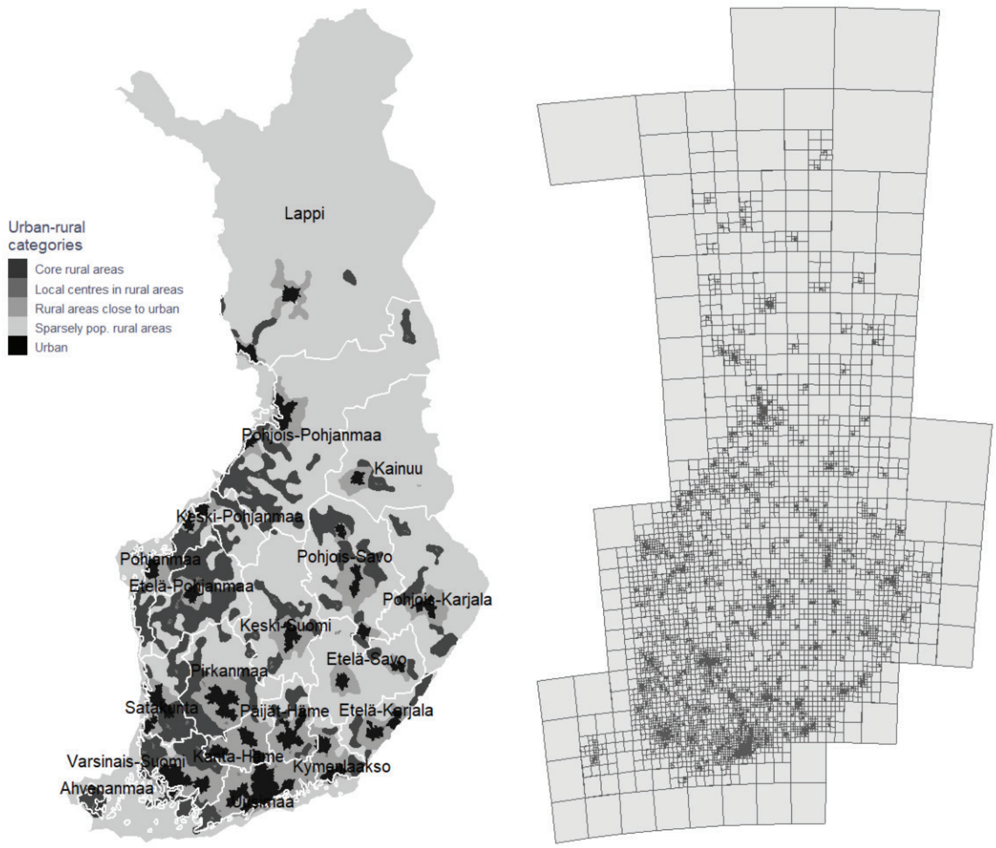

Figure 2: Urban-rural categories, regions, and mobile phone data grids in Finland. In the Figure, urban classes have been combined into a single class to make urban areas stand out more clearly.

areas. Local centres in rural areas are population centres which are located outside of urban areas. Rural areas close to urban areas are areas that have a rural character but are functionally connected and are close to urban areas. Core rural areas have intensive land use, with a relatively dense population and a diverse economic structure at the local level. Sparsely populated rural areas consist of small, dispersed settlements that are located at a distance from each other, and most of the land area is forested. Because the typology is implemented using a nationwide 250m x 250m cell grid, the urban-rural category of the mobile phone grids was determined based on the largest population of the typology on a grid.

3.2 Using a grid database to estimate average monthly population

We estimate local recreation activity with a population data that are compiled from the YKR database (Monitoring System of Spatial Structure and Urban Form), which is created and maintained by the Finnish Environment Institute, and it comprises data on population, housing, workplaces, and travel to work from the year 2019 for each of 319,841 square-shaped populated grid cells (250m x 250m) into which the territory of Finland is divided (Figure 2). The YKR database was used to estimate the volumes of seasonal populations by population grids (see equation 1, $Population_{ij}$).

The average monthly population ($Population_{ij}$) describes the population after considering the monthly use patterns of primary homes and summer cottages (see Adamiak et al., 2017). For 2019 it was calculated as:

$$Population_{ij} = Pop_i + (sh2019_i * users * use_j) - (RP2019_i * access * use_j) \quad (2),$$

where the variable Pop_i denotes the registered population of a given grid i in the year 2019. The variable $sh2019_i$ stands for the number of summer cottages in grid i in 2020 and the constant *users* denotes the average number of people using one summer cottage, which is 4.7, according to the Finnish Free Time Residence Barometer (Voutilainen et al. 2021). The variable *access* describes the shares of grid populations that had access to a summer cottage in

2020, and based on the LVVI (2020) study it was set to 0.43. The variable *use* describes the monthly use of summer cottages in 2021 and it is based on the Finnish Free-Time Residence Barometer (Voutilainen et al., 2021). The parameters used in the calculation are derived from different years because comprehensive surveys on recreational use are rarely carried out in Finland. The Finnish Free Time Residence Barometer was carried out in March and April 2021, with a random sample of 5000 second-home owners.

3.3 Using mobile phone data to estimate average monthly population

We also estimate local recreational activity using Telia's Crowd Insights commercial mobile phone activity data, which reports the number of people dwelling in an area over a night, making it possible to distinguish multi-local living from day-to-day mobility. The dataset covers all of Finland and estimates the average number of people per month living in the grids (abbreviation $Population_{ij}$ in equation 1), as visualised in Figure 1. Mobile phone data have been successfully utilised earlier in studies mapping the extent of multi-local living (Rannanpää et al., 2022) and related mobility in Finland during the Covid-19 pandemic (Willberg et al., 2021). The utilised mobile phone data are based on the period from March 2020 to February 2021, which allows it to be compared with data from the Finnish Free-Time Residence Barometer (Voutilainen et al., 2021). Mobile phone data contain information on the connection of mobile phones to base stations and this approach makes the material more comprehensive compared to, for example, localized call data, because the material also includes subscriptions that were not used (see Burkhard et al., 2017).

Table 1: Description of the variables used in regression modelling.

Row vector	Variable	Description	Data source, year
Category	Urban area (dummy)	Area belongs to urban area in urban-rural typology (coded as 1 if area belongs to category and 0 if not).	SYKE, 2018
Category	Sparsely populated rural area (dummy)	Area belongs to sparsely populated rural area in urban-rural typology (coded as 1 if area belongs to category and 0 if not).	SYKE, 2018
Category	Rural area close to urban area (dummy)	Area belongs to rural area close to urban area in urban-rural typology (coded as 1 if area belongs to category and 0 if not).	SYKE, 2018
Category	Local centre of rural areas (dummy)	Area belongs to local centre of rural areas in urban-rural typology (coded as 1 if area belongs to category and 0 if not).	SYKE, 2018
Land use	Water cover (%)	Proportion of water areas from the total surface of the grid.	CORINE, 2018
Land use	Forest cover (%)	Proportion of forest areas from the total surface of the grid.	CORINE, 2018
Land use	Second homes from land cover (%)	Proportion of leisure areas from the total surface of the grid.	CORINE, 2018
Land use	Second homes (%)	Proportion of second homes from the total number of residential buildings in the grid.	YKR, 2020
Land use	Average value for zonation index	Average value for zonation index in grid which indicates biodiversity value of the forests. The higher the numeric value is, the higher the biodiversity value is in the grid.	Zonation, 2018
Land use	Proportion of nature reserve from the total area (%)	Proportion of nature reserves from the total surface of the grid.	CORINE, 2018
Location	Distance to the city over 50,000 inhabitants (km)	Distance from the grid centroid to the nearest city over 50,000 inhabitants. Distance is calculated based on Digiroad (2018) network.	Own calculation, 2020
Location	Distance to the city over 200,000 inhabitants (km)	Distance from the grid centroid to the nearest city over 200,000 inhabitants. Distance is calculated based on Digiroad (2018) network.	Own calculation, 2020
Location	Distance to the primary school (km)	Distance from the grid centroid to the nearest primary school. Distance is calculated based on Digiroad (2018) network.	Own calculation, 2020
Infra-structure	Availability of broadband (%)	Proportion of the population with access to broadband.	Traficom, 2020
Population	Population density (100 inhabitants/km^2)	Population density of area.	YKR, 2020

Despite the dynamic aspects of mobile phone data, its use entails several challenges. In Finland, Telia enjoys roughly one-third of the market share (Data.Traficom, 2023) and therefore, in mobile phone data, the number of people has been weighted to represent the total population based on the operator's market share in individuals' place of residence. Second, it should be noted that estimating multi-local living with the monthly average population is an approximate variable, as it includes all overnight mobility that crosses municipal boundaries. According to estimates, a significant part of mobility is related to second homes, about 90,000,000 annual overnight stays and leisure tourism, about 45,000,000 annual overnight stays which together cover more than 60% of all mobility in Finland (Rannanpää et al. 2022).

3.4 Modelling the monthly changes in the recreational activity with spatial regression analysis

Our second objective was to develop a model that could predict local recreational activity using mobile phone data and other explanatory variables that could be easily compiled across many places. These covariates include urban-rural category (size of the grid), location (distance to urban centres of various sizes, services, and national parks), land use statistics (including water access, forest cover, and biodiversity of forest areas), basic infrastructure (broadband availability), and other statistics (population density, teleworking potential) (Table 1). We estimated a varied set of candidate regression models, including several functional forms where we defined linear relationship between the mobile phone data and the population statistics and other regressors in R. The changes in the estimated local recreational activity in mobile phone data were analysed using a regression model that explains the monthly difference $DPopulation_{ij}$ from average monthly recreational activity of the grid based on the following model:

$$DPopulation_{ij} = \alpha + \beta Category + \beta Location + \beta Land + \beta Infrastructure + \beta Population + \varepsilon \quad (3),$$

where:

- *Category* refers to urban-rural category of the grid;
- *Location* describes the location of the mobile phone grid with respect to the urban structure, services and national parks;
- *Land* refers to the land use of the grid and the biodiversity values of the forest areas;
- *Infrastructure* refers to the broadband availability of the grid; and
- *Population* describes the population density of the permanent population of the grid.

Regression models were estimated using spatial regressions (SAR) because the monthly differences in the recreational activity were spatially autocorrelated indicating that the values of variables at nearby grids are not independent from each other (Tobler, 1970). Main source of spatial autocorrelation in the recreational activity relates to human activity, because the data are affected by processes that connect different places, including spatial interaction and spatial diffusion processes; or by phenomena that extend over space to occupy regions rather than point locations (Odland, 1988). Based on the spatial dependence diagnostics functions from R's spdep package (Bivand, 2022), the SAR model is estimated using a spatial error model, where the error terms across different spatial units are correlated. The spatial error model is defined as follows:

$$y = X\beta + \varepsilon \text{, where } \varepsilon = \lambda W\varepsilon + \xi \quad (4).$$

In the regression model, λ is the spatial autoregressive coefficient for the error lag (to distinguish the notation from the spatial autoregressive coefficient ρ in a spatial lag model), and ξ is an uncorrelated and homoscedastic error term. Spatial error dependence may be interpreted as a nuisance (and the parameter λ as a nuisance parameter) in the sense that it reflects spatial autocorrelation in measurement errors or in variables that are otherwise not crucial to the model. The spatial regression is used because traditional nonspatial models might give biased or inefficient estimators of regression coefficients if spatial autocorrelation is omitted because it violates the assumption of independently and identically distributed (i.i.d.) errors of most standard statistical procedures (Anselin & Bera, 1998).

4 Results

4.1 Recreational activity in GIS databases

The change in the average population and local recreation activity during the year occurs in large areas (Figure 3). The grid and mobile phone data have remarkable differences because the latter detects monthly variations in average population much better than static gird data which ignores mobility. This different ability of the databases to estimate

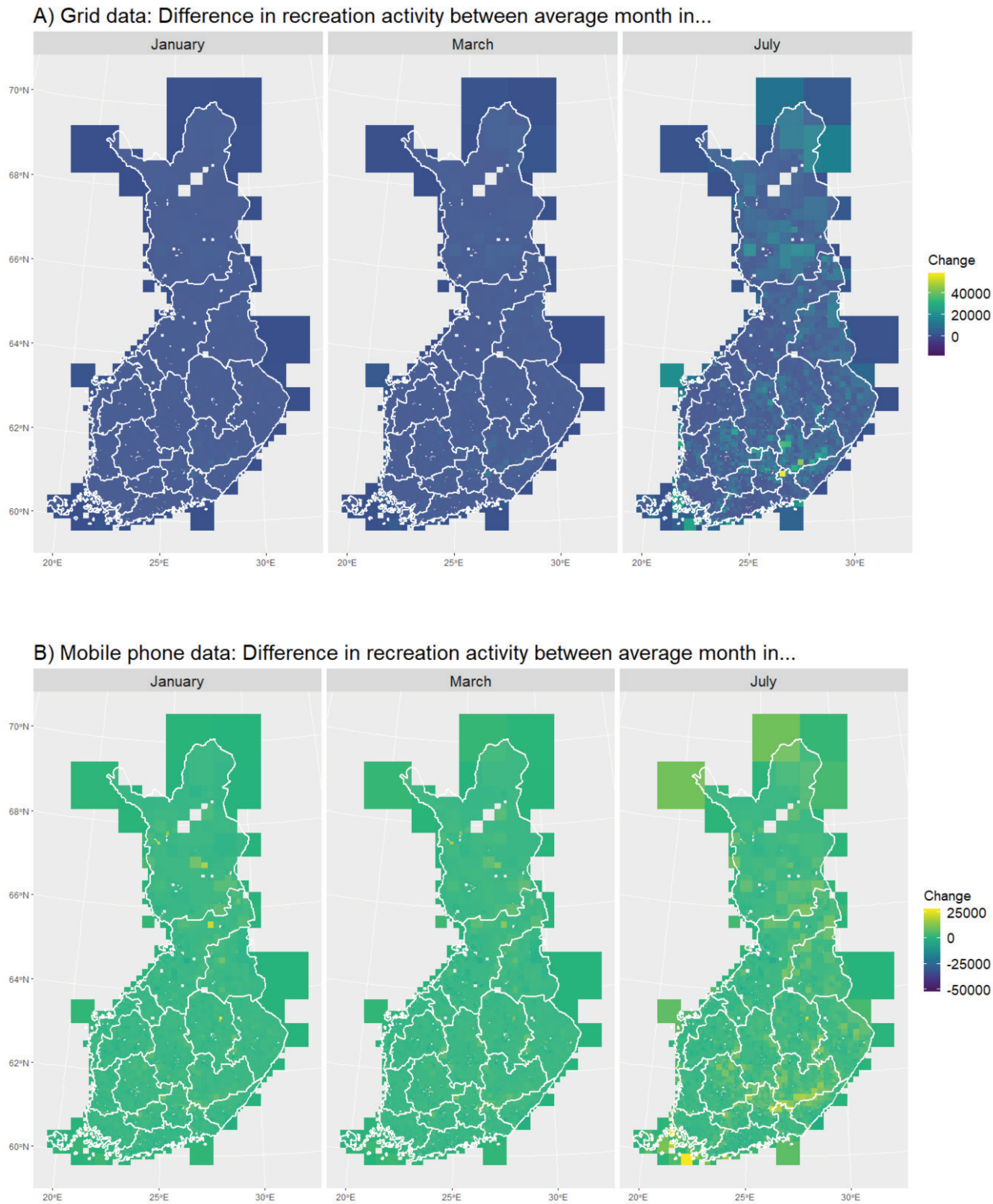

Figure 3: Differences in the local recreational activities by grid data and mobile phone data approaches.

the local recreation use is most evident in January and March. During these months the grid data cannot detect temporal variation in the average population around the tourism centres in Lapland (Figure 3). In July, when people spend more time in their second homes than in January, the differences between databases decrease. The geographical changes in the recreation activity are remarkable, especially in July (Figure 3) when local recreational activity increases mostly on the Baltic coast, Lakeland Finland, and the Eastern and Northern parts of Finland.

The total local recreational activity in Finland is 654–683 million visits, depending on the type of database. In the urban-rural classes, the local recreation activity statistics vary considerably between calculations. The widest differences are found between mobile phone data and permanent population statistics (Table 2). With mobile phone data, the total annual recreation activity of the sparsely populated rural areas is 50.5% higher than the corresponding figure for the permanent population statistics. The change in recreational activity demonstrates the high impact of multi-local living on temporal recreational use of areas. Moreover, in the local centre of rural areas and in the core rural areas, the permanent population statistics underestimate the recreational activity, as the difference between permanent population statistic and mobile phone data estimations are 13.6% and 7.1% (Table 2). In contrast, the permanent population statistics of the other urban-rural categories tend to overestimate recreational activities (Table 2).

Table 2. Differences in local recreational activity by methods in urban-rural classes. Negative percentage values indicate underestimation and positive values overestimation of the local recreation activity.

Data source	Estimates for local recreational activity	Inner urban area	Outer urban area	Urban fringe	Rural area close to urban area	Local centre of rural area	Core rural area	Sparsely populated rural area
Permanent population statistics	Total annual activity (n, million visits)	242.2	155.0	84.4	31.8	54.3	73.4	41.3
	Average monthly activity (n, million visits)	20.2	12.9	7.0	2.6	4.5	6.1	3.4
Average monthly populations based on grid data	Total annual activity (n, million visits)	219.4	141.7	82.2	29.1	66.1	79.1	64.9
	Difference in activity during the whole year compared with permanent population statistics (%)	9.4	8.6	2.6	8.3	-21.8	-7.7	-57.1
	Activity in January (n, million visits)	16.1	10.3	5.7	2.1	3.9	5.1	3.2
	Activity in July (n, million visits)	18.3	12.0	7.7	2.5	7.9	8.4	9.4
	Difference in activity between January and July (%)	-13.7	-16.3	-34.7	-17.0	-105.4	-65.7	-196.0
Average monthly populations based on mobile phone data	Total annual activity (n, million visits)	200.7	140.2	79.6	30.7	61.6	78.6	62.2
	Difference in activity during the whole year compared with permanent population statistics (%)	17.1	9.6	5.7	3.4	-13.6	-7.1	-50.5
	Difference in activity during the whole year compared with the average monthly populations of grid data (%)	8.5	1.1	3.1	-5.4	6.7	0.6	4.2
	Activity in January (n, million visits)	13.1	9.4	5.2	2.1	4.0	5.2	4.0
	Activity in July (n, million visits)	17.6	12.7	7.6	2.8	6.6	8.3	7.9
	Difference in activity between January and July (%)	-34.0	-34.6	-44.2	-35.0	-65.8	-57.8	-97.7

The differences in monthly recreational activity in urban and rural areas confirm the changing geographical pattern of recreational activity (Table 2). In the mobile phone data, the largest changes in recreational activity occur in sparsely populated rural areas, where the activity in July increased by 97.7% compared to the activity in January (Table 2). Furthermore, in the core rural and local centre of the rural area, the activity increases by almost 65.8% and in core rural areas by 57.8% (Table 2). The corresponding changes in urban areas and rural areas close to urban areas are smaller. Although, even in these categories the amount of recreational activity increases in July because mobility activity is higher then. The smallest increase occurs in the inner urban areas, where the growth in the activity is about 34% (Table 2). However, this is less than the increase in mobility activity between January and July (42%), so overall multi-local living reduces recreational activity in urban areas and in rural areas close to urban areas.

The volumes of the recreational activity in regions are further investigated with mobile phone data by using the regional recreational activity profiles. These profiles demonstrate that multi-local living changes the volumes of recreational activities between the regions and between urban–rural areas within the regions (Figure 4). In particular, the mobility

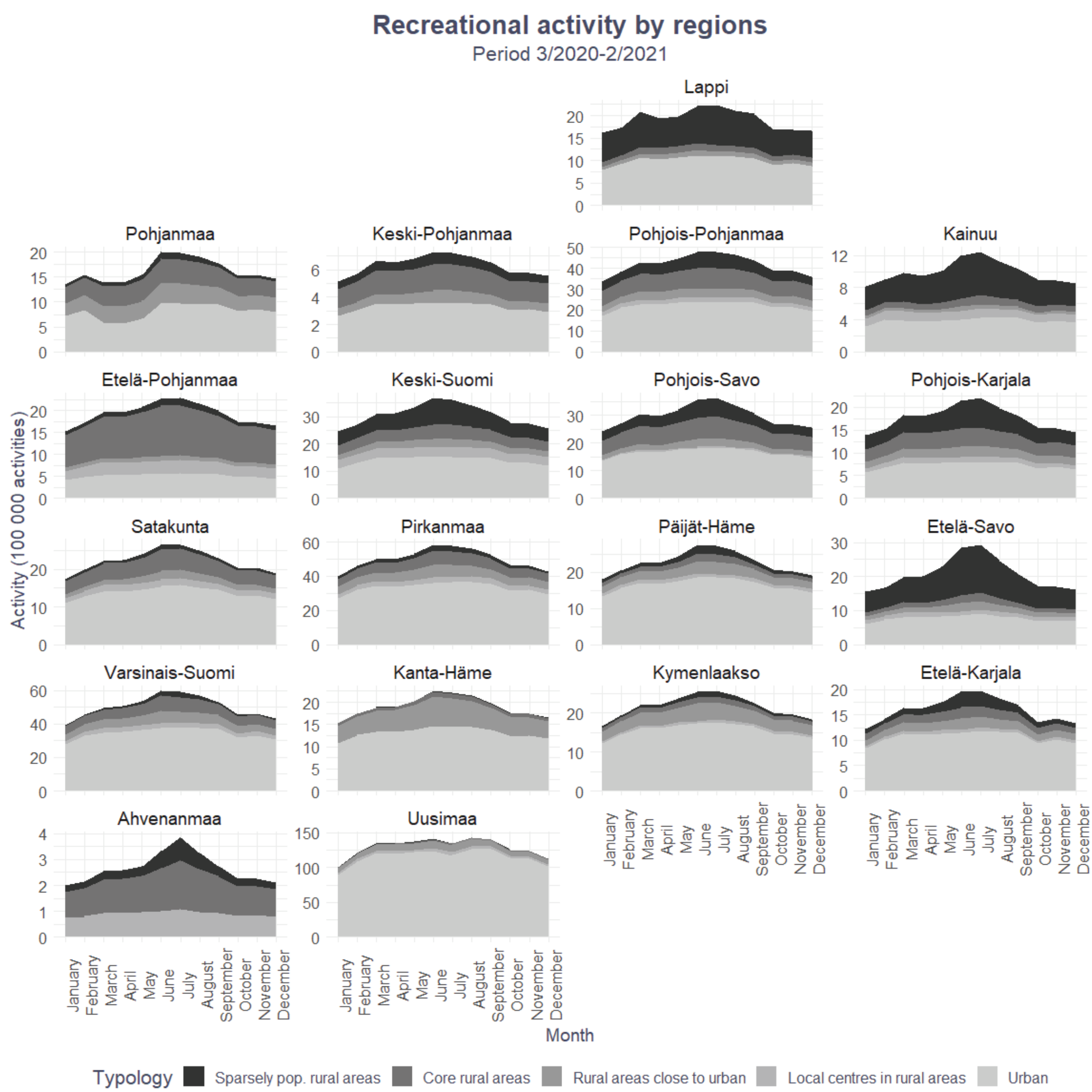

Figure 4: Monthly variation of recreational activity by region. Calculation is based on mobile phone data.

from urban to rural areas during the summer can be detected from the recreation activity profiles. For instance, the volume of recreational activities in the Etelä-Savo region increased by 88.7% from January to July, while in the Uusimaa region the volume increased by 35.4% during the same time period. These activity changes relate to the change in the average population of the regions. The biggest change in the average population occurs in Uusimaa region in July, when the average population drops by 64,616 inhabitants compared to January. In contrast, the average population in Etelä-Savo region increases by 52,842 inhabitants in July compared to January. However, there are also temporal variations in the recreational activities because, for example, one of the highest peaks in the recreational activities in Lappi region is in spring (Figure 4). The regional profiles of recreational activities also highlight the mobility of people between cities and rural areas. For instance, in the Etelä-Savo region the change in recreational activity concerns main sparsely populated rural areas as the increase corresponds to 58.3% and in all rural areas it is 79% of the total increase of recreational activities.

4.2 Modelling differences in the recreational activity of the mobile phone data

The local recreational monthly activity changes in average populations are analysed using regression analysis to detect the kind of areas where the recreational activity varies during the year (Table 3). The ability of the models to explain variation in recreational activity varies between months. The best goodness of fit measured with r-squared value is obtained in July when the models explain 48% of the total variation in recreational activity (Table 3). The r-squared value is about 10% in March and 6% in January, which indicates that the changes in recreation activity are more random during the winter and spring than in the summer. The following interpretation of the regression coefficients focuses on the SAR model as based on AIC values and Lagrange multiplier diagnostics (LMerr 3431,7, p-value <0,001) this model seems to explain the recreation activity and allocation of the average population better than the OLS model does (Table 3).

The regression models explain the changes in the local recreational activity of the grids during the year. The comparisons of regression coefficients between models reveal the

Table 3. Results from the regression analyses explain differences in local recreation activity between monthly average populations and average population in 2020 in mobile phone data (%).

Variable	Difference in January, SAR	Difference in March, SAR	Difference in July, SAR
Population density (100 inhabitants/km^2)	0.011	-0.030 *	0.036 *
Urban area (dummy)	-1.835 *	1.021	-8.077 ***
Sparsely populated rural area (dummy)	-2.175 **	-1.904	7.756 ***
Rural area close to urban area (dummy)	0.358	-0.919	-0.100
Local centre of rural areas (dummy)	0.371	1.230	-0.602
Water cover (%)	-0.067 ***	-0.104 ***	0.203 ***
Forest cover (%)	-0.042 ***	-0.008	0.037 *
Second homes from land cover (%)	0.222 *	0.028	0.804 ***
Second homes (%)	-0.009 ***	-0.012 ***	0.022 ***
Average value for zonation index	4.826 **	-4.781 *	1.238
Proportion of nature reserve from the total area (%)	0.057	0.064	-0.111 *
Distance to the city with over 50,000 inhabitants (km)	34.499 ***	47.828 ***	0.377
Distance to the city with over 200,000 inhabitants (km)	8.540 **	2.753	35.106 ***
Distance to the primary school (km)	-0.280 ***	-0.612 ***	1.140 ***
Availability of broadband (%)	0.032 ***	0.026 ***	-0.059 ***
Constant	-24.007 ***	3,334 *	12.513 ***
Lambda	0.074	0.081	0.103
Observations	13358	13358	13358
R^2 (based on lm-model)	0.062	0.104	0.476
AIC	112690	118580	116580
Note:	*p**p***p<0.01		

differences in population changes in different months. For an urban variable, the smaller negative coefficient in January model than in July model (Table 3), shows that there will be more recreational use in urban areas in January than in July (see Table 3). Similarly, a location close to services, such as schools, or the high availability of broadband increases the growth of the recreation activity in January and March compared with July (Table 3). However, the increasing distance to the city, which has over 200,000 inhabitants, increases the recreation activity in January and July.

Respectively, recreation activity increases in July in sparsely populated rural areas, while it decreases in these areas in January. Moreover, long distances to services and poor availability of broadband are associated with increasing recreational activity in July (Table 3). These variables imply that the increase in local recreation activity is somehow linked to the residential environment, as people move from denser urban areas to rural areas to compensate for the lack of the nature in urban environments (Strandell & Hall, 2015). This interpretation is strengthened by other variables because the recreational activity increases in July also in areas where forests and water bodies account for a large proportion of the surface area, whereas these variables decrease the recreational activity in January (Table 3). In March, only water coverage decreases the recreational activity. The activity growth that takes place in July also occurs in areas where the number of second homes is high based on the proportion of building stock (Table 3).

Compared with July, in March, the increase of the recreational activity is explained by the high proportion of second homes in the land use, which indicates that activity growth takes place especially in tourism centres in the Eastern and Northern parts of Finland (Table 3). The interpretation of the growing recreational activity around the tourism centres is partly supported by the regression coefficients of the proportion of nature reserve from the total grid area as the increasing proportion of nature reserves decrease the recreational activity in July (Table 3). The largest nature reserves in Finland are located in the Eastern and Northern parts of the country. The interpretation of the activity increase in March is also supported by the coefficient of the zonation index, that is, biodiversity value of the forests, which indicates that activity growth in March occurs in areas with low zonation values (Table 3).

5 Discussion of the main results

Multi-local living remarkably changes recreational activities during the year and highlights the need to identify temporal changes at local and regional levels. The results of this study demonstrate that the spatial variations in the multi-local living and recreational use of the areas are remarkable and that temporal spatial clustering is occurring as well as urban–rural movement. The variation in recreational activity seems to be the largest between January and July, when the changes in recreational activity were also explained by different variables in the regression models. The difference between the official population statistics and mobile phone data was remarkable, which demonstrates the poor ability of the static population statistics to detect the temporal variations in recreational activity. For instance, in sparsely populated areas, the total difference in recreational activities was 50.5%, which underlines the need to develop comprehensive statistics on the recreational use of areas. The planning of recreational use without considering multi-local living results in inaccurate estimates of recreational activity, especially in rural areas.

Mobility and seasonal population changes can only be partly explained by regression modelling. The results demonstrate that there are random changes in recreational activities that cannot be modelled with the variables used in this study, especially in January and March. This shows that recreational use differs depending on the season and that it is spatially structured in different ways. In the summer, the changes in recreational activity are mainly explained by the variables that describe the location and land use of the area, such as water and forest covers, which indicate that activity increases in areas with second homes, while in the winter recreational activity is concentrated on leisure centres that are close to services, such as primary schools.

Although, the seasonal analysis offered a deeper understanding of the associations between multi-local living and recreational activities, it also raises new research questions. More detailed location information of mobile data might reveal the recreation activities in more detail. In future research, this information could be used to estimate the change in recreation, which is required to assess of the effects of restoration actions after the improved environmental quality. Also, combining mobile data with data from applications that track activities might serve as key to obtain more detailed information of the service needs of nature visitors. Furthermore, our analysis demonstrated the inaccuracy of the official population statistics in describing the temporal recreational use of areas.

The main limitation of the analysis is related to the databases used to calculate recreational activity. Because multi-local living is a relatively new phenomenon in recreational studies, we lack information as to how the seasonal population behaves with respect to close-to-home recreation, as the questionnaires on recreational activity are based on uni-locality thinking, where individuals are tied to one place of residence. However, recreational use for those in second homes can differ from that of those in permanent residences because the environments can vary widely and thus enable and encourage the use of different recreational activities (Strandell & Hall, 2015). This is an obvious research question for the future. Our study also encourages the development of data collection procedures, such as questionnaires on recreational activity, also from the viewpoint of multi-locality.

6 Conclusions

This study provides a comprehensive picture of the effects of multi-local living on recreational activities across different areas. The results indicate that multi-locality alters the spatial pattern of the recreational use of areas leading to both overestimation and underestimation of recreational activities in urban and rural areas. This can result in increasing inequality in the allocation of recreational resources. The significance of multi-local living is underscored by its greater variability compared to seasonal changes in recreational activities during the year, thereby modifying the geographical distribution of recreational use throughout the year. Understanding the impact of multi-local living and mobility on recreational use of areas enables the efficient allocation of resources for land use planning and local and regional targeting and prioritisation of recreational activities. Otherwise, urban areas may be disproportionately favoured for recreation at the expense of rural areas, whose actual recreational use might remain underrepresented.

The findings underlined that this so called “invisible population” of multi-local living is necessary to consider in planning, which includes policy measures on land use, coordination of multi-level governance, and cross-sectoral interrelations (Alonsopérez et al., 2022). There are incentives to incorporate multi-local living into the planning and allocation of recreational resources, especially if urbanisation and regional population concentration continue, while the popularity of multi-spatiality in rural areas remains strong or even increases. The positive potential of multi-local living could be utilised in rural areas where the permanent population is declining and aging, and infrastructure and services are scarce.

However, significant challenges remain in allocating public funds for recreational services based on seasonal population fluctuations. Multi-locality which focuses on leisure time is inherently seasonal, leading to peaks in demand. The mobile phone data could offer a solution by enabling the monitoring and balancing of recreational activity demand and supply and thus promote cost efficiency in organising recreational activities because it more accurately detects variations in the seasonal population.

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