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Identifying counter-urbanisation using Facebook's user count data

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ABSTRACT

Identifying the growing widespread phenomenon of counter-urbanisation, where people relocate from urban centres to rural areas, is essential for understanding the social and ecological consequences of the associated changes. However, its nuanced dynamics and complex characteristics pose challenges for quantitative analysis. Here, we used near real-time Facebook user count data for Belgium and Thailand, with missing data imputed, and applied the Seasonal-Trend decomposition using Loess (STL) model to capture subtle urban and rural population dynamics and assess counter-urbanisation. We identified counter-urbanisation in both Belgium and Thailand, evidenced by increases of 1.80% and 2.14% in rural residents (night-time user counts) and decreases of 3.08% and 5.04% in urban centre night-time user counts from March 2020 to May 2022, respectively. However, the counter-urbanisation in Thailand appears to be transitory, with rural users beginning to decline during both day and night as COVID-19 restrictions were lifted. By contrast, in Belgium, at the country level, there is as yet no evidence of a return to urban residences, though daytime numbers in rural areas are decreasing and in urban centres are increasing, suggesting an increase in commuting post-pandemic. These variation characteristics observed both between Belgium and Thailand and between day and night, extend the current understanding of counter-urbanisation. The use of novel social media data provides an effective quantitative perspective to comprehend counter-urbanisation in different settings.

1. Introduction

The rapid urbanisation in the past few centuries, characterised by influx of population and the associated transformation of natural landscapes (Leyk et al., 2020), has exacerbated various urban problems, including severe air pollution (Mage et al., 1996; Zhang et al., 2022), spreads of infectious diseases (Kolimenakis et al., 2021; Lowe et al., 2021), congestion (Çolak et al., 2016), and rising inequality (Sulemana et al., 2019). As a result, some city dwellers choose to move out of urban environments and settle in rural areas, leading to an increased proportion of the population living in rural areas (Crankshaw & Borel-Saladin, 2019; Gurrutxaga, 2021; McManus, 2022). This phenomenon was first noticed in the United States in the 1970s (Beale, 1976; Berry, 1980), and then also observed in Europe (Champion, 1989; Kontuly et al., 1986; Rowe et al., 2019) and Australia (Hugo, 1994). Various terms such as counter-urbanisation, metropolis decentralisation, population deconcentration (Mitchell, 2004), as well as urban decline (Bourne, 1980) and city shrinkage (Haase et al., 2016) have been used to describe this phenomenon – we refer to it as 'counter-urbanisation' from hereon in.

Originally, the attractions of rural idylls and the pursuit of a better quality of life in the countryside were considered the primary factors leading to counter-urbanisation (Halfacree, 2009). However, more recent studies across a range of contexts have shown that complicated motivations exist behind the relocation from urban centres to rural areas, such as economic factors (Gkartzios, 2013; Gkartzios & Halfacree, 2023; Gkartzios & Scott, 2015; Halfacree, 2008, 2012; Wang, 2023).

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Recently, the COVID-19 pandemic has brought attention to more widespread counter-urbanisation trends (Gkartzios & Halfacree, 2023; McManus, 2022; Rowe, González-Leonardo, & Champion, 2023). People have moved away from crowded urban environments to mitigate infection risks, while concurrent lifestyle changes associated with remote work and online learning have reduced the necessity for certain groups to live in cities (Tammaru et al., 2023). There is evidence of an increase in counter-urbanisation during the initial phase of the COVID-19 pandemic in some high-income countries such as Spain (González-Leonardo et al., 2022), Australia (Borsellino et al., 2022), Germany (Stawarz et al., 2022) and Britain (Rowe, Calafiore, et al., 2023). However, the understanding of counter-urbanisation in low- and middle-income countries remains relatively limited compared to the extensive evidence from high-income countries, despite recent work in Latin American and South African countries (Posel & Casale, 2021; Rowe, Cabrera-Arnau, et al., 2023). Moreover, comparisons between these countries and high-income countries remain lacking.

Previously, counter-urbanisation has been quantitatively assessed mainly using census and register data, which record changes in demography and domestic migration during long time periods (Crankshaw & Borel-Saladin, 2019; Tammaru et al., 2023). However, most resident registration and census data refer to single points in time and often have time lags, particularly in low and middle-income countries (Stawarz et al., 2022; United Nations Population Fund, 2019). More importantly, they are usually reported based on administrative units, within which urban and rural areas can coexist (Hall et al., 2006). Recently, novel datasets of human locations obtained through mobile phones could also infer human mobility and map population distribution changes, including mobile phone call detail records (CDRs) (Deville et al., 2014; Lai et al., 2019; Meredith et al., 2021; Steele et al., 2021; Woods et al., 2022), Google data (Lai et al., 2021; Rogers et al., 2023; Ruktanonchai et al., 2018) and data collected from social media platforms (Fiorio et al., 2017; Hawelka et al., 2014; Huang et al., 2020; Luo et al., 2016; Shepherd et al., 2021). However, their applications in identifying counter-urbanisation have limitations. CDRs collected by towers in peripheral regions can encompass both urban and nearby suburban or rural residents (Barbosa et al., 2018), as the recorded locations are those of cell towers rather than those of the phone owners. Obtaining Google data is challenging due to strict protocols (Lai et al., 2021; Rogers et al., 2023; Ruktanonchai et al., 2018). Commonly used social media data, such as geo-located tweets, are spatiotemporally sparse (Huang et al., 2020; Huang & Wong, 2016). Therefore, quantitatively measuring population redistribution remains challenging because of the high requirements for temporal and spatial dimensions of the population data.

This is particularly true for counter-urbanisation, as, by its nature and in contrast to urbanisation, it involves small changes in populations spread out across relatively large areas, particularly during the early stages of the process. These difficulties, together with the diversity and complex patterns of counter-urbanisation, means most previous research on the subject used in-depth interviews with counter-urban movers to explore their new lifestyles and counter-urbanisation narratives (Gkartzios, 2013; Gkartzios & Scott, 2015; Halfacree & Rivera, 2012; Hansen & Aner, 2017; Remoundou et al., 2016). However, this approach makes it difficult to collect massive fine spatial data for measuring counter-urbanisation patterns for a large population across the country and over time. Consequently, a quantitative assessment becomes important for comparisons and predictions within broader contexts (Smith, 2007).

In this study, we quantitatively assessed counter-urbanisation by capitalising on gridded user count data from Facebook users, generated by the Data for Good programme at Meta (Maas, 2019), to address these research gaps. We explored the counter-urbanisation phenomenon by measuring the relative changes in night-time Facebook user counts in urban centres, suburban and rural areas, as these reveal shifts in users' residential locations. Additionally, we compared the trends during night-time and daytime to understand if new rural residents continue to commute to urban locations. As Facebook data extends past the end of the most intensive COVID-19 restrictions, our study is also able to identify areas where counter-urbanisation trends may continue after the pandemic, as well as those that only experienced a temporary increase in rural residents in response to the pandemic. It thereby contributes to extending existing understanding of counter-urbanisation during the pandemic. Additionally, this study provides a unique insight into the different dynamic characteristics between Belgium and Thailand, which are representative of a high-income country and a middle-income country, respectively. Finally, our study demonstrates the potential of using novel data sources and our methodology to detect plausible population dynamics across a wide range of countries for which the Facebook data exists, and its utility for achieving a more nuanced and comprehensive understanding of quantitative counter-urbanisation than has been possible to date.

2. Data and Methodology

2.1. Study area

We selected Belgium, a high-income country, and Thailand, a middle-income country, as examples for this study. These particular countries were chosen because our team has a good in-depth understanding of the population dynamics in both, and both countries have a high percentage of Facebook app usage, with nearly 54% and 67% of their respective total population (World Population Review, 2023). In addition, among countries with available Facebook user count data over two years, Belgium and Thailand have more granular datasets within their respective high- and middle-income country categories, providing their user count data with finer spatial detail. Their other contrasting characteristics, from their geographical locations in Europe and Asia to their differing urbanisation levels – 98% for Belgium and 52% for Thailand (World Bank, 2021) – make them representative of a much wider group of countries. Belgium is one of the most urbanised countries around the world, while Thailand has witnessed one of the most rapid increases in urbanisation over the past two decades (World Bank, 2021). In addition, the two countries vary enormously in the proportion of areas with missing data (tiles with very low counts, which are removed by Facebook due to privacy concerns). Specifically, Belgium and Thailand have varied missing data proportions of approximately 65% and 10%, respectively. This is useful, as one goal of our method was to develop an imputation approach to address the issue of missing data within the Facebook dataset. Ideally, we would have also included a low-income country in this study; however, this was not possible due to their very limited Facebook usage and sparse data availability.

2.2. Facebook data

The Data for Good programme at Meta provides anonymised and aggregated data on the number of Facebook app users who have agreed to share the location history of their mobile devices (Maas, 2019). These numbers, collected in tiles (Microsoft, 2022) during the COVID-19 pandemic, present the user count within three daily time-windows: 00:00–07:59, 08:00–15:59, 16:00–23:59. If a user appeared on different tiles during one time-window, the same user was assigned to the location on which they appeared most frequently. For Belgium, the data range at tile level is from March 6, 2020 to May 21, 2022, while for Thailand, it spans from March 25, 2020 to May 22, 2022. The data also includes the corresponding baseline values of user counts collected before the start date, and the percent change of the user count compared to their baselines. The baseline denotes the mean number of users who have location service enabled for at least 90 days before the day when the Facebook population maps were generated (Maas, 2019). The baseline covered December 2019, January 2020 and February 2020 in Belgium and Thailand, which can be regarded as the pre-pandemic period. As each time window and each day of the week has its own precise baseline, each grid cell actually has a total of 21 unique baselines. The percentage change ($p_{i,t,d}$) of user counts at tile i during one time-window t on a date d was calculated by dividing the differences between the user number $N_{i,t,d}$ and the baseline $b_{i,t,d}$ by the corresponding baseline value.

$$p_{i,t,d} = \left(N_{i,t,d} - b_{i,t,d}\right) / \left(b_{i,t,d} + \epsilon\right) \times 100\% \tag{1}$$

where ϵ is a small value, usually 1 (Maas, 2019).

Additionally, the local time needs to be considered when analysing people's activities in different countries, as three time-windows are provided by Meta in Coordinated Universal Time (UTC). The night-time data representing where people live is collected during 0:00–07:59 UTC in Belgium and 16:00–23:59 UTC in Thailand. The daytime data, which represents people being at work or engaging in daily activities, is captured during 08:00–15:59 UTC in Belgium and 00:00–07:59 UTC in Thailand.

2.3. WorldPop population datasets

We used the WorldPop population counts dataset: Unconstrained 2000–2020 United Nations (UN) adjusted (100 m resolution) (WorldPop, 2020) to estimate the missing baselines in our data imputation method. WorldPop produced the global gridded population data at a resolution of 3 arc-seconds, using statistical demographic or census data of every country and a random forest-based dasymetric redistribution (Stevens et al., 2015; WorldPop, 2020). Specifically, the data for Belgium used Belgium's 2014 Population Register aggregated at admin level 4. For Thailand, the input data source was 2010 Population and Housing Census aggregated at admin level 2 (WorldPop, 2020). The WorldPop population datasets are openly available on WorldPop Data Repository Hub (https://hub.worldpop.org/project/categories?id=3).

2.4. Classification of urbanisation degree

A degree of urbanisation classification map from the 2020 Global Human Settlement Layer (Schiavina et al., 2022) was matched with Facebook user count tile data to identify whether tiles were located in urban centres, suburban or rural areas. This classification map was generated by combining built-up areas and population density data (Schiavina et al., 2022), using the uniform definition of the urban centre, urban cluster and rural areas endorsed by the UN Statistical Commission (Dijkstra et al., 2021; European Commission, 2021. It is available on the Global Human Settlement Layer webpage (https://ghsl.jrc.ec.europa.eu/degurbaDefinitions.php).

2.5. Facebook data pre-processing

2.5.1. Missing data imputation

A key challenge in the use of Facebook user count data is the absence of small count numbers, a result of privacy protection techniques applied to ensure the locations of individuals or small groups cannot be identified. In addition to reporting aggregated numbers per tile, if a tile had a baseline or user count number below ten for a specific time and date, both values are excluded, retaining only their percent change in the records (Maas, 2019). As a result, some countries may have many tiles with null values for population and baseline numbers (see Supplementary Table A1). Taking Belgium as an example, two-thirds of tiles had incomplete records, and 82.87% of the rural tiles lacked specific user count values.

Given that these missing data are not distributed randomly (Supplementary Table A1), simply deleting the incomplete records could lead to biased results (Afghari et al., 2019). Therefore, we designed an imputation method to estimate these missing values, thereby enabling identification of urban-rural dynamic diurnal distributions using Facebook data. The overview of this missing data imputation for Facebook user count is presented in Fig. 1.

Our imputation method included two primary steps: 1) estimating the missing baseline values (see the details below) and subsequently 2) calculating the missing user count numbers of tiles with incomplete data, using all missing baselines estimated in step 1, along with their corresponding percent change and Equation (1). We chose this method rather than directly estimating missing user counts because each tile had only seven baseline values for a specific time-window during the study period. These values were exclusively related to the day of the week within a given time-window, unlike the user numbers, which varied daily. More importantly, the baseline period refers to the pre-COVID-19 pandemic period in most countries; it is therefore free of the impacts of lockdown restrictions. The estimation of missing baseline values (the first step of the imputation method) has two key components: 1A) replacing the missing baseline value with an existing baseline from another day; and, if one does not exist, 1B) using estimates from the regression models based on WorldPop population data, due to the significant linear relationships observed between Facebook baselines and WorldPop population data (see Supplementary Fig. A3-A6).

2.5.1.1. (1A) substituting missing baseline values with those on other dates. If a tile lacked baseline values for specific days of the week (e.g., Wednesday), we would substitute the missing baseline using available baseline values of the same tile in other days (e.g., the mean baseline values of this tile on workdays). We separately calculated the mean baseline of workdays and weekends due to the differences in people's activities between workdays and weekends (Shepherd et al., 2021). When a tile lacked the baseline on one of the workdays but had baseline values on other workdays of the week, the mean baseline value of workdays was used to replace this missing baseline; however, if all workdays were excluded, then the mean baseline of weekends was used for substitution. Similarly, for missing weekend baselines, we first used the weekend average; if unavailable, the workday average was employed as an alternative.

We did this because there were very strong correlations (Pearson's R mostly in excess of 0.99) between the complete baselines for different days of the week (see Supplementary A2.1). The baseline of a day of the workdays was most strongly correlated with the average value of the workdays, whereas the baseline of a weekend day had the highest correlation with the mean of the weekends, with Pearson's R greater than 0.999 in both Belgium and Thailand.

2.5.1.2. (1B) estimation of missing baseline values for the tiles that lacks all baselines. Most incomplete tiles lacked baseline values on all dates. Tiles with incomplete records for the entire study period were presumed to have baseline values of less than 10. This is because, regardless of the population number collected on any given day over the 27 months, the records were removed due to their baselines falling below 10. We employed linear regression models using existing Facebook baselines from all complete records and WorldPop spatial population datasets of 2019 to estimate the missing baseline on different days of the week (See Supplementary A2.2). We further constrained our imputation by setting the maximum value of 10 (as 10 is the cut-off Facebook uses for excluding numbers) and the minimum value of 0 for the estimated missing baselines. For example, if the missing baseline during 00:00–07:59 UTC on Monday was estimated as 30 based on the regression result with other population data, it would be manually adjusted as 10. Finally, the missing user count was calculated based on the imputed baseline value and Equation (1).

To assess the accuracy of models generated for tiles with sparse baselines, we tested our method using tiles whose baselines were between 10 and 20, as these were the tiles with the lowest baselines for which we had validation data. The assumption behind this test was that if our imputation method was successfully able to predict the low user

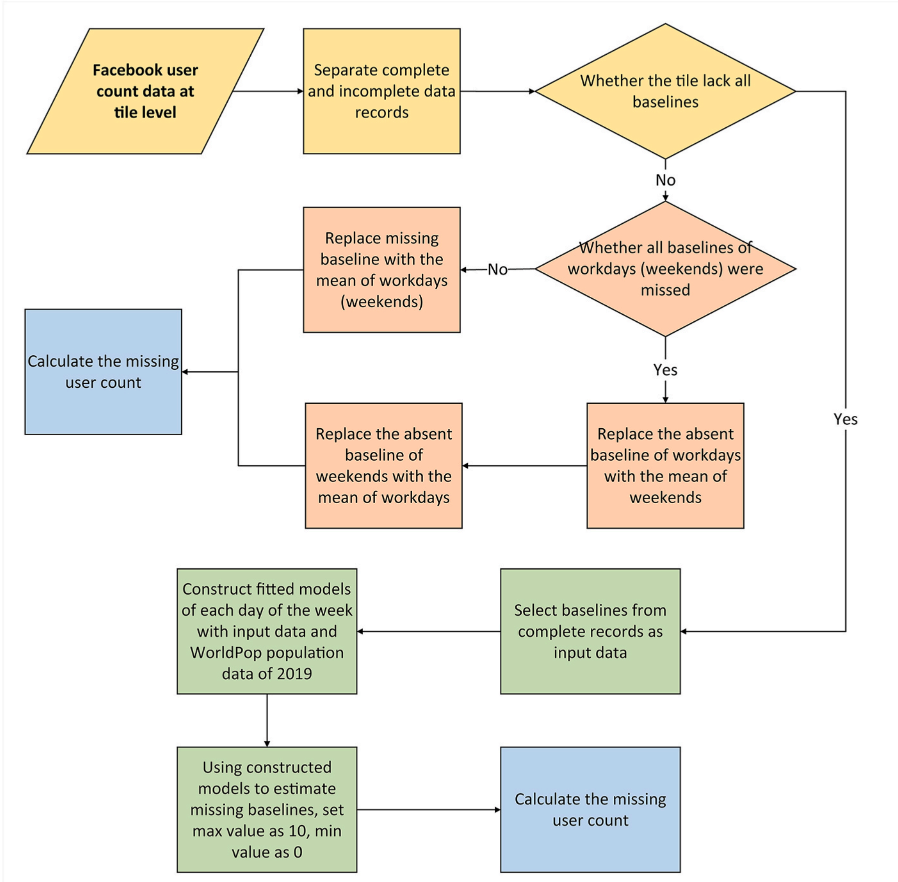

Fig. 1. Schematic overview of missing data imputation for Facebook user count data. Two components of step 1 of the imputation method are described in the orange panels (1A) and green panels (1B), respectively. The Step 2 of the method is depicted in the blue panels. The yellow panels represent data preparations.

numbers for tiles with baselines between 10 and 20, then it would also work for tiles between 0 and 10 baselines (see Supplementary A2.2.3 for full Methods for these validation tests). Furthermore, we conducted sensitivity analyses by modifying the input spatial population data to evaluate the robustness of models. It showed that the trends were highly consistent when we altered the input population data as LandScan (Rose et al., 2020) for both Belgium and Thailand (see Supplementary C). However, using WorldPop as input data had lower root-mean-square error (RMSE) and mean-absolute-error (MAE) values compared to other transformations (Supplementary Ta ble A3).

After our imputation method, both Belgium and Thailand obtained approximately 99.9% of total data records that could be used for subsequent analysis. Using night-time data as an example, in Belgium, 23.35% of the baseline user count, located in missing tiles that account for 67.05% of the total tiles, has been imputed. Of this, the estimated rural baseline user count represents 59.44% of the total in rural areas. Meanwhile, in Thailand, 0.02% of the baseline user count, residing in missing rural tiles that comprise 12.00% of the total tiles, has been estimated. Detailed imputation records for all steps can be found in Supplementary A3.

2.5.2. Correction factor

The total number of active users at a time-window collected by Facebook had an overall trend and daily fluctuations, due to limitations from the internet access and user data access options (Maas, 2019). Following Yabe et al. (2020), we used a correction factor to eliminate the fluctuations in the daily number of observed users, with the assumption that the representativeness of Facebook data in urban/suburban/rural areas remains stable during the study period. We did this to prevent the potential impact of changes in the total number of users collected on the results, which might mask the respective variation trends within urban centres, suburban and rural areas. The user count $N_{i,t,d}$ in tile i in time-window t on date d was multiplied by daily user adjustment factor k to get the corrected number N':

$$N'_{i,t,d} = N_{i,t,d} \times k_{t,d} \tag{2}$$

$$k_{t,d} = M_t \Big/ \sum_i N_{i,t,d} \tag{3}$$

$K_{t,d}$ represented the adjustment factor of time-window t in date d. The total number of users at time t on date d is $\sum_i N_{i,t,d}$ and the M_t referred to the median of sum user counts for all tiles at time t for each day d.

2.6. Data analysis and trend decomposition

In previous research, counter-urbanisation was measured either by the increasing migration from urban to rural areas using migration data (Borsellino et al., 2022; González-Leonardo, et al., 2022; Rowe, Calafiore, et al., 2023; Stawarz et al., 2022), or by the declining proportion of the population living in urban areas using population statistics (Crankshaw & Borel-Saladin, 2019; Gurrutxaga, 2021; McManus, 2022). Our study focused on the latter method, assessing the counter-urbanisation phenomenon by comparing long-term trends in night-time user count data across urban centres, suburban and rural areas that arise from the result of people's migration. We used the user count during night-time on workdays as it could reveal the redistribution of users' residences, considering that people are likely to be mostly at home during that time.

The weekly averages of daily user count numbers on workdays were calculated to reduce variability in the data. Additionally, we explored commuting patterns by comparing the changes in user redistributions between night-time and daytime, as well as comparing the workday averages with patterns on weekends.

To eliminate the short-term seasonal variation of population dynamics due to holidays (Charles-Edwards & Bell, 2015; Lai et al., 2022), we applied Seasonal-Trend decomposition using Loess (STL) to differentiate long-term trends from seasonal and remainder components of the high-frequency population dynamics data using the 'stl' function in R version 4.2.2. The STL method, proposed by Cleveland et al. (1990), is a filtering procedure for decomposing a time series into the following components:

$$S_{raw} = S_{trend} + S_{seasonal} + S_{residual} \tag{4}$$

where the original data (S_{raw}) was decomposed into trend (S_{trend}), seasonal ($S_{seasonal}$) and remainder ($S_{residual}$) components. The seasonal components are found by locally estimated scatterplot smoothing of the seasonal sub-series (Woods et al., 2022). Trends were estimated by removing the seasonal component, smoothing the remainder and iteratively adding the separated overall level of seasonal component time series. The remainder component, representing the variabilities in the original series that are difficult to explain by trend and seasonal components, was identified by subtracting the sum of seasonal and trend components from the original series (Cleveland et al., 1990). A more detailed description of the STL decomposition procedure can be found in Cleveland et al. (1990). The STL procedure has been extensively utilised to decompose complete time-series datasets and detecting nonlinear patterns (Anderson et al., 2021; Boulton et al., 2022; Li et al., 2022; Smith et al., 2022; Woods et al., 2022), due to its insensitivity to outliers, its ability to handle different seasonal types, and its computational efficiency (Cleveland et al., 1990; Theodosiou, 2011). At the tile level, we applied simple linear regression to the trend component of each grid to determine their overall changes, which is a common combined measurement (Aguilera et al., 2015; Anderson et al., 2021; Li et al., 2022). For each tile i,

$$St_i = \beta_{0i} + \beta_{1i} \times W + \varepsilon_i \tag{5}$$

where St_i indicated the deseasoned user count for tile i, W was the week number, β_{0i} and ε_i were the intercept and error term, respectively. The slope β_{1i} obtained from the linear regression, represented the user count changes per week for tile i after eliminating seasonal variation.

3. Result

3.1. The distribution and diurnal dynamics of facebook user count in Belgium

From March 2020 to May 2022, nearly 60% of urban centres experienced a significant decrease in user count, indicating a dispersal of night-time settled users within these areas. However, a notable increase in users was observed in the northern region, particularly around the Port of Antwerp, which could potentially be attributed to increased port activities. In over 50% of rural areas, there was a significant increase in user count, with a higher concentration in the southern region. The density of users was highest in the capital city of Brussels and the northern region of Flanders (Fig. 2).

The trend from STL decomposition of Belgium showed that the changes in Facebook user count during night-time and daytime on weekends were similar in both urban centres and rural areas. Specifically, a decreasing trend was noted in urban centres, while an increasing trend was observed in rural areas (Fig. 3). However, the trends during night-time and daytime differed markedly on workdays, particularly in urban centres and rural areas. In urban centres, we observed a decreasing trend during night-time for the entire period; during the daytime there was only a decreasing trend until mid-July of

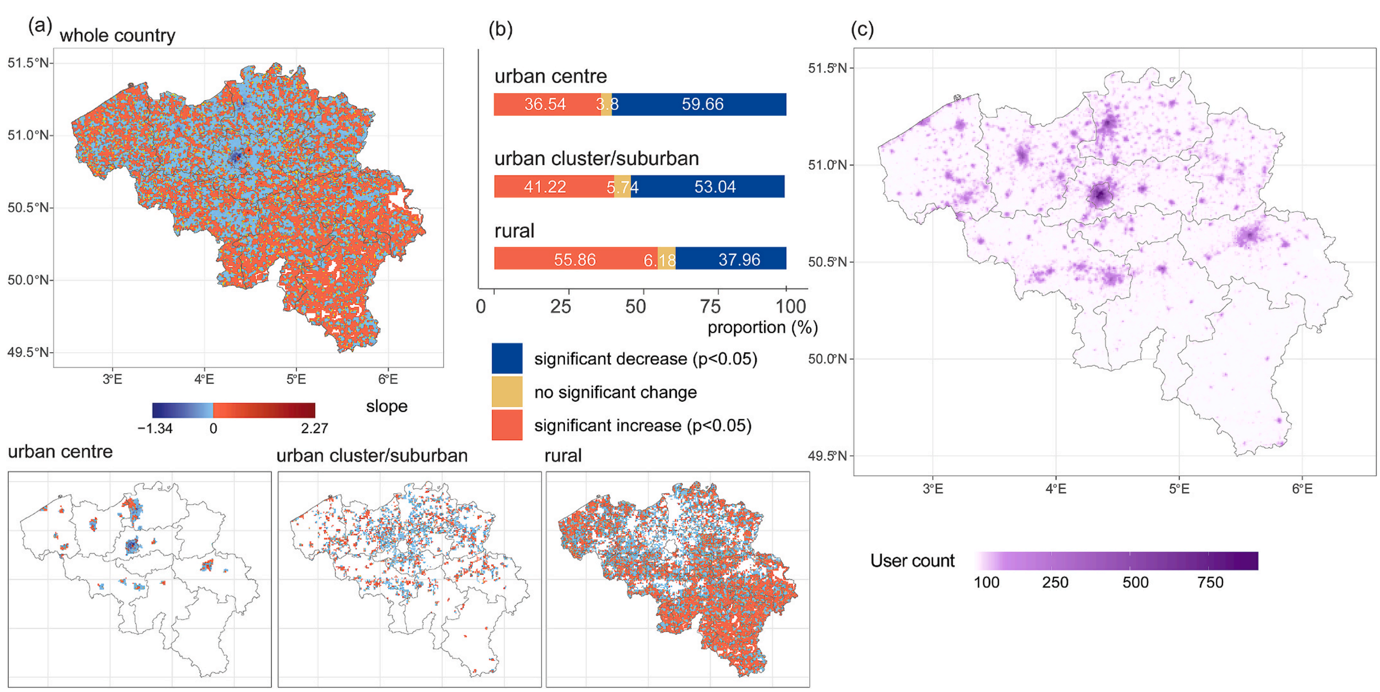

Fig. 2. Distribution of Facebook user count and their changes in Belgium during night-time on workdays. (a) Distribution of weekly changes in user count during the study period (from the first week in March 2020 to the third week in May 2022), segmented into urban centres, urban cluster/suburban and rural areas. The overall trend was determined from the slope by applying linear regression to the trend component from Seasonal-Trend decomposition using Loess (STL) method. (b) Proportion of tiles showing significant decrease (in blue) or significant increase (in red) in the total number of tiles in urban centres, urban clusters/suburban and rural areas during the study period. (c) Distribution of average Facebook user count in May 2022. Country and administrative boundaries were sourced from the Global Administrative Areas (GADM) spatial database (version 4.1).

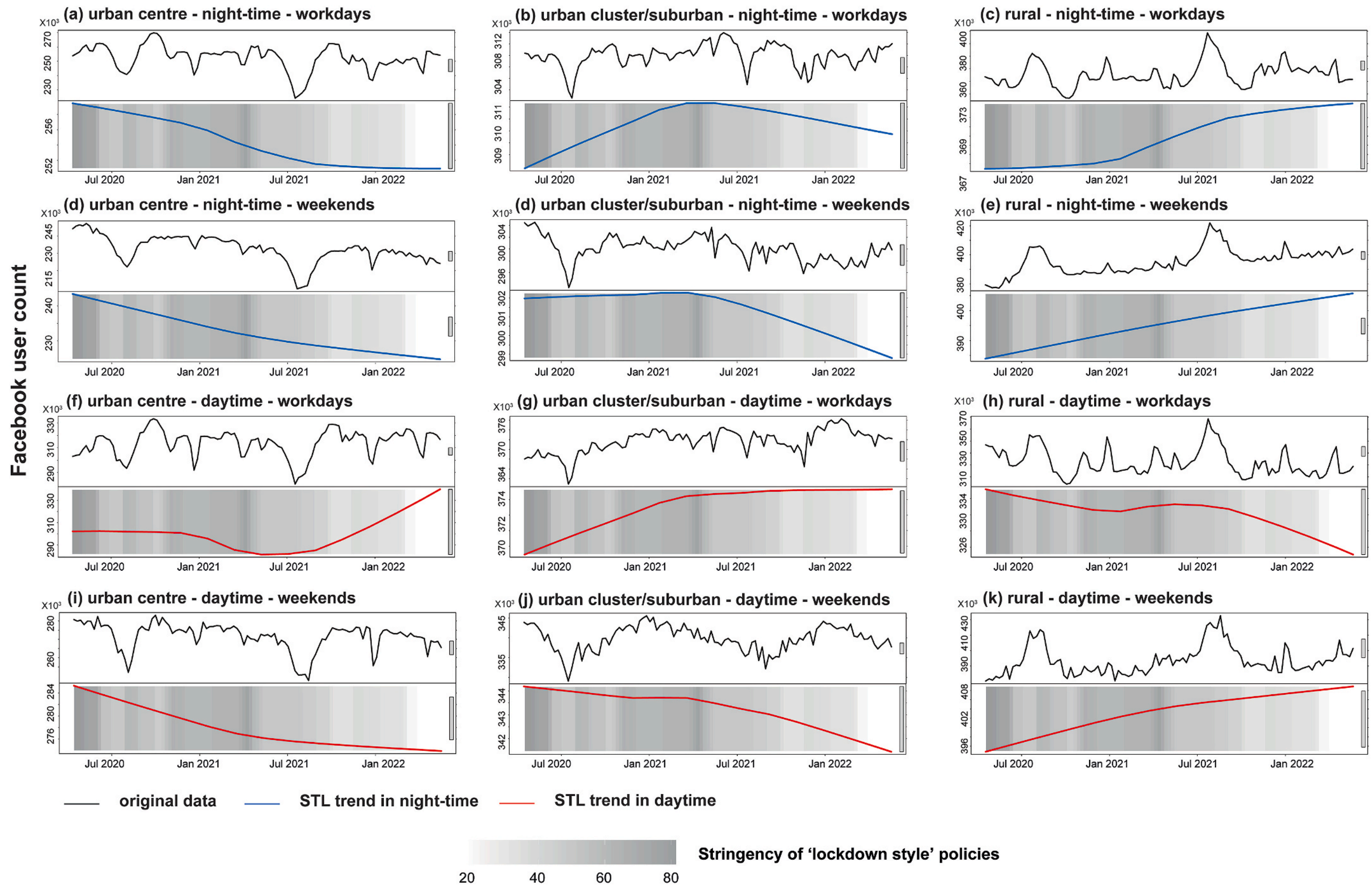

Fig. 3. The weekly Facebook user count across urban centres, urban clusters/suburban, and rural areas in Belgium from March 2020 to May 2022, along with their decomposed trend component of the Seasonal-Trend decomposition using Loess (STL) (See other components in Supplementary Fig. B1), reported on workdays and weekends separately during night-time with blue trend lines and daytime with red trend lines. The lockdown 'stringency index', calculated by Oxford COVID-19 Government Response Tracker (Hale et al., 2021), was plotted (grey backgrounds of varying intensities) to qualitatively assess if the STL decomposed Facebook data captures known changes in human mobility affected by the COVID-19 pandemic.

2021, followed by an increasing trend. The opposite was largely observed in rural areas – an upward trend during the night, particularly after December 2021, while a declining overall trend was observed during the day, with a drop greater from September 2021.

In addition to the overall trend, examining the seasonal components and remainders could enhance our understanding of population dynamics (Supplementary Fig. B1). The seasonal components exhibited that population in urban centres decreased sharply every year in July during both night-time and daytime on workdays, while in rural areas, a great increase occurred in July at that time. Additionally, the remainders from STL in this study likely captured holiday population movements. The positive values in rural areas occurred during some weeks in April and December during both night-time and daytime, which appeared to be corresponding to the Easter and Christmas holidays, respectively. Conversely, negative values occurred in urban centres during the same periods.

To further understand the redistribution characteristics of Facebook users within the country, we analysed their changes at the regional level (Fig. 4). A decrease in the number of urban centre dwellers was observed in the capital of Brussels and the Flemish region, with decrease of 6.90% and 2.40%, respectively. In the urban centres of the Walloon region, the user count initially increased, followed by a decrease, resulting in a minimal net change, which indicated temporary increases during the pandemic. In the Flemish region, there was an initial upward trend in user count in suburban and rural areas, followed by a continuous decline. However, in the Walloon region, the number of users in suburban and rural areas increased by 2.50% and 3.40%, respectively. Daytime variations revealed distinct patterns in daily activity (refer to Supplementary Fig. B3), including increases of 1.68% and 4.10% in urban centres of the Flemish and Walloon regions, respectively, contrasted with decreases of 2.80% and 2.10% in rural areas in these respective regions. In combination, the results suggest a complex picture of Facebook users' movements in Belgium during and directly after the pandemic.

3.2. The distribution and diurnal dynamics of facebook user count in Thailand

In Thailand, the Facebook user count experienced a significant decrease in 80.8% of urban centre tiles during night-time on workdays from March 2020 to May 2022, while 58.84% of the rural tiles exhibited a significant increase. The high reduction slope of user count in Bangkok indicated a trend of relocation away from the capital city. Users in suburban areas showed a notable increase. In rural areas, particularly in the southern and central areas known for rubber and oil palm plantations (Jaroenkietkajorn et al., 2021; Li & Fox, 2012), as well as in zones predominantly cultivating paddy rice (Xu et al., 2021), there was a noticeable increase in user count. This rise could potentially indicate a migration of people towards plantation and agricultural areas. The density of users was highest in the capital city of Bangkok (Fig. 5).

Unlike Belgium, the trends of Facebook user count change were consistent during night-time and daytime, as well as on workdays and weekends, when observed separately for urban centres, suburban and rural areas in Thailand (Fig. 6). In urban centres, apart from a

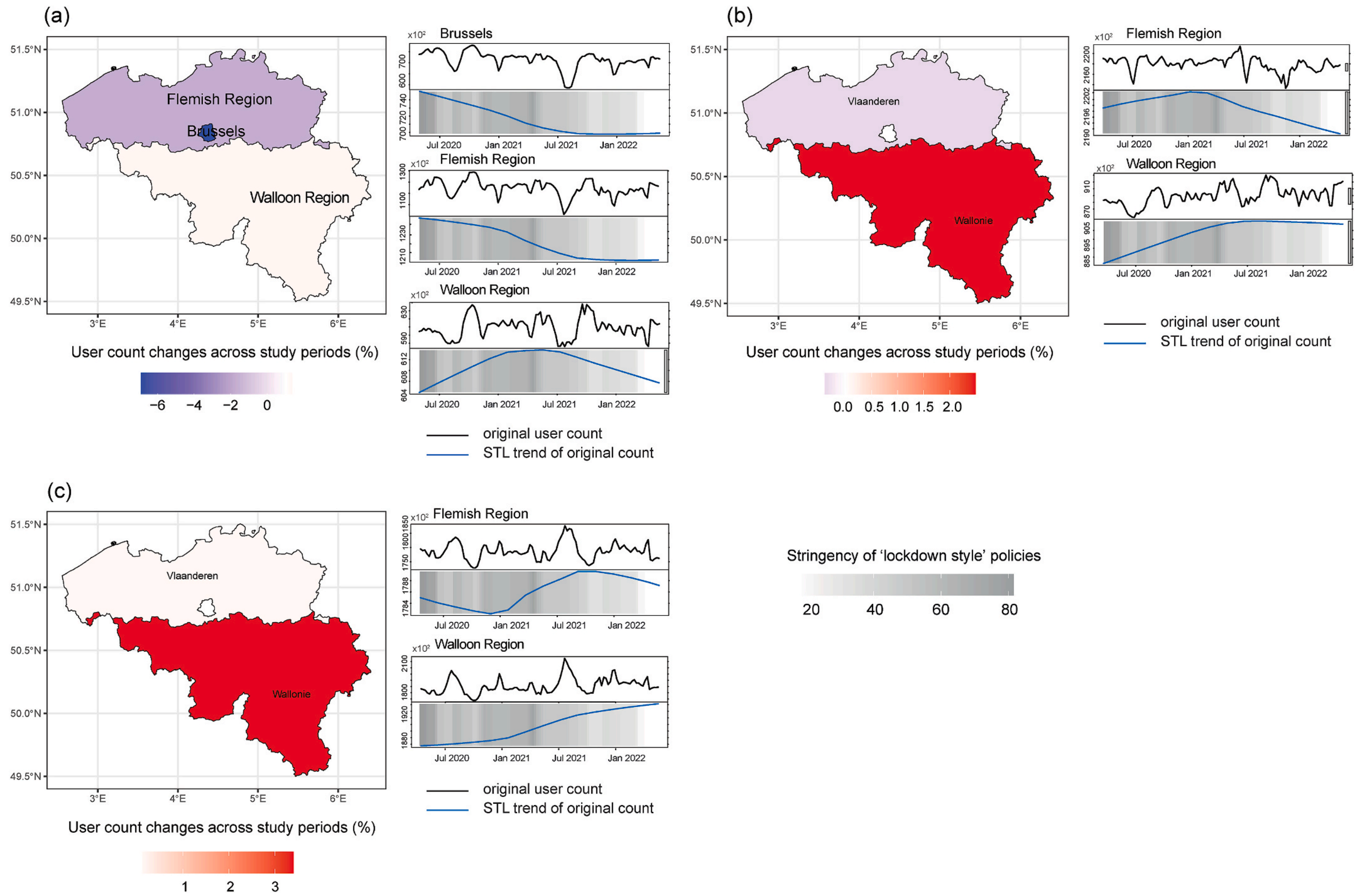

Fig. 4. Changes in weekly Facebook user count during night-time on workdays at the regional level in Belgium from March 2020 to May 2022 across (a) urban centre, (b) urban cluster/suburban and (c) rural areas. The left map exhibits percentage changes relative to the start week, while the right presents user count changes and their decomposed trend component of the Seasonal-Trend decomposition using Loess (STL) method. There are no suburban and rural areas within Brussels. The lockdown 'stringency index' from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021) is represented by varying intensities of grey backgrounds. Country and regional boundaries were sourced from the Global Administrative Areas (GADM) spatial database (version 4.1).

continuous decrease in user count during daytime on the weekends, the trends displayed a decrease first, followed by stabilisation from the end of August 2021 with some indication of an increase towards the end of the time series. Conversely, an upward trend was observed in rural areas with a greater increase rate from January of 2021, followed by a slight decline since the end of August of 2021 during night-time and mid-October of 2021 during workdays' daytime. In suburban areas, an overall increasing trend was observed, with a slight decrease from January to the end of August of 2021. It is noteworthy that the turning points or changes in the slope of the trends occurred near the time when the strictness of restrictions suddenly increased.

Seasonal components in Thailand exhibited a sharp drop in user count in July and August each year in urban centres and suburban areas, with a peak occurring during the same period in rural areas (Supplementary Fig. B2). Remainders from STL detected the lowest value in urban centres and suburban areas, and the highest value in rural areas occurred in the week at the end of December and the mid-April in Thailand, possibly aligning with the New Year and Songkran holidays.

Within the country, the decline in urban centre dwellers predominantly occurred in the southern region, the capital city of Bangkok and the central region, with decrease of 7.20%, 6.85% and 2.81%, respectively (see Fig. 7). Although all regions experienced an increase in rural users initially, this trend reversed after the end of August 2021, with the exception of the central region surrounding Bangkok, which consistently attracted people. Additionally, similar patterns in daytime trends were observed as these night-time trends at the regional level (see Supplementary Fig. B4).

3.3. Comparison of Facebook user count changes between Belgium and Thailand

Belgium and Thailand exhibited different characteristics in the distribution of Facebook users. Belgium had multiple densely populated areas, whereas in Thailand, users were primarily concentrated in Bangkok. The percent changes in user count were lower in Belgium than in Thailand across all three urban-rural classifications (Fig. 8), with a smaller proportion of grids experiencing corresponding changes. During night-time, in urban centres, Belgium had a 3.08% decrease in user count with 59.66% of its grids showing a significant decrease (Fig. 2), while Thailand experienced a more widespread decrease, with 80.8% of decreasing grids leading to a 5.04% overall reduction (Fig. 5). Their changes in rural areas were modestly different, with increases of 1.80% and 2.14%, respectively. Users in Thailand demonstrated a higher tendency to move to suburban areas, with an increase of 1.56%, compared to 0.43% in Belgium. Conversely, in Belgium during the daytime, user count increased by 1.21% in urban centres and by 1.17% in suburban areas, indicating that people's daytime activities are concentrated in non-rural areas.

The trends in user count changes also showed different characteristics between the two countries (Figs. 3 and 6). Belgium displayed different patterns between night-time and daytime on workdays, reflecting differences in residential locations and daily activity zones,

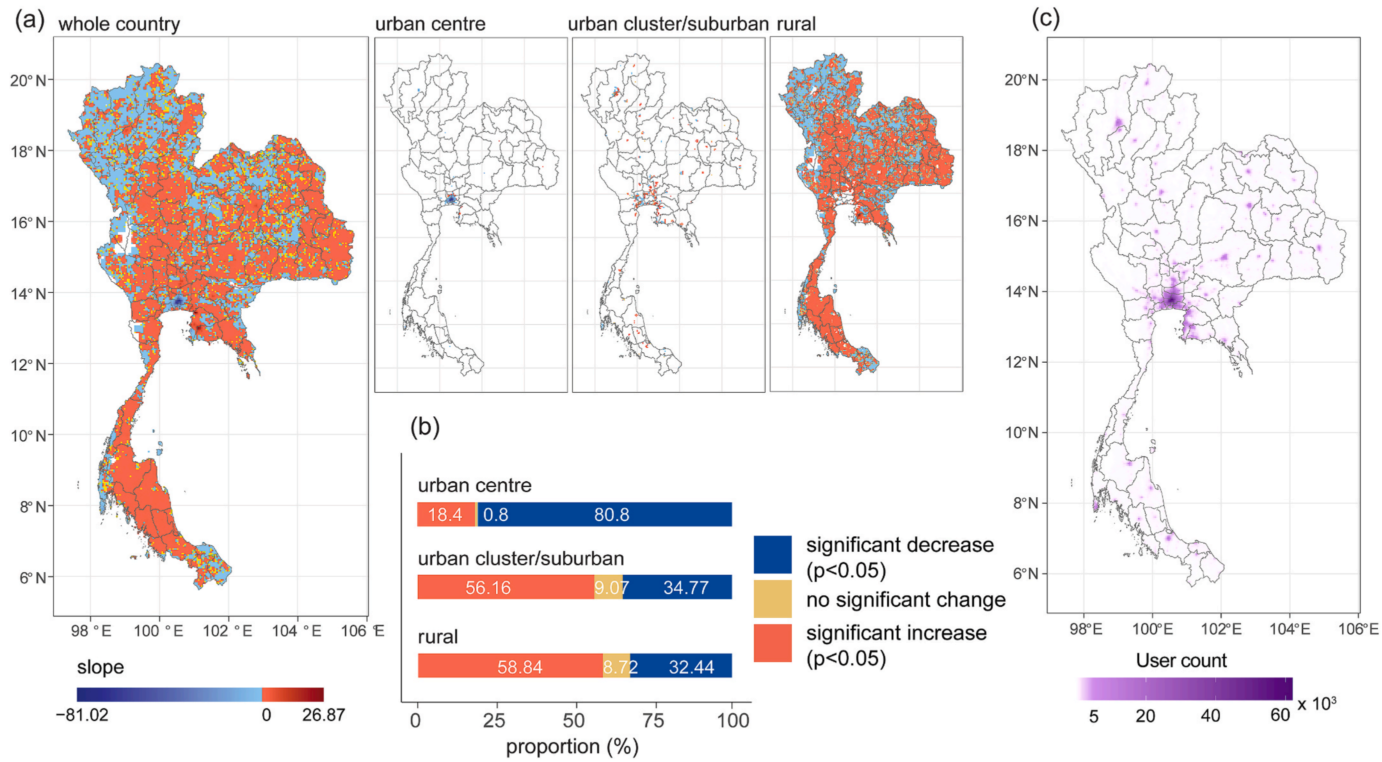

Fig. 5. Distribution of Facebook user count and their changes in Thailand during night-time on workdays. (a) Distribution of weekly changes in user count during the study period (from the fourth week in March 2020 to the third week in May 2022), segmented into urban centre, urban cluster/suburban and rural areas. The overall trend was determined from the slope by applying linear regression to the trend component from Seasonal-Trend decomposition using Loess (STL) method. (b) Proportion of tiles showing significant decrease (in blue) or significant increase (in red) in the total number of tiles in urban centres, urban clusters/suburban and rural areas during the study period. (c) Distribution of average Facebook user count in May 2022. Country and administrative boundaries were sourced from the Global Administrative Areas (GADM) spatial database (version 4.1).

potentially indicative of commuting behaviours. Conversely, in Thailand, the trend of user count during night-time and daytime remained consistent, both at the country and regional levels, presenting little changes between their home locations and daily activity areas.

4. Discussion

We explored counter-urbanisation trends for Belgium and Thailand during 2020–2022 by analysing changes in users' distribution across urban centres, suburban, and rural areas using Facebook user count dataset and STL decomposition method. The rich information on distributions of Facebook users during daytime and night-time, as well as on workdays and weekends, together with our approach, improves our understanding of their counter-urbanisation characteristics, making it an important compliment to other traditional population data in this regard.

4.1. Counter-urbanisation characteristics in Belgium and Thailand

The results showed that both Belgium and Thailand experienced counter-urbanisation from March 2020 to May 2022, reflecting by the redistribution from urban centres to rural areas. This phenomenon evidenced by: 1) an increased user count in rural areas coupled with a decreased in urban centres (Fig. 8); 2) more than 50% of rural areas showed a significant increase and over 50% of urban centre areas exhibited a significant decrease (Figs. 2 and 5); and 3) a trend of increasing user count in urban centres and a decreasing trend in rural areas during night-time on workdays throughout the study period, although a reverse trend was observed in Thailand after the end of August 2021 (Figs. 3 and 6).

The turning point or slope change of user count dynamic trends aligned well with alterations of the stringency index of 'lockdown' restrictions (Figs. 3 and 6). It not only indicated the impact of lockdowns and restrictions of the pandemic on people's movements and activities, but also served as evidence supporting the reliability of our processed data in accurately capturing population distribution and dynamics given the known effects that 'lockdown' restrictions have had on human mobility data elsewhere (Borsellino et al., 2022; Romanillos et al., 2021; Shepherd et al., 2021).

User count trends in Belgium varied between daytime and night-time (Fig. 3). The user count in urban centres during the daytime on workdays was trending downwards until July 2021, when the government ended compulsory work-from-home measures (The Brussels Times, 2021). Subsequently, people gradually gathered in the urban centres for work and daily life. The user count change in the night-time reflected the choice of people to move out of the urban centres and into rural areas during the study period. During the first year of the pandemic in Belgium, people were more inclined to move to the suburbs, where the population increased both day and night in 2020, while the rural night user count only rose slightly. Subsequently, more people moved to the countryside after the announcement of the extension of the compulsory work-from-home measure in January 2021 (FPS, 2022). As of yet, no trend of moving back to urban centres has been observed since the end of the pandemic, particularly in the Walloon regions. It appears that these urban-to-rural migrants in Belgium chose to relocate to rural areas and seem to stay there after the pandemic, but are still linked to urban centres as evidenced by the more recent decreases in daytime rural user counts (and increases in urban daytime user counts), most probably for work or education (Mitchell, 2004).

However, there was no difference in trends during daytime and night-time in Thailand (Fig. 6). Firstly, the observation that over 80% of urban centre grids showed a widespread decrease suggests it was

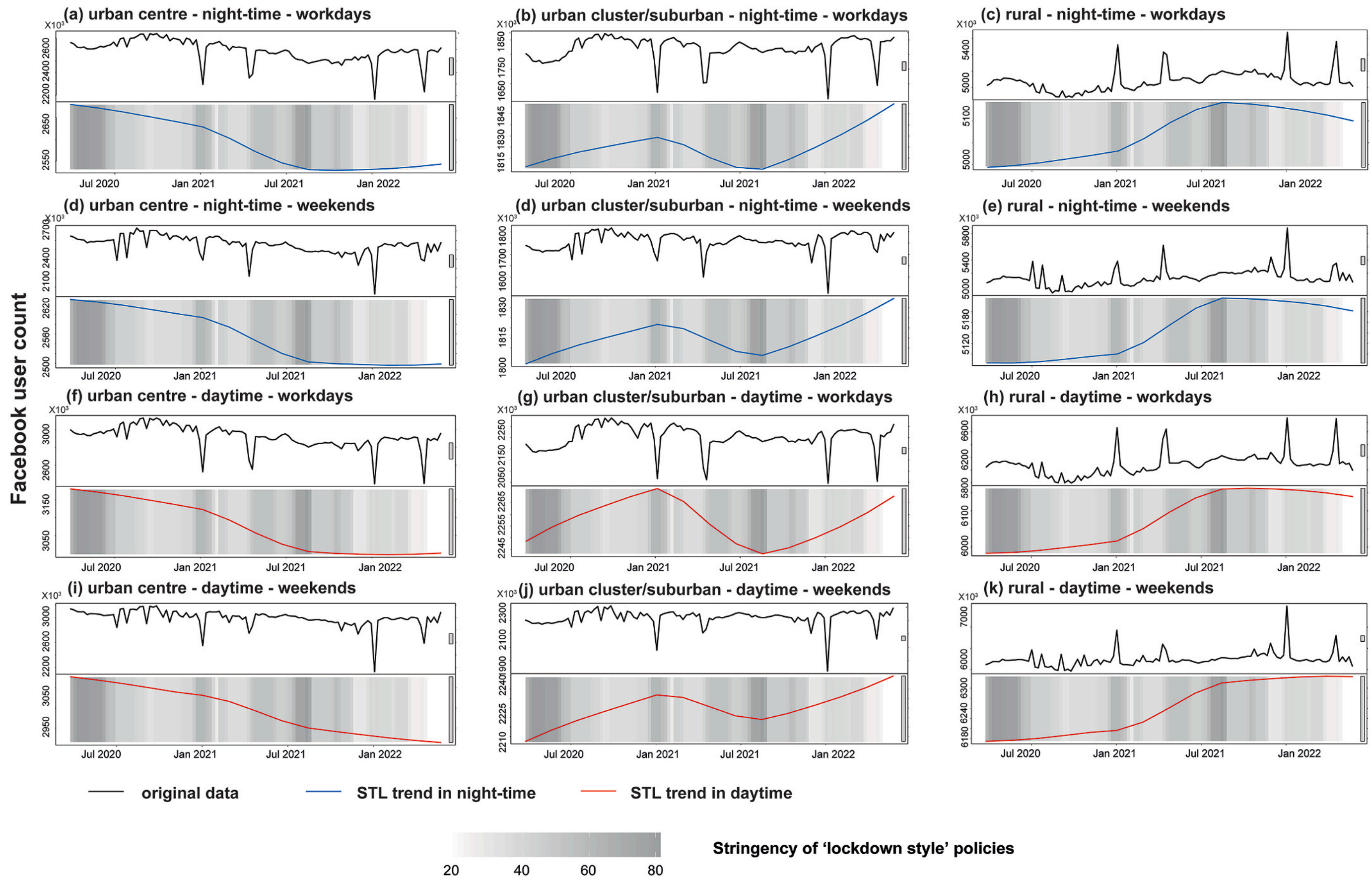

Fig. 6. The weekly Facebook user count across urban centres, urban clusters/suburban, and rural areas in Thailand from March 2020 to May 2022, along with their decomposed trend component of the Seasonal-Trend decomposition using Loess (STL) (See other components in Supplementary Fig. B2), reported on workdays and weekends separately during night-time with blue trend lines and daytime with red trend lines. The lockdown 'stringency index', calculated by Oxford COVID-19 Government Response Tracker (Hale et al., 2021), was plotted (grey backgrounds of varying intensities) to qualitatively assess if the STL decomposed Facebook data captures known changes in human mobility affected by the COVID-19 pandemic.

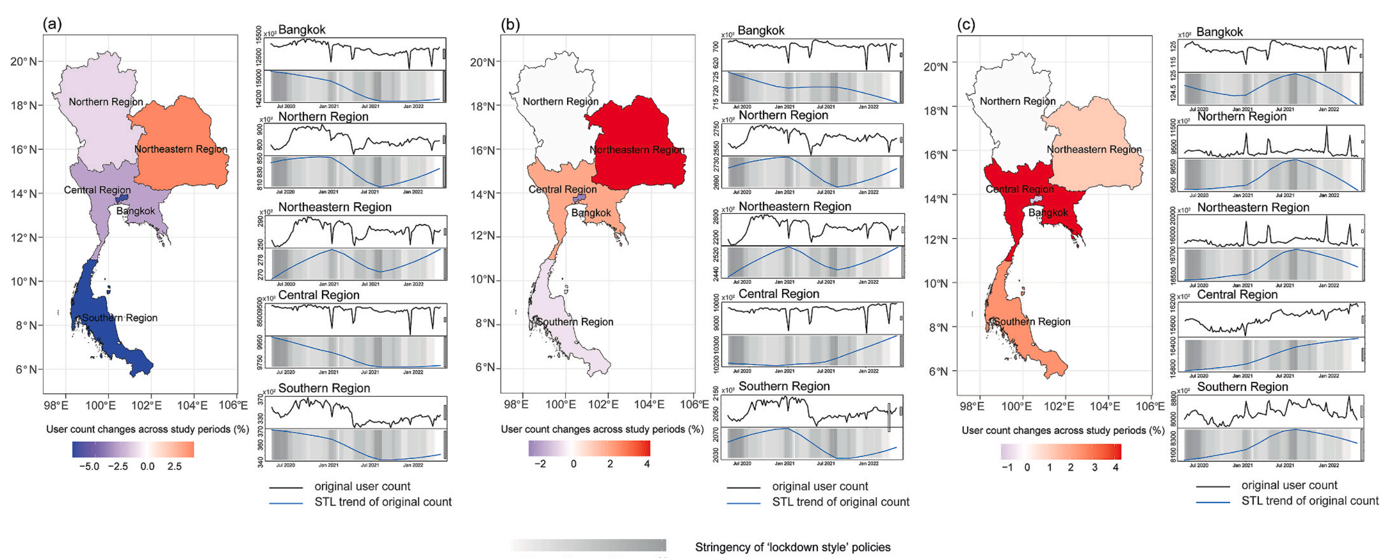

Fig. 7. Changes in weekly Facebook user count during night-time on workdays at the regional level in Thailand from March 2020 to May 2022 across (a) urban centre, (b) urban cluster/suburban and (c) rural areas. The left map exhibits percentage changes relative to the start week, while the right presents user count changes and their decomposed trend component of the Seasonal-Trend decomposition using Loess (STL) method. The lockdown 'stringency index' from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021) is represented by varying intensities of grey backgrounds. Country and regional boundaries were sourced from the Global Administrative Areas (GADM) spatial database (version 4.1).

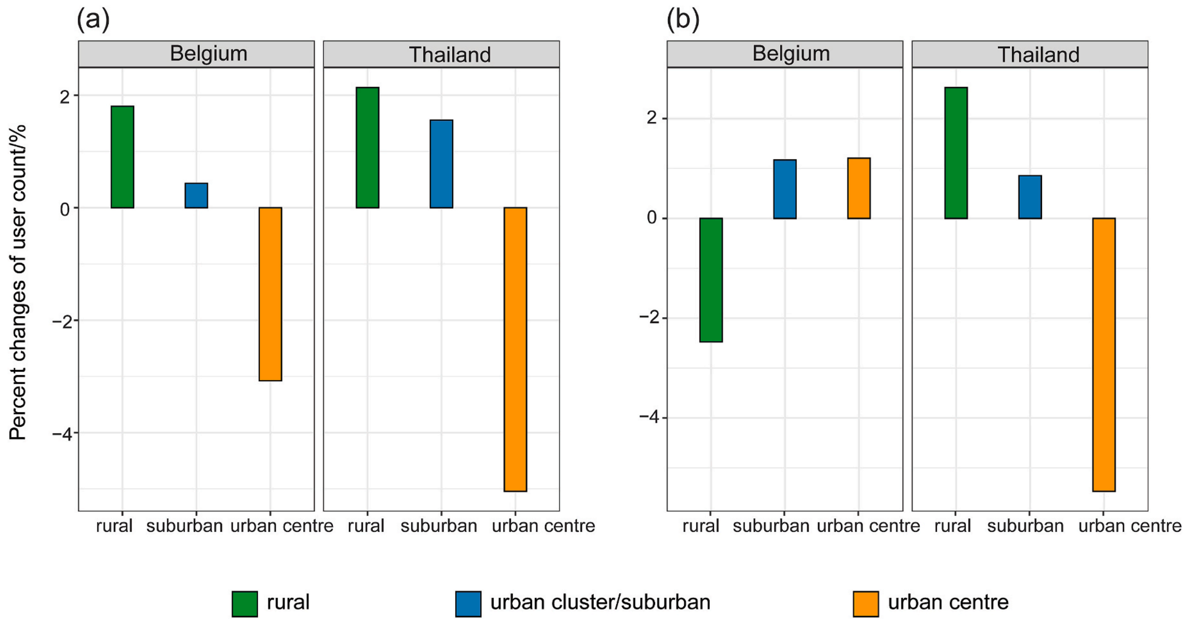

Fig. 8. Comparison of Facebook user count changes in Belgium and Thailand during (a) night-time and (b) daytime. The percent change in user count during the study period (from the start week of their data in March 2020 to the ending week in May 2022) was calculated using the trend component of weekly user count from Seasonal-Trend decomposition using Loess (STL) method.

possibly driven by a strong push factor (Fig. 5). The trends of a declining user count in urban centres and an increasing count in rural areas are likely due to the economic recession during the pandemic. The pandemic that broke out in early 2020 dealt a heavy blow to tourism in Thailand, which had contributed 20.3% of the national total gross domestic product and provided 21.8% of total employment in 2019 (World Travel and Tourism Council, 2020). Since March 2020, Thailand's tourism and related business sectors have contracted, causing millions of workers to face poverty and unemployment each month (Parks et al., 2020). This may be the contributing factor to a proportion of the population leaving urban centres and returning to rural areas. When the Thai government eased its COVID-19 travel restrictions in November 2021 (dpa, 2021), the user count in urban centres showed an increase while a downward trend was observed in rural areas. This trend aligns with observations from previous narratives and interviews, where people relocated to rural areas to reduce living expenses and seek support from family networks during an economic recession (Gkartzios, 2013; Gkartzios & Scott, 2015; Wang, 2023).

We believe that the counter-urbanisation observed in Thailand is more likely a case of displaced-urbanisation during the pandemic, and that increases in rural population are due to unemployment and economic pressure forcing them to return to rural areas (Gkartzios, 2013; Mitchell, 2004). Data from a phone survey conducted between April 27 and June 15, 2021, which interviewed approximately 2000 adults and was funded by the World Bank through Gallup Poll, supports this observation. The survey results showed an 8% decrease in employment in urban areas and the capital city. Conversely, employment in rural areas and the northern region presented an 8%, largely attributed to many of the interviewees returning to agriculture after losing their jobs during the pandemic (World Bank Group, 2021). Our findings of rising user counts in rural areas, particularly in areas with palm plantations, rubber, and paddy rice cultivation (Fig. 5), further corroborate this phenomenon. This phenomenon may be a temporary result of the pandemic, and the trend of people moving back to urban centres following the easing of travel restrictions has been noted in Fig. 6.

Our study employed quantitative population data to reveal complex dimensions of counter-urbanisation – whether new rural residents maintain links with urban centres by daily commuting, and whether migrations have persisted after COVID-19 restrictions were lifted. The aggregated data we used could not account for differences at the individual or household level (Maas, 2019). Dialogues or interviews with these urban-rural migrants are still necessary when exploring their diverse counter-urbanisation stories and truly understanding the nuanced reasons as to why individuals move. However, our method enables us to capture key additional information over census based methods, and offers a promising new approach for more in-depth large-scale studies in the future (Smith, 2007).

4.2. *The effect of missing data imputation*

This study proposed a data imputation method to deal with the missing values of Facebook user count data. The incorporation of external data from different sources in the first step (1B) was likely to introduce errors, even if the errors were not as large as those that arose from directly replacing the near real-time population numbers with the static population dataset. Our imputation models appear to underestimate the population count for sparse tiles (Supplementary Fig. A7). Nonetheless, deleting observations to address incomplete records (Afghari et al., 2019), which were highly uneven distribution (Supplementary Table A1), could lead to biased results. After testing the imputation method using tiles between 10 and 20 baselines, we believe that Facebook user count data after data imputation is a reasonable proxy variable for population.

4.3. *Limitations*

In addition to uncertainties introduced in the process of data imputation mentioned above, there were other limitations of this study resulting from the potential bias of Facebook user count data. It should be emphasised again that the Facebook data in this study refers to Facebook users who have agreed to location services being enabled and therefore may not be representative of the dynamics of the total population. Results for each country may be influenced by smart mobile device penetration, Facebook app usage, and the use of location services (Maas, 2019; Shepherd et al., 2021). For example, the coverage of Facebook users in Belgium was around 54% at the end of 2020, while in Thailand it was approximately 67% (World Population Review, 2023). This suggests that any potential bias in the analysis of population dynamics of Thailand inferred from Facebook users may be lower than that of Belgium. However, these biases are not expected to affect the conclusions, as Facebook users are usually skewed towards young and middle-aged groups, those with high intensity of mobility (Rowe, Calafiore, et al., 2023). A recent study from the United Kingdom showed that Facebook users were highly related to census data and also exhibited no strong relationships between the distribution of Facebook users and age, ethnicity and population density (Gibbs et al., 2021). In addition, the consistency between the inflection points of user count trends and the strictness of COVID-19 restrictions as illustrated in Figs. 3 and 6, could also reinforce the reliability of our results based on Facebook user count. Utilising detailed users' profiles, if possible, like distribution of age and gender in future analysis, may provide further assessment of the representativeness of Facebook users' data for different countries, as well as potential bias in inferred conclusions and improve the accuracy of analytical results.

Despite the uncertainties and limitations of Facebook user count data, their contribution to the study of counter-urbanisation is still evident. It has a fine temporal resolution that could provide detailed population distribution data in near real-time (Maas, 2019). Daily data across three time-windows offers a detailed depiction of users' activities, contributing to the identification of counter-urbanisation characteristics and inference of potential causes. Furthermore, Facebook data covers more than 100 countries, allowing for a broader range of comparisons, although not global due to the limitation of Facebook app access. The counter-urbanisation of more countries and their potential drivers across space and time could be explored in the future. However, it is suggested to select the country carefully, for example, choosing the country with access to the Facebook app and over 50% of Facebook user coverage to reduce the bias caused by under-representation.

5. Conclusions

Our study highlights the potential of Facebook user count data, with rich diurnal information, to assess counter-urbanisation, its distinct characteristics, and potential causes. While both Belgium and Thailand displayed a trend of redistribution from urban to rural areas, whether consistent or temporary, their patterns are different. New rural residents in Belgium seem to retain links with urban centres through daily commuting and show no indication of returning to urban areas post-pandemic. In contrast, in Thailand, they appear to have entirely left the urban environment, but have mostly done so temporarily, and are now returning to the cities post-pandemic. The data imputation method we have developed is effective in estimating the missing data and improving analysis in rural areas, taking Belgium and Thailand as examples. This method could both protect privacy and reduce bias from that. The imputed Facebook data could provide a new perspective for understanding counter-urbanisation.

Data availability

The Facebook user count data for this study are not publicly available due to licensing agreements. It can be requested through correspondence with the corresponding authors. The population data from other sources and urbanisation classification are available from the data sources listed in Data and Methodology.

Ethics approval

Ethical clearance for collecting and using secondary population data in this study was granted by the institutional review board of the University of Southampton (No. 79237). We only have access to the anonymised aggregated data from Facebook, and all direct identifiers, as well as any characteristics that might lead to identification were omitted from the data before we obtained them.

CRediT authorship contribution statement

Qianwen Duan: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jessica Steele:** Writing – review & editing, Methodology, Data curation. **Zhifeng Cheng:** Writing – review & editing, Data curation. **Eimear Cleary:** Writing – review & editing, Data curation. **Nick Ruktanonchai:** Writing – review & editing. **Hal Voepel:** Writing – review & editing, Data curation. **Tim O'Riordan:** Data curation. **Andrew J. Tatem:** Writing – review & editing, Data curation. **Alessandro Sorichetta:** Writing – review & editing, Methodology, Conceptualization. **Shengjie Lai:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Felix Eigenbrod:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Methodology, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.habitatint.2024.103113.

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