



RECAST: Training Workshop



Overview: Digital Footprint Data

Structure

1. Introduction to human mobility
& digital footprint data

2. Opportunities of
digital footprint data

3. Challenges of digital
footprint data

Human Mobility

Causes



Place inequalities



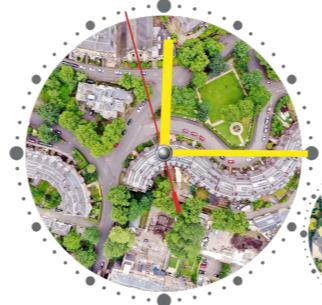
Population inequalities



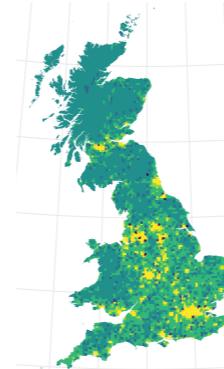
Individual inequalities

Geographical scale

Local urban mobility



Internal migration



International migration



Impacts

Place inequalities

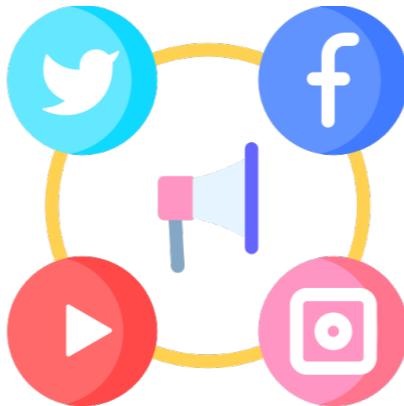
Population inequalities

Individual inequalities

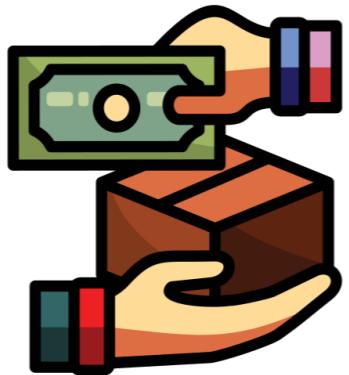
Digital Footprint Data?



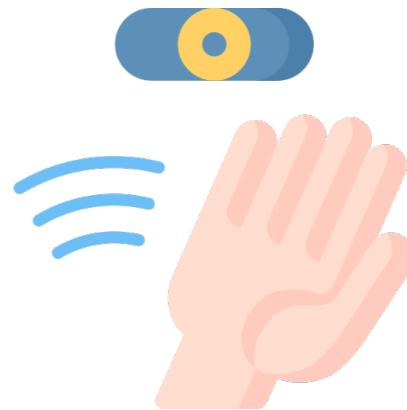
Internet



Social media



Commercial & transactional



Sensor



Imagery

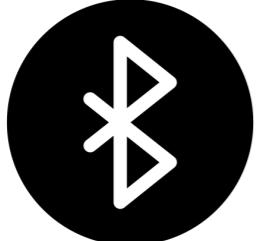
Data for Mobility



CDR/XDR
~100m-1km
~30min



GPS
~5-20m
~10-25min



Bluetooth
~1-10m

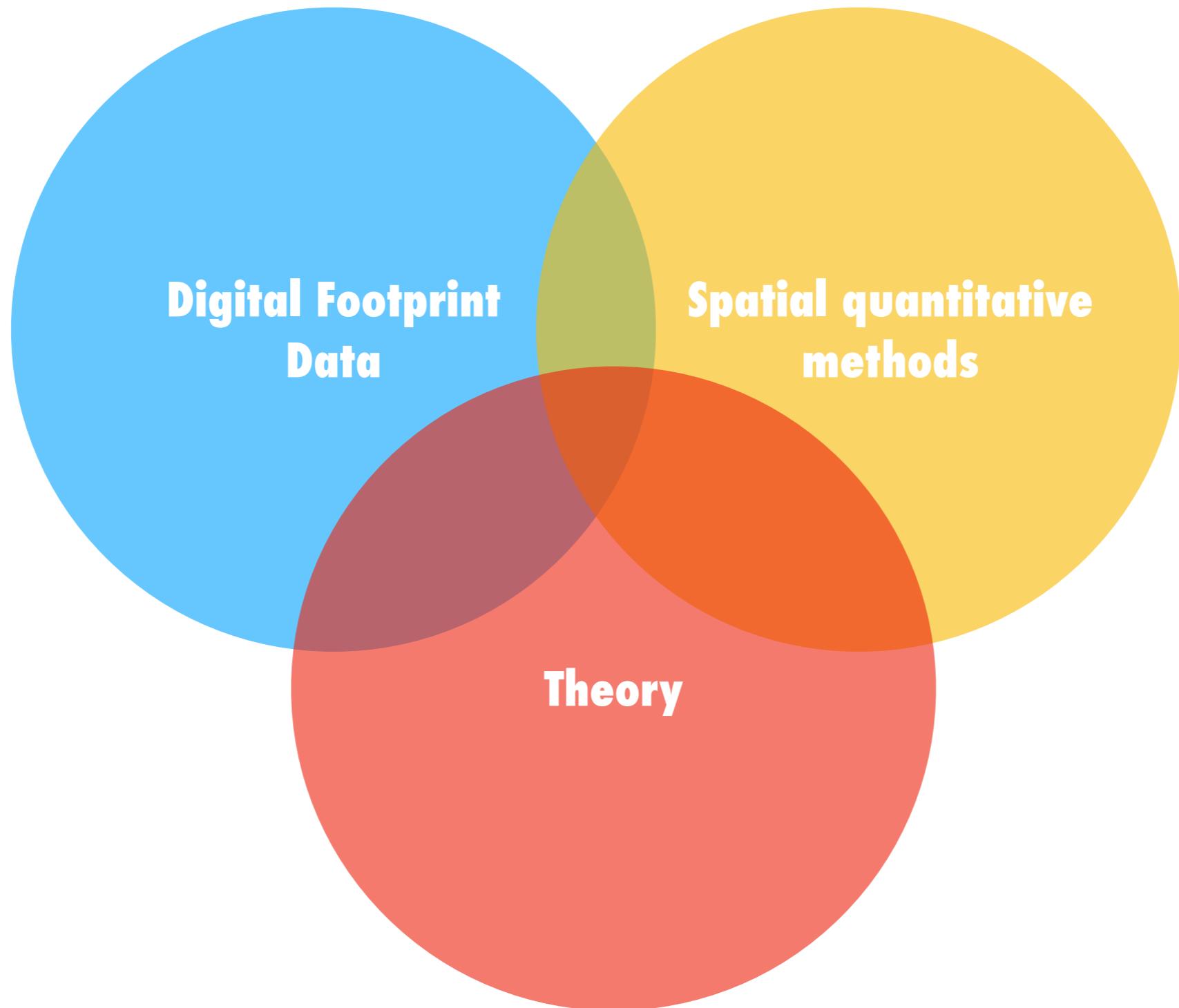


Smart card
location



Source: Rowe and Patias (2020)

Warning **Not** collected for research purposes



“Although ‘big data’ and, more recently, ‘big code’ may have captured the limelight, theory is invaluable and should not be disregarded” (Franklin 2023: 178)

Opportunities

High resolution

Geographical and temporal granularity



To travel or not to travel: 'Weather' is the question. Modelling the effect of local weather conditions on bus ridership 

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^d School of Civil Engineering, The University Queensland, 4072, Australia

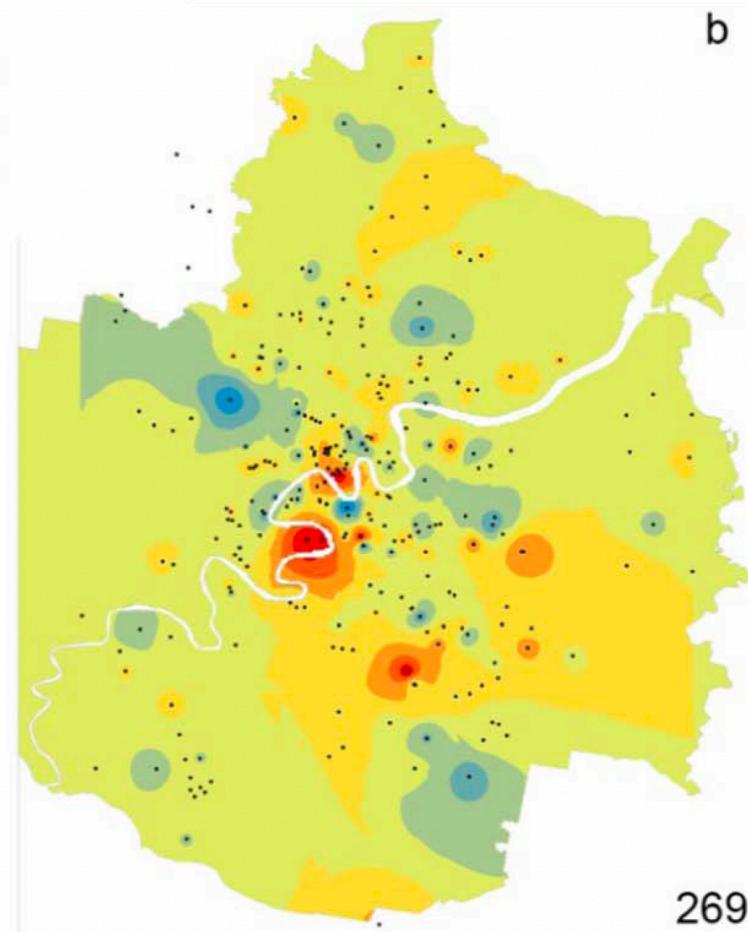
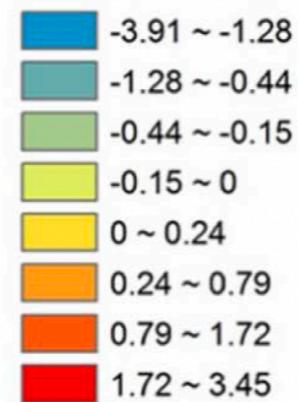
ARTICLE INFO

Keywords:
Public transport
Weather
Time-series modelling
Travel behaviour

ABSTRACT

While the influence of weather on public transport performance and ridership has been the topic for some research, the real-time response of transit usage to variations in weather conditions is yet to be fully understood. This paper redresses this gap by modelling the effect that local weather conditions exert on hourly bus ridership in sub-tropical Brisbane, Australia. Drawing on a transit smart card data set and detailed weather measurements, a suite of time-series regression models are computed to capture the concurrent and lagged effects that weather conditions exert on bus ridership. Our findings highlight that changes in particularly temperature and rainfall were found to induce significant hour-to-hour changes in bus ridership, with such effects varying markedly across both a 24 h period and the transit network. These results are important for public transport service operations in their capacity to inform timely responses to real-time changes in passengers' travel demand induced by the onset of particular weather conditions.

Rainfall



b

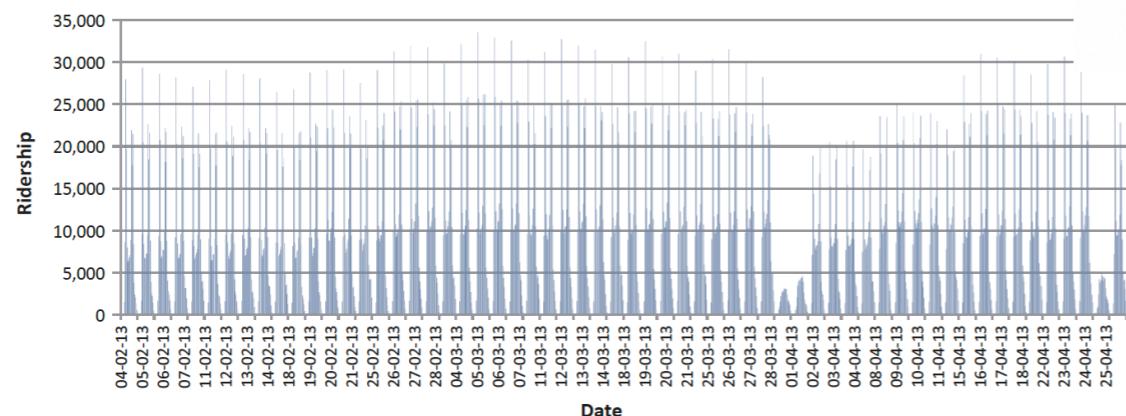


Fig. 6. Weekday hourly ridership.

269

Greater geographical coverage

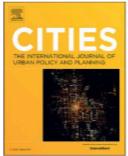
Assessing stay-at-home at a global scale



Contents lists available at ScienceDirect

Cities

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



Sensing global changes in local patterns of energy consumption in cities during the early stages of the COVID-19 pandemic

Francisco Rowe^{a,*}, Caitlin Robinson^b, Nikos Patias^a

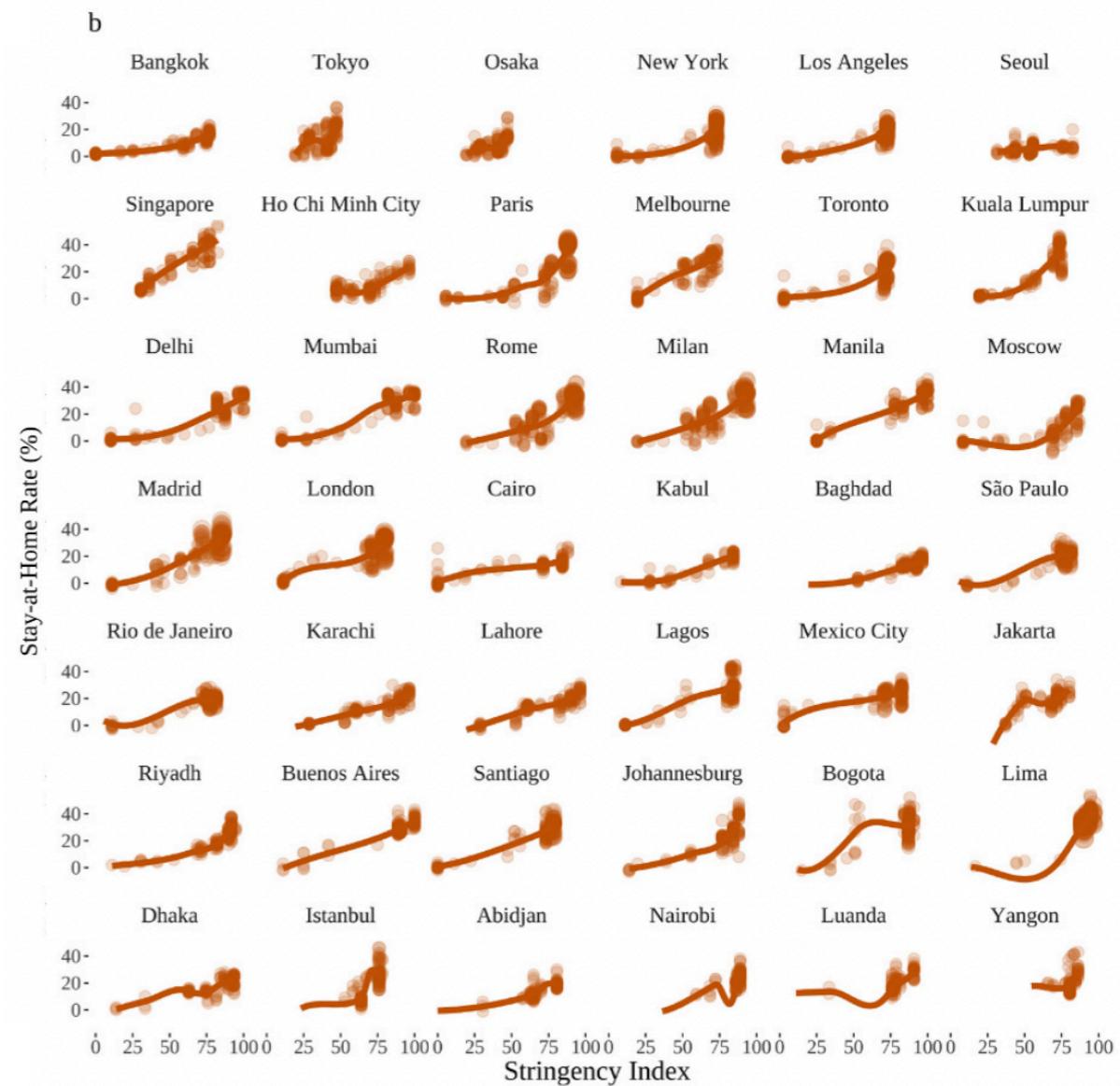
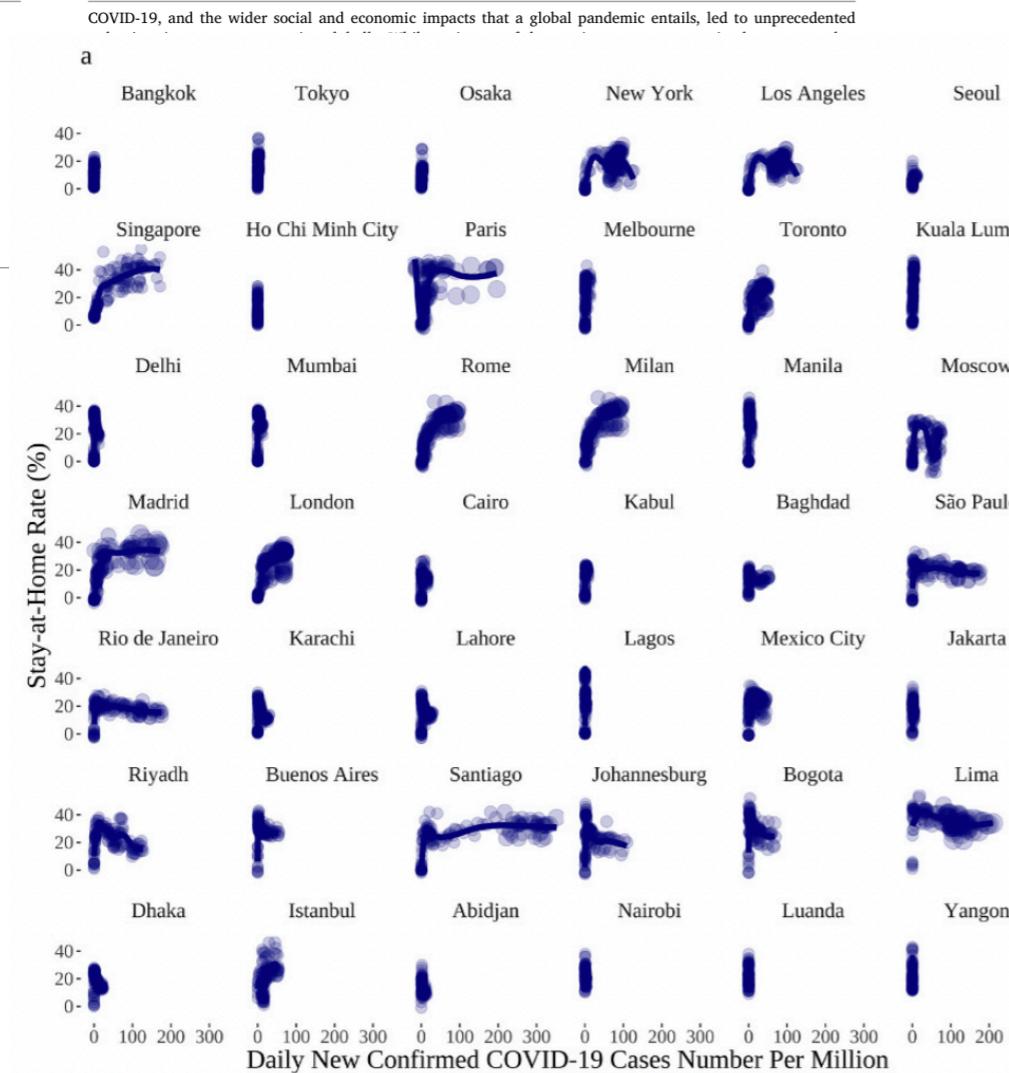
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ARTICLE INFO

ABSTRACT

Keywords:
COVID-19
Urban energy use
Mobility
Night-time light satellite imagery
Cities



Near real-time availability

Measuring population movement during COVID-19

Received: 24 February 2022 | Revised: 1 May 2022 | Accepted: 3 May 2022
DOI: 10.1002/psp.2578

RESEARCH ARTICLE

Understanding patterns of internal migration during the COVID-19 pandemic in Spain

Received: 31 March 2022 | Accepted: 17 November 2022
DOI: 10.1002/psp.2637

RESEARCH ARTICLE

Urban exodus? Understanding human mobility in Britain during the COVID-19 pandemic using Meta-Facebook data

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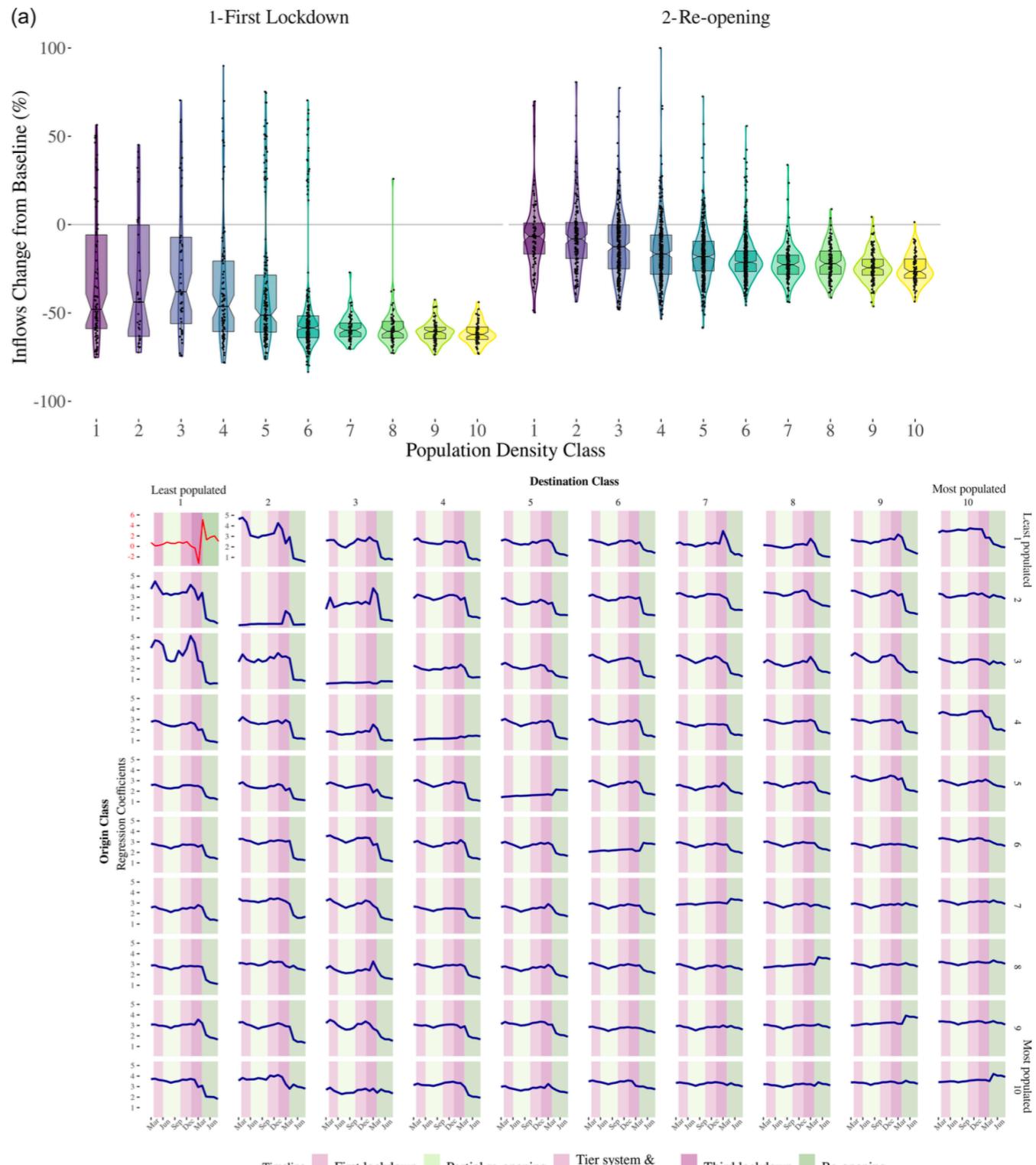
Funding information
Engineering and Physical Sciences Research Council; Alan Turing Institute

Abstract

Existing empirical work has focused on assessing the effectiveness of nonpharmaceutical interventions on human mobility to contain the spread of COVID-19. Less is known about the ways in which the COVID-19 pandemic has reshaped the spatial patterns of population movement within countries. Anecdotal evidence of an urban exodus from large cities to rural areas emerged during early phases of the pandemic across western societies. Yet, these claims have not been empirically assessed. Traditional data sources, such as censuses offer coarse temporal frequency to analyse population movement over infrequent time intervals. Drawing on a data set of 21 million observations from Meta-Facebook users, we aim to analyse the extent and evolution of changes in the spatial patterns of population movement across the rural–urban continuum in Britain over an 18-month period from March 2020 to August 2021. Our findings show an overall and sustained decline in population movement during periods of high stringency measures, with the most densely populated areas reporting the largest reductions. During these periods, we also find evidence of higher-than-average mobility from high-density population areas to low-density areas, lending some support to claims of large-scale population movements from large cities. Yet, we show that these trends were temporary. Overall mobility levels trended back to precoronavirus levels after the easing of nonpharmaceutical interventions. Following these interventions, we found a reduction in movement to low-density areas and a rise in mobility to high-density agglomerations. Overall, these findings reveal that while COVID-19 generated shock waves leading to temporary changes in the patterns of population movement in Britain, the resulting vibrations have not significantly reshaped the prevalent structures in the national pattern of population

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Apple Maps

Mobility Trends Reports

Learn about COVID-19 mobility trends. Reports are published daily and reflect requests for directions in Apple Maps. Privacy is one of our core values, so Maps does not associate your data with your Apple ID and Apple does not keep a history of where you have been.



COVID-19 Community Mobility Reports



See how your community is moving around differently due to COVID-19

Near real-time availability

Measuring climate-induced population displacement

REGIONAL STUDIES, REGIONAL SCIENCE
2022, VOL. 9, NO. 1, 665–668
<https://doi.org/10.1080/21681376.2022.2135458>



REGIONAL GRAPHIC

OPEN ACCESS

Date: 2022-08-13

Using digital footprint data to monitor human mobility and support rapid humanitarian responses

Francisco Rowe

ABSTRACT

Global warming is increasing the frequency of extreme weather events leading to an increased risk of large-scale population displacements. Since June 2022, Pakistan has recorded destructive flash flooding resulting from melting glaciers and torrential monsoon rainfall. Emergency responses have documented flood-related deaths, injuries and damaged infrastructure – less is known about population displacements resulting from recent floods. Information about these populations and mobility is critical to ensure the appropriate delivery of humanitarian assistance where it is most needed. Lack of granular spatial data in real time has been a key barrier. This article uses digital footprint data from Meta Facebook to identify the patterns of population displacement in Pakistan in near-real time.

ARTICLE HISTORY

Received 28 September 2022; Accepted 3 October 2022

KEYWORDS

digital footprint data; human mobility; population displacement; flooding; Pakistan; geographical data science

Global warming is increasing the frequency of extreme weather events, natural disasters and large-scale population displacements. Pakistan is a current example of such events. Since June 2022, Pakistan has suffered destructive flash flooding. As of 3 September 2022, a third of the country was estimated to be underwater (Scarr et al., 2022). Pakistan has the largest number of glaciers outside the polar regions and higher temperatures have led to excess water from melting ice in the Himalayas. Sudden outbursts of melting glacier water coupled with torrential monsoon rainfall and long-term deforestation have thus contributed to landslides, floods and the overflowing of the Indus River, which stretches 2880 km across Pakistan from north to south. Since June 2022, 33 million people are estimated to have been affected, over 1500 killed and over 6000 injured as a result of damaged or collapsing housing and public infrastructure (Scarr et al., 2022). The south-eastern province of Sindh is the worst affected area (Scarr et al., 2022).

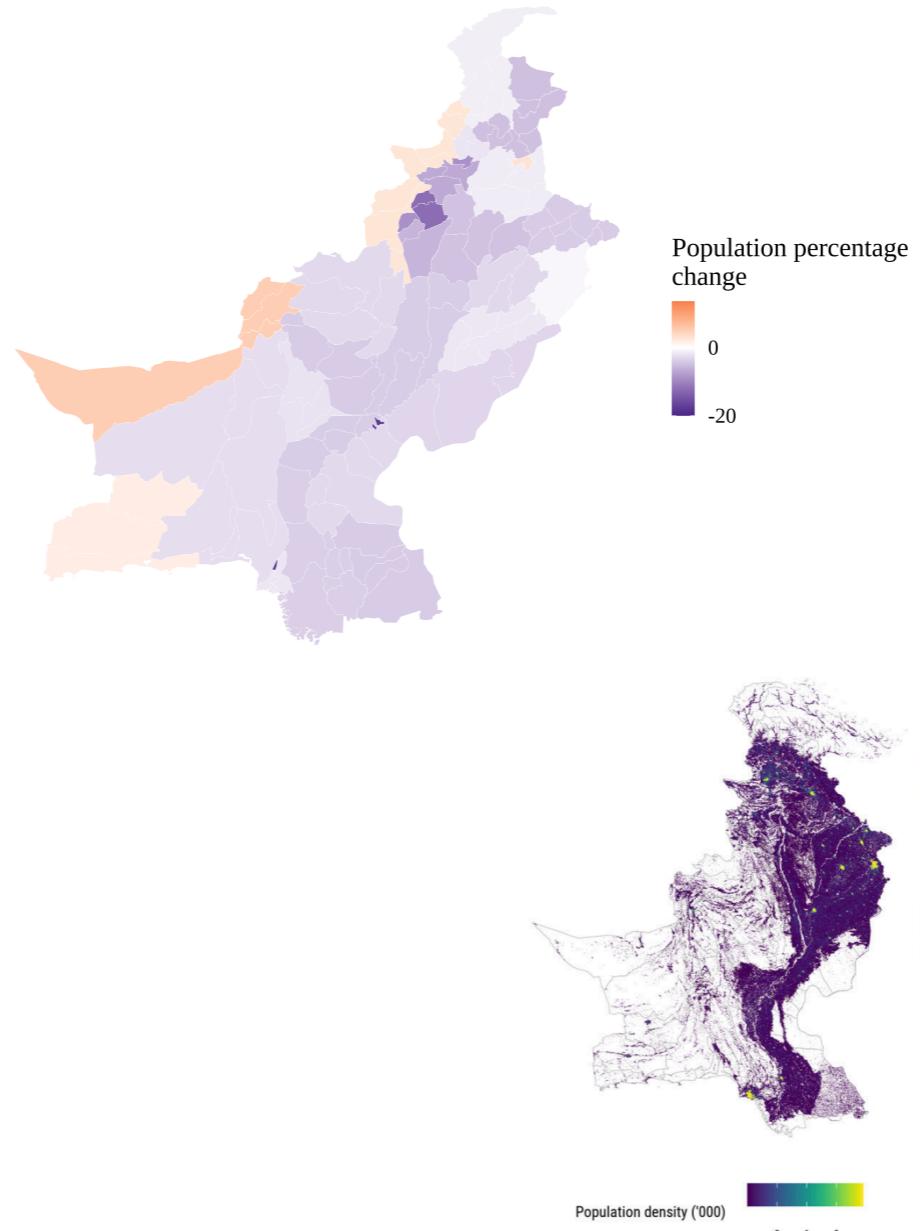


Figure 2. (a) Population density; and (b) human mobility flows on 15 August. Sources: (a) Global human settlement layer; and (b) Meta Facebook Data for Good.

Near real-time availability

Measuring conflict-induced population displacement

Sensing population displacement from Ukraine using Facebook data:
Identifying potential settlement areas within host countries

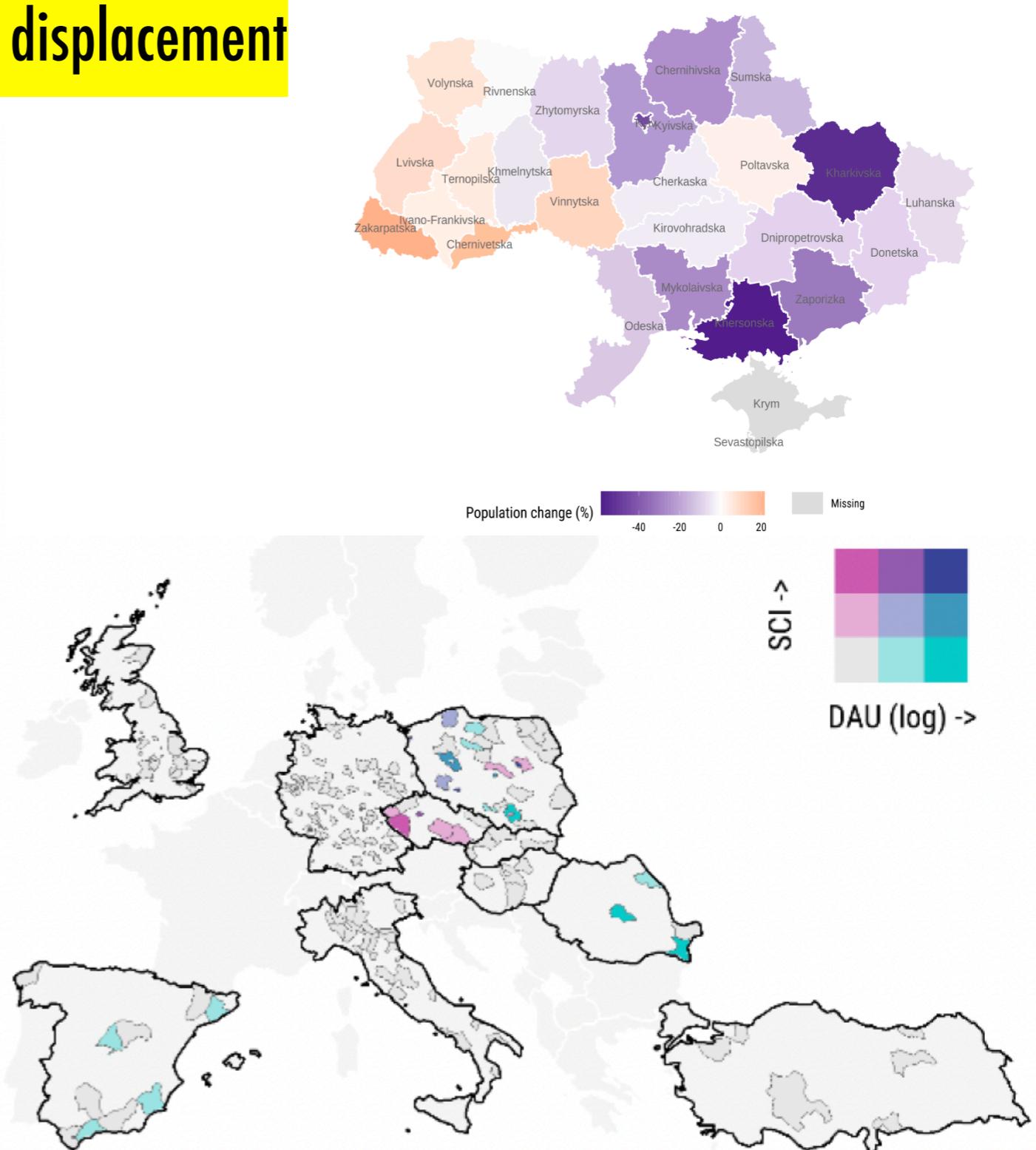
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Abstract: The escalation of conflict in Ukraine has triggered the largest refugee crisis in Europe since WWII. As of mid-April 2023, over 8.2 million people have fled Ukraine. Large-scale efforts have been made to identify the major receiving countries. However, less is known about the sub-national areas within host countries where refugees have migrated. Identifying these areas is key for the appropriate allocation of humanitarian aid. By combining digital Facebook API data and traditional data from Eurostat, this paper aims to identify and characterise potential settlement areas of Ukrainians across the main destination countries in Europe. We identify high concentrations of Ukrainians in urban areas with a pre-existing diaspora and tight labour market conditions across southern, northern-west and central Poland and the city of Prague in Czech Republic. We also find potential settlements in key urban agglomerations with a moderate diaspora and high levels of unemployment in Spain. Only in Romania, refugees seem to have settled in rural areas which show a moderate diaspora but low levels of unemployment. Potential settlement areas in Germany, Italy and the United Kingdom are spread across the country. Surprisingly, we do not identify potential settlement areas in bordering regions with Ukraine within neighbouring countries, suggesting that refugees may have used them only as transit points. Our findings point out that different packages of humanitarian assistance may be needed according to the number of refugees and the characteristics of settlement areas.



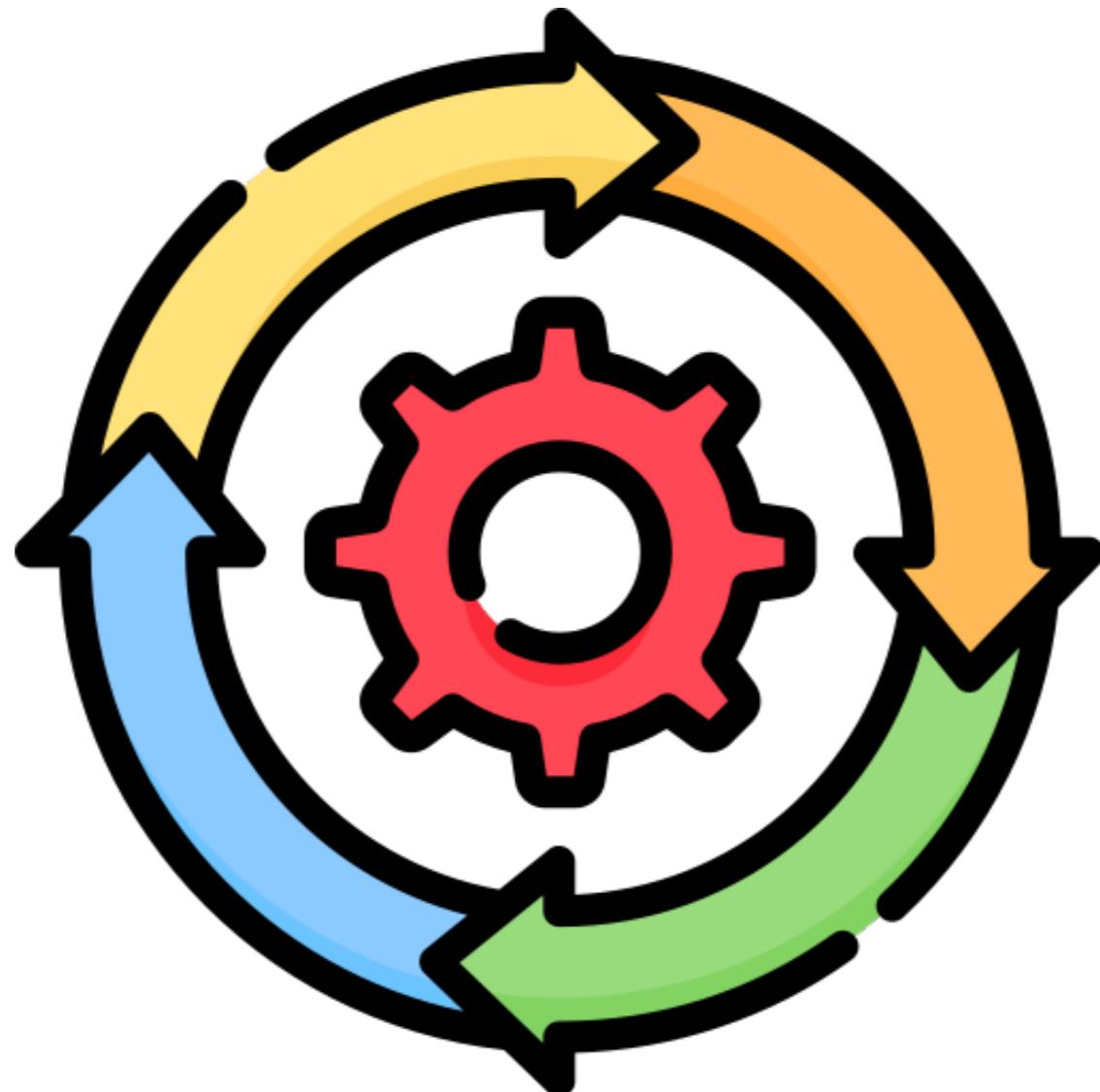
Challenges

Epistemology

Strengthening interdisciplinary
collaborations

Enriching existing
theories

Embracing data-
driven thinking



1. Dynamic perspective
2. Focusing on distribution extremes

Data

Accessibility & discoverability

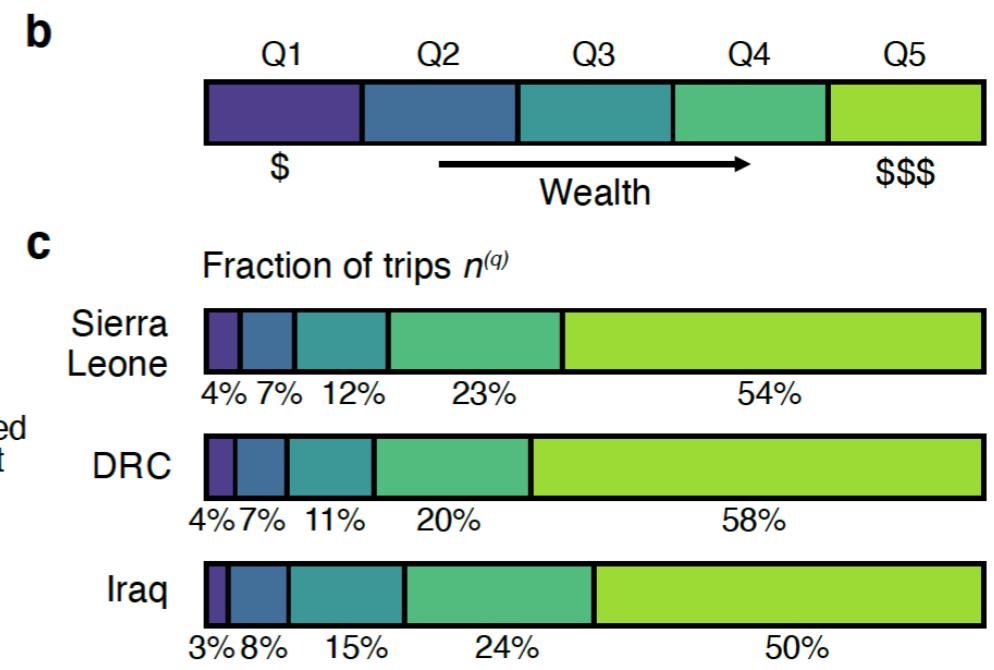
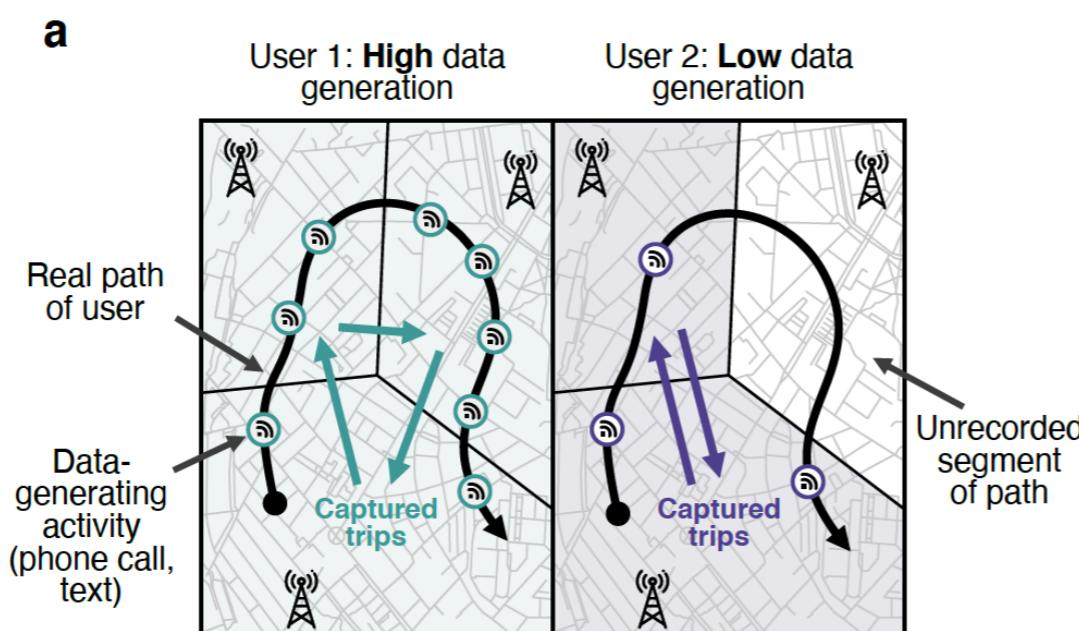
Variable standards in who & how

Integration & interoperability

Unrelated digital data environments

Spatial, social and demographic **biases**

Urban, educated, wealthy, young & middle-age individuals



Methodology

Adoption of data science & ML/AI

Lack of standard practice

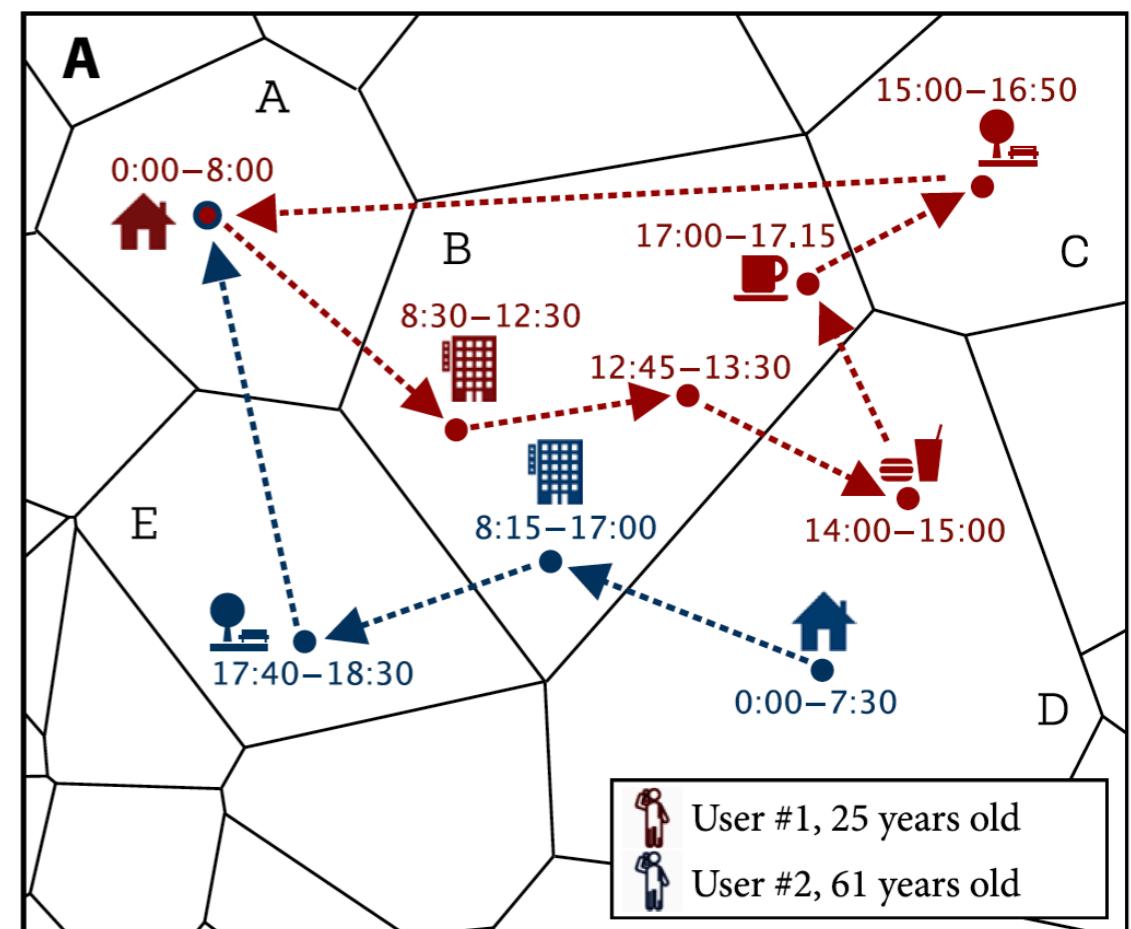
Data engineering & validation

Generalisation of observed patterns

Re-weighting /resampling sp. post-stratification

Infusing socio-economic & demographic attributes

device_id	latitude	longitude	timestamp
488bb45a-fbd4-458e	48.8	30.2	1643674140
76549c5b-56ab-4e1	51.5	31.1	1643674140
910db600-1f54-4bfd	47.1	37.6	1643674140
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2175e67e-a541-4acf	47.7	35.6	1643674140



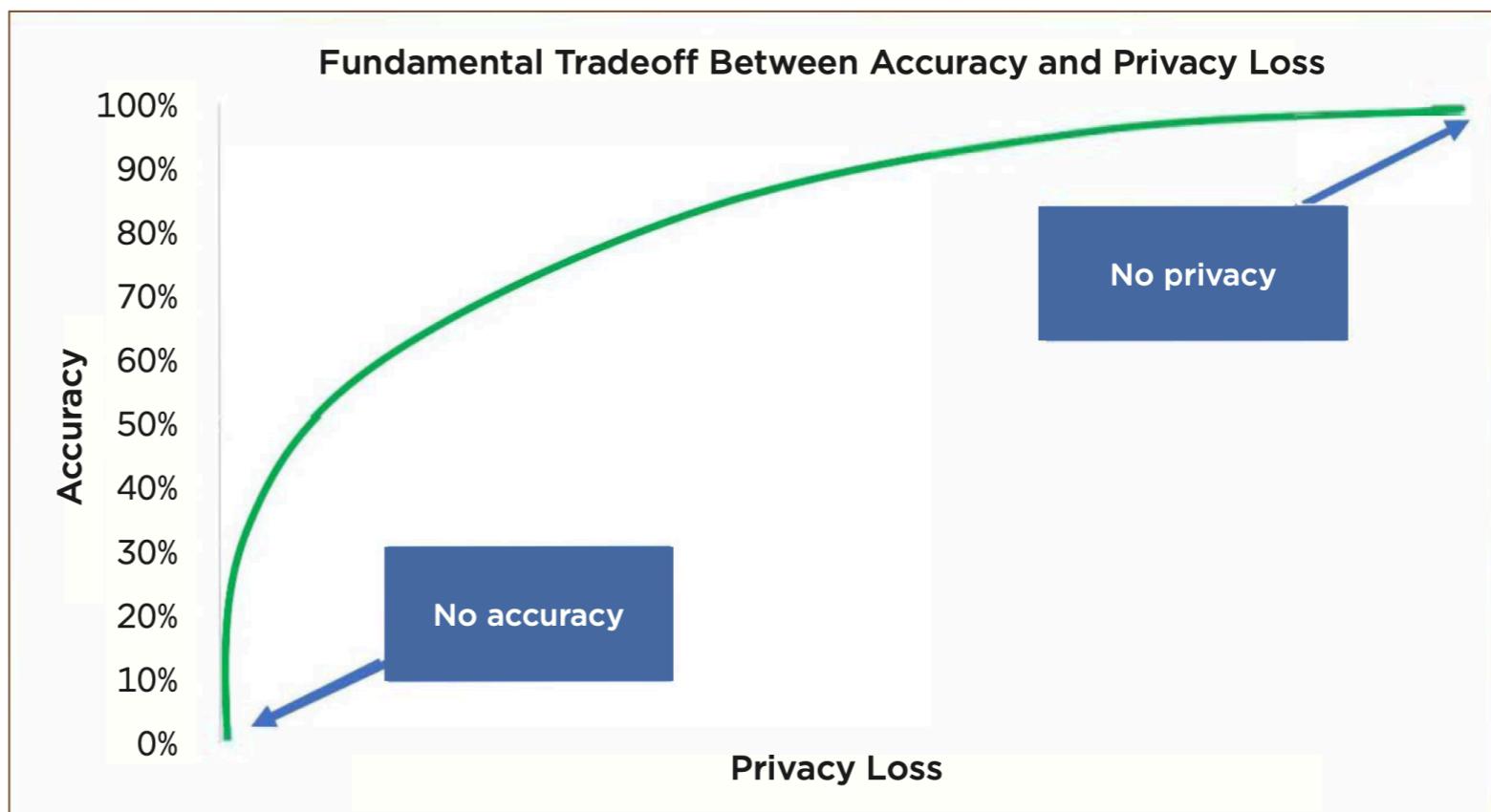
Source: Oliver, Lepri and Sterly et al. (2020)

Ethics & Privacy

Anonymisation

Privacy vs Accuracy

Barriers to replicability & reproducibility



Source: US Census Bureau 2022

Conclusions

Final Remarks (I)

- Digital footprint data offer opportunities to enhance our **understanding of human mobility & migration** and improve **transport, navigation systems, pandemic responses & urban spaces**.

Yet...

- **Key epistemological, ethical, data and methodological challenges** exist and need to be addressed in order to unleash the opportunities offered by digital footprint data

Final Remarks (II)

- Protocols for ensuring **FAIR** data & generating **anonymised** & **synthetic** data
- **Trusted** research digital environments
- Frameworks for **assessing** & **correcting** data generation & usage biases
- Repository of **standard tools** & **practices** for data engineering & validation
- Expanding & developing new **dynamic theories**

Overview: Meta-Facebook Mobility Data

Data for Good

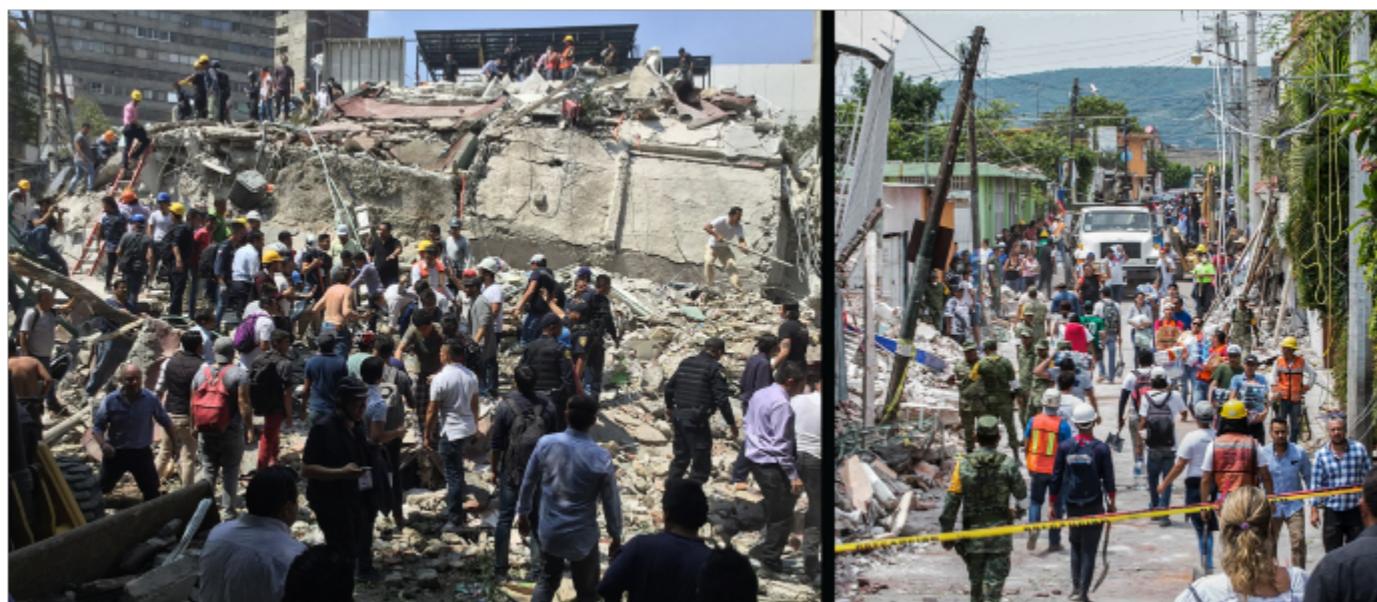


Access to privacy-preserving data for partners to tackle social problems

Data on human mobility during crisis

Two datasets:

Facebook Population
Movements



Population

Who?

Number of Facebook users (mobile app users w/ location services device setting on)

Spatial resolution:

Administration areas

Microsoft Bing Tiles - 2.5-6 Km²

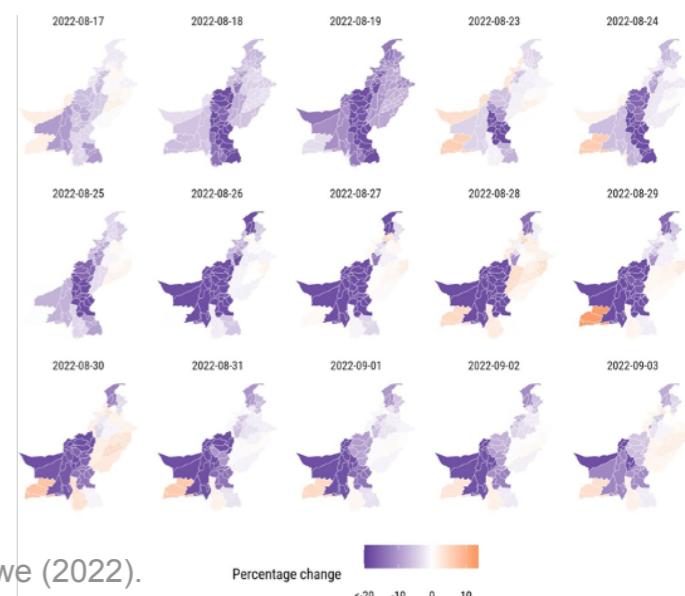
Near real-time - Time window: 00:00, 8:00 and 16:00 (Pacific Time)

The location where users **spent most time** within each 8-hour window

Period covering the entire event & **baseline period**

No information for units w/ less than 10 obs.

Datasets are discontinued after 90 days after the last data update



Boliva Dengue Fever Outbreak Feb 27 2023

Updated 28 may 2023 • 27 feb 2023 – 28 may 2023

Facebook Population During Crisis • Bolivia

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

Turkiye Turkey Earthquake Full Country Version Feb 8 2023

Updated 9 may 2023 • 5 feb 2023 – 9 may 2023

Facebook Population During Crisis • Turkey

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

The Avalanche in Nathu La, Sikkim, India

Expiring soon

Updated 18 abr 2023 • 4 abr 2023 – 18 abr 2023

Facebook Population During Crisis • India

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

The Tornadoes in Central Indiana, US

Expiring soon

Updated 14 abr 2023 • 1 abr 2023 – 14 abr 2023

Facebook Population During Crisis • United States

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

The Flooding Across Southern Bahia, Brazil

Updated 8 may 2023 • 25 abr 2023 – 8 may 2023

Facebook Population During Crisis • Brazil

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

The Tornadoes in Central Oklahoma, US

Updated 3 may 2023 • 20 abr 2023 – 3 may 2023

Facebook Population During Crisis • United States

Facebook Population During Crisis shows the number of Facebook users observed in a location following a crisis compared to a precrisis baseline period. It can help responders identify areas that are heavily impacted by a disaster, analyze how populations are reacting and where they go when they evacuate, and make strategic decisions about how to position services or supplies.

[Mapa](#) [Acerca de](#) [Documentación](#) [Descargar](#) [Files](#)

dfd4mobility - main - RStudio

YML _quarto.yml x pop x

Go to file/function Addins Environment History Connect

lat lon quadkey country date_time n_baseline n_crisis n_difference density_baseline density_crisis percent_change clipped_z_score

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22	-53.77468	-67.80762	21203313310	AR	2020-03-25	744.89443	844.00718	9.911275e+01	2.936362e-04	3.352763e-04	13.287772118	1.753375632
23	-46.58906	-71.05957	21201303211	AR	2020-03-25	28.24359	30.99641	2.752817e+00	1.113358e-05	1.231312e-05	9.413403232	1.722454450
24	-31.98943	-68.33496	21023111011	AR	2020-03-25	50.97665	55.63972	4.663070e+00	2.009492e-05	2.210251e-05	8.971470041	3.597761895
25	-33.10074	-69.03809	21023110333	AR	2020-03-25	177.90497	169.44916	-8.455816e+00	7.012986e-05	6.731256e-05	-4.726428657	-0.760884130
26	-26.62781	-66.22559	21030022313	AR	2020-03-25	12.30690	11.41608	-8.908164e-01	4.851361e-06	4.534965e-06	-6.694394279	-0.941107565
27	-33.02708	-68.33496	21023111233	AR	2020-03-25	202.83372	213.98650	1.115278e+01	7.995673e-05	8.500473e-05	5.471508841	1.441755596

Showing 1 to 27 of 37,486 entries, 14 total columns

Console Terminal x Background Jobs x

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R is a collaborative project with many contributors. Type 'contributors()' for more information and

Environment History Connect

Global Environment 93 MiB

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2020_03_pop.rds 2020_04_pop.rds 2020_05_pop.rds 2020_06_pop.rds 2020_07_pop.rds 2020_08_pop.rds 2020_09_pop.rds 2020_10_pop.rds 2020_11_pop.rds 2020_12_pop.rds 2021_01_pop.rds 2021_02_pop.rds 2021_03_pop.rds 2021_04_pop.rds 2021_05_pop.rds 2021_06_pop.rds 2021_07_pop.rds 2021_08_pop.rds

Movement

Who?

Number of Facebook users in different spatial units at two points in time

Spatial resolution:

Administration areas

Microsoft Bing Tiles - 2.5-6 Km²

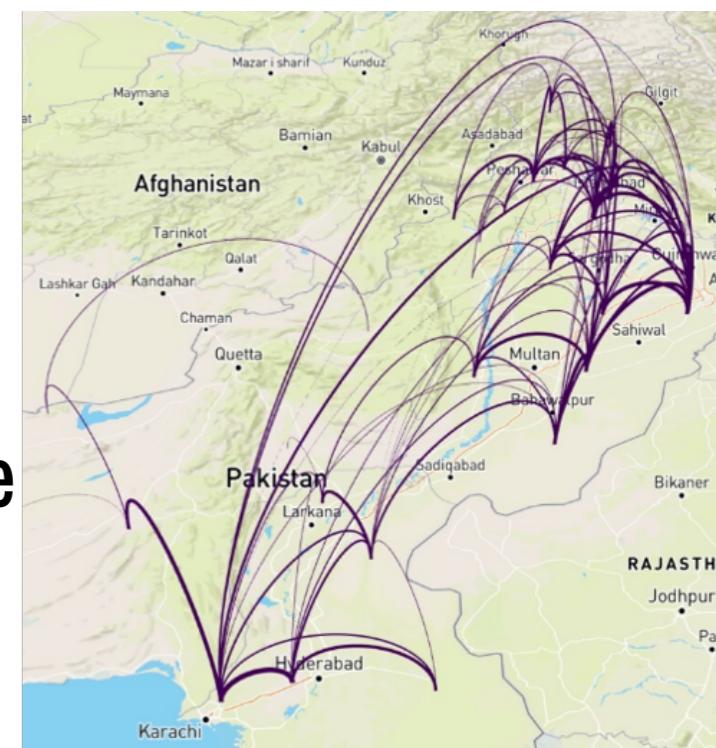
Near real-time - Time window: 00:00, 8:00 and 16:00 (Pacific Time)

Comparison of locations where users **spent most time** within each 8-hour window

Period covering the entire event & **baseline period**

No information for units w/ less than 10 obs.

Datasets are discontinued after 90 days after the last data update



Source: Rowe (2022).

39 datasets

Most recent ▾

The Flooding in Lugbe, Abuja, Nigeria

New

Updated 7 jul 2023 • 24 jun 2023 – 7 jul 2023

Movement Between Places During Crisis • Nigeria

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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The Flooding Across Santiago Metropolitan Region and O'Higgins, Chile

New

Updated 6 jul 2023 • 23 jun 2023 – 6 jul 2023

Movement Between Places During Crisis • Chile

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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The Tornado in Moss Point, Mississippi, US

New

Updated 3 jul 2023 • 20 jun 2023 – 3 jul 2023

Movement Between Places During Crisis • United States

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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Mayon Volcano Eruption Philippines 20 June 2023

New

Updated 3 jul 2023 • 20 jun 2023 – 3 jul 2023

Movement Between Places During Crisis • Philippines

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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The Wildfires in Quebec Province, Canada

Updated 20 jun 2023 • 8 jun 2023 – 20 jun 2023

Movement Between Places During Crisis • Canada

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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Nairobi Flooding Study June 8 2023

Updated 5 jul 2023 • 8 jun 2023 – 5 jul 2023

Movement Between Places During Crisis • Kenya

Movement Between Places During Crisis shows how many Facebook users moved from one area to another and if this movement is more or less than a normal day before a crisis or event.

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Movement During COVID-19

discontinued

Four Latin American countries:

Argentina, Chile, Colombia and Mexico

Period:

March 2020 - May 2022

Microsoft Bing Tiles - 2.5-6 Km²

Baseline:

45 days ending on March 10th 2020



dfd4mobility - main - RStudio

_quarto.yml x mov x

Filter

	geometry	date_time	start_polygon_id	start_polygon_name	end_polygon_id	end_polygon_name	length_km	tile_size	country	level	n_crisis	n_
1	LINESTRING (-72.685546875 -41.83679436036388, ...	2020-03-23 08:00:00	61151	Hualaihué	61151	Hualaihué	0.00000	11	CL	LEVEL4	100	
2	LINESTRING (-71.982421875 -36.66838662873227, ...	2020-03-23 08:00:00	61070	Chillán	61088	San Nicolás	22.19227	11	CL	LEVEL4	44	
3	LINESTRING (-72.333984375 -36.527262572333214, ...	2020-03-23 08:00:00	61088	San Nicolás	61088	San Nicolás	0.00000	11	CL	LEVEL4	80	
4	LINESTRING (-71.45507812500001 -33.9433287203...,	2020-03-23 08:00:00	61219	San Pedro	61219	San Pedro	16.22905	11	CL	LEVEL4	21	
5	LINESTRING (-71.279296875 -33.79737760634471, ...	2020-03-23 08:00:00	61215	Melipilla	61219	San Pedro	16.24293	11	CL	LEVEL4	25	
6	LINESTRING (-71.279296875 -34.23448100875922, ...	2020-03-23 08:00:00	60980	Las Cabras	61219	San Pedro	32.37471	11	CL	LEVEL4	15	
7	LINESTRING (-71.455078125 -34.08903002544869, ...	2020-03-23 08:00:00	60980	Las Cabras	61219	San Pedro	16.20127	11	CL	LEVEL4	15	
8	LINESTRING (-71.455078125 -34.52462999448535, ...	2020-03-23 08:00:00	61002	Palmilla	61006	Santa Cruz	16.08960	11	CL	LEVEL4	52	
9	LINESTRING (-71.279296875 -34.52462999448535, ...	2020-03-23 08:00:00	61002	Palmilla	61006	Santa Cruz	22.75414	11	CL	LEVEL4	19	
10	LINESTRING (-70.927734375 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	33.62182	11	CL	LEVEL3	14	
11	LINESTRING (-70.224609375 -18.56292709925129, ...	2020-03-23 08:00:00	60894	Arica	60894	Arica	0.00000	11	CL	LEVEL3	8740	
12	LINESTRING (-71.806640625 -39.300266145437504, ...	2020-03-23 08:00:00	61105	Pucón	61105	Pucón	15.12543	11	CL	LEVEL4	40	
13	LINESTRING (-70.22460937500001 -18.3962099511...,	2020-03-23 08:00:00	60894	Arica	60894	Arica	0.00000	11	CL	LEVEL3	13222	
14	LINESTRING (-71.103515625 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	16.82405	11	CL	LEVEL3	26	
15	LINESTRING (-70.751953125 -30.372845781329808, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	0.00000	11	CL	LEVEL3	17	
16	LINESTRING (-71.103515625 -30.524383776418823, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	16.82405	11	CL	LEVEL3	28	
17	LINESTRING (-71.630859375 -30.977579345438294, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	0.00000	11	CL	LEVEL3	18	
18	LINESTRING (-71.279296875 -30.524383776418823, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	23.79280	11	CL	LEVEL3	12	
19	LINESTRING (-71.982421875 -39.300266145437504, ...	2020-03-23 08:00:00	61105	Pucón	61105	Pucón	15.12543	11	CL	LEVEL4	20	
20	LINESTRING (-71.806640625 -39.16410803901017, ...	2020-03-23 08:00:00	61105	Pucón	61105	Pucón	21.41136	11	CL	LEVEL4	11	
21	LINESTRING (-70.927734375 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	0.00000	11	CL	LEVEL3	448	
22	LINESTRING (-71.279296875 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	16.82405	11	CL	LEVEL3	91	
23	LINESTRING (-70.22460937500001 -18.3962099511...,	2020-03-23 08:00:00	60894	Arica	60894	Arica	26.21689	11	CL	LEVEL3	11	
24	LINESTRING (-70.927734375 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	16.79773	11	CL	LEVEL3	19	
25	LINESTRING (-71.455078125 -30.675685824903944, ...	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	16.81092	11	CL	LEVEL3	29	
26	LINESTRING (-70.048828125 -18.56292709925129, ...	2020-03-23 08:00:00	60894	Arica	60894	Arica	0.00000	11	CL	LEVEL3	212	
27	LINESTRING (-71.27929687500001 -30.8267512407...,	2020-03-23 08:00:00	60853	Limarí	60853	Limarí	0.00000	11	CL	LEVEL3	460	

Showing 1 to 27 of 72,973 entries, 23 total columns

Console Terminal x Background Jobs x

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```
> View(mov)
>
```

Checking Installation Status

Software



R



Studio



Quarto



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