Measuring population mobility using mobile phone data

Shengjie Lai

University of Southampton, UK

09/09/2024

WorldPop

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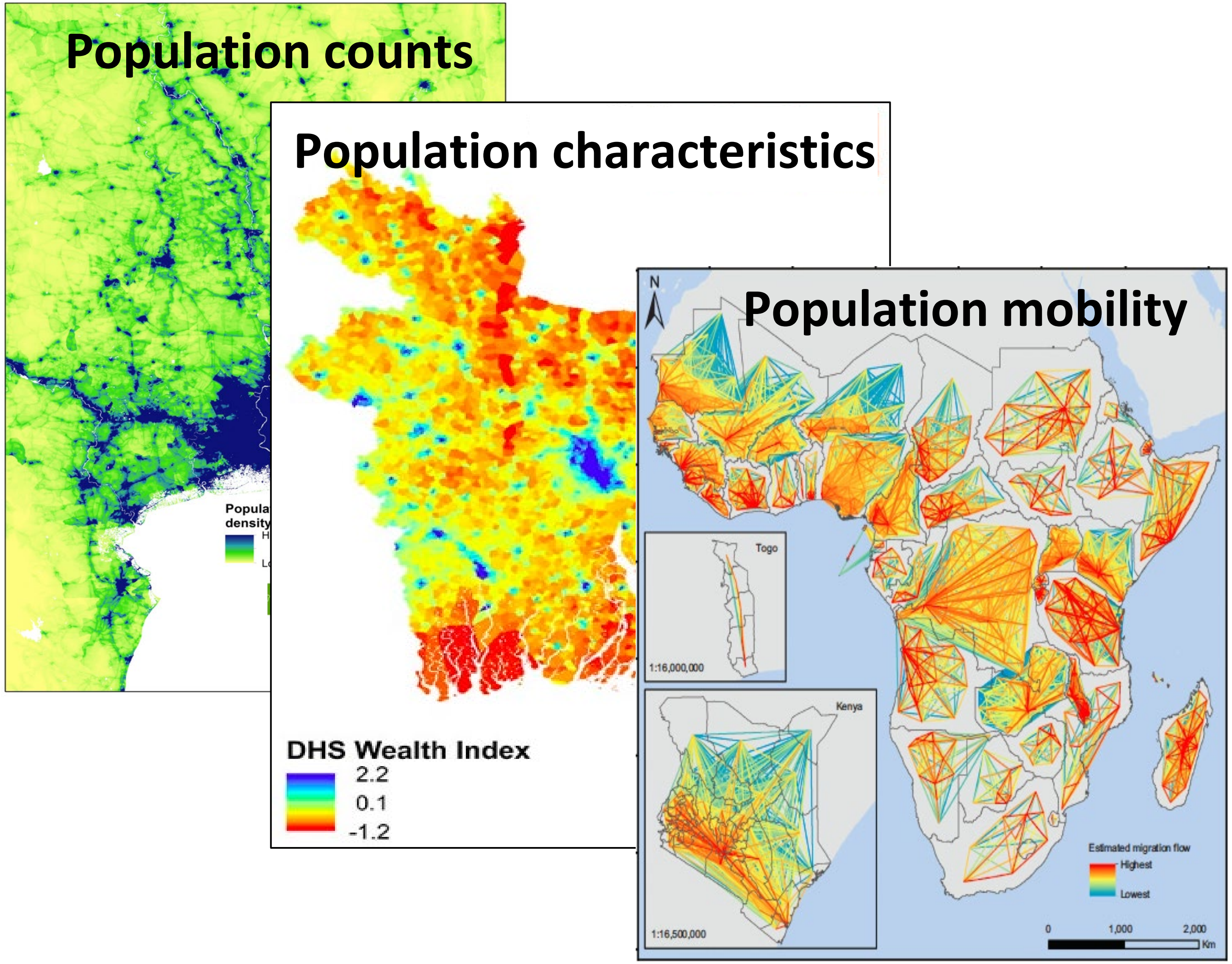
UNIVERSITY OF Southampton



Applied research and implementation group

40+ staff and students based at University of Southampton

Mapping small area demographics and health/development metrics for low and middle income countries

Open data, open peer-reviewed statistical methods, user engagement, capacity strengthening

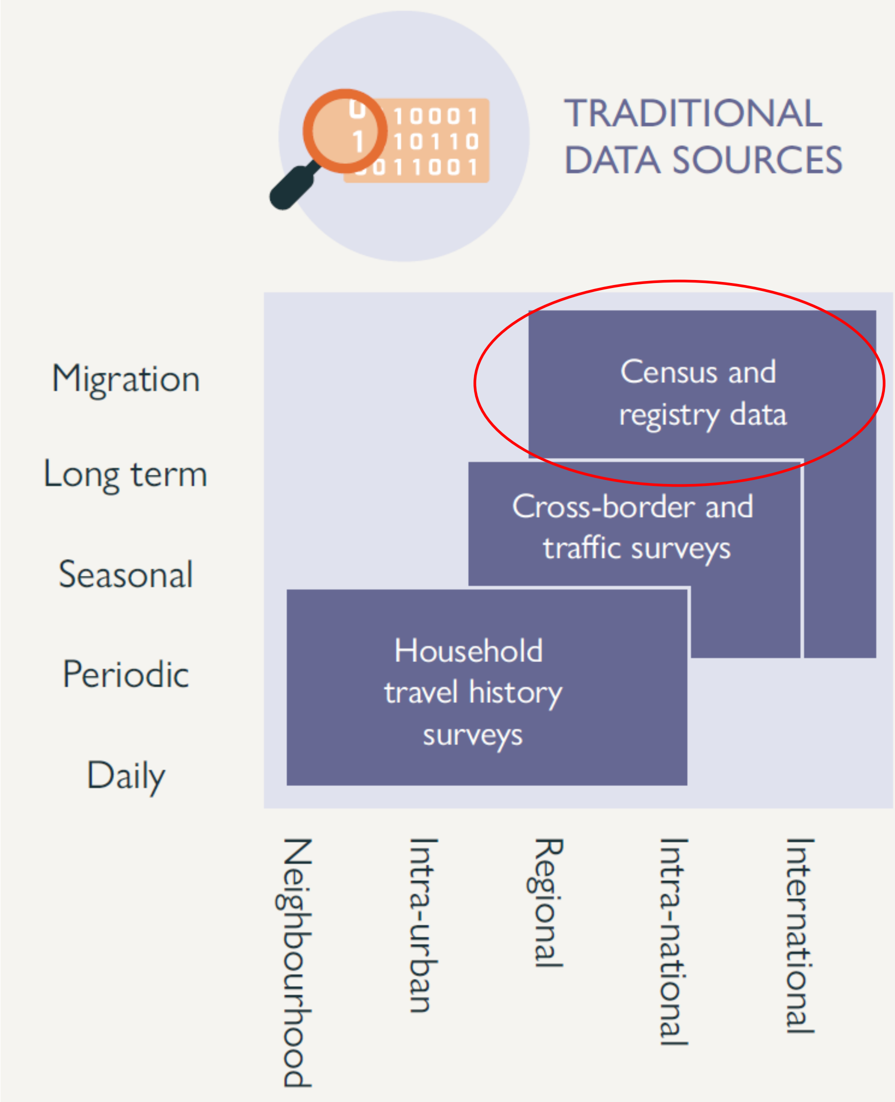
Multiple partnerships with National Statistical Agencies, Ministries of Health, UN agencies

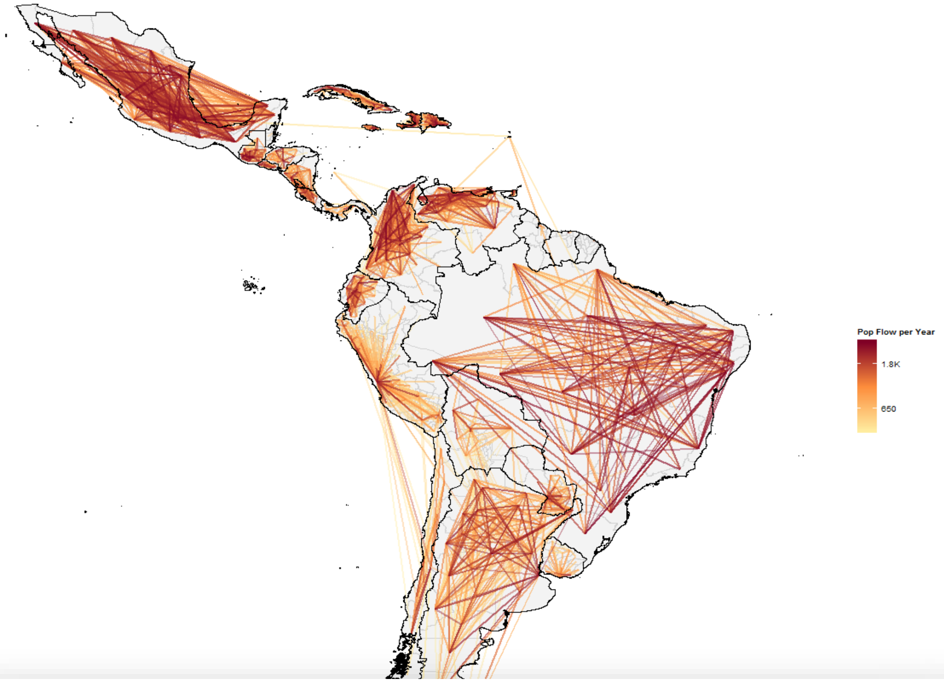
People don’t stay still….

Air travel networks in 21st century

Data sources for measuring population mobility

Sources of data for measuring population mobility





The Use of Census Migration Data to Approximate Human Movement Patterns across Temporal Scales

Amy Wesolowski[1]*, Caroline O. Buckee[2,3], Deepa K. Pindolia[4,5,6], Nathan Eagle[2,7], David L. Smith[8,9], Andres J. Garcia[4,5], Andrew J. Tatem[4,5,9]

RESEARCH **Open Access**

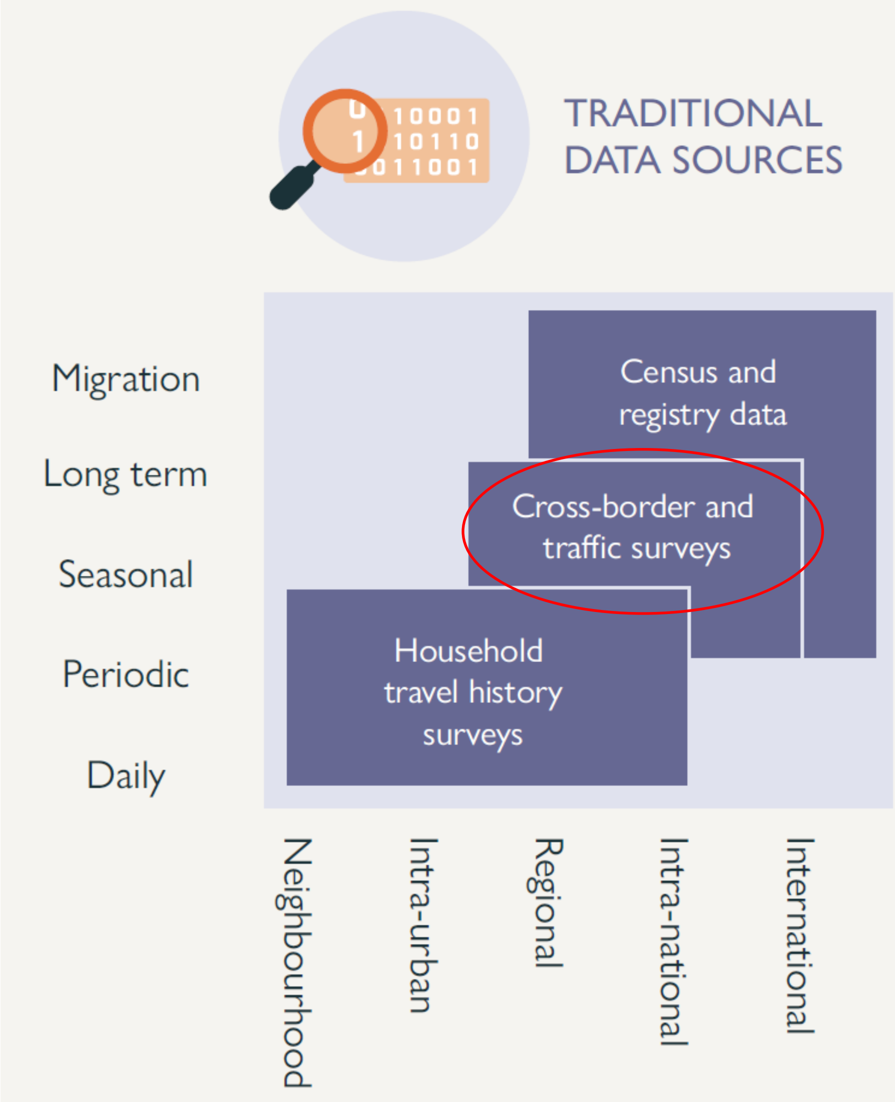
CrossMark

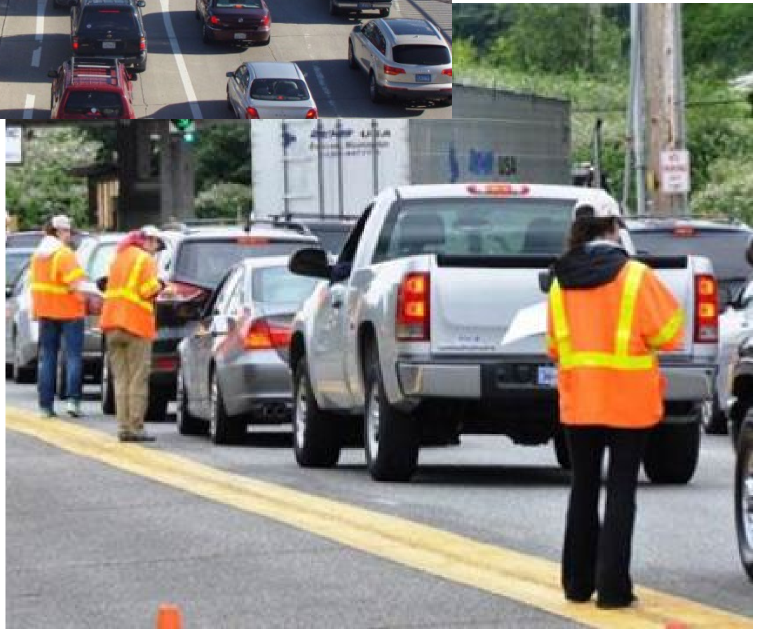
Census-derived migration data as a tool for informing malaria elimination policy

Nick W. Ruktanonchai[1,2*], Darlene Bhavnani[3], Alessandro Sorichetta[1,2], Linus Bengtsson[2,4], Keith H. Carter[5], Roberto C. Córdoba[6], Arnaud Le Menach[3], Xin Lu[2,4], Erik Wetter[2,7], Elisabeth zu Erbach-Schoenberg[1,2] and Andrew J. Tatem[1,2,8]

Tatem, Int Health 2015; Ruktanonchai et al, IJHG 2018; Lai et al, JTM 2019; Tatem et al, IOM Practitioners Handbook 2023

Sources of data for measuring population mobility





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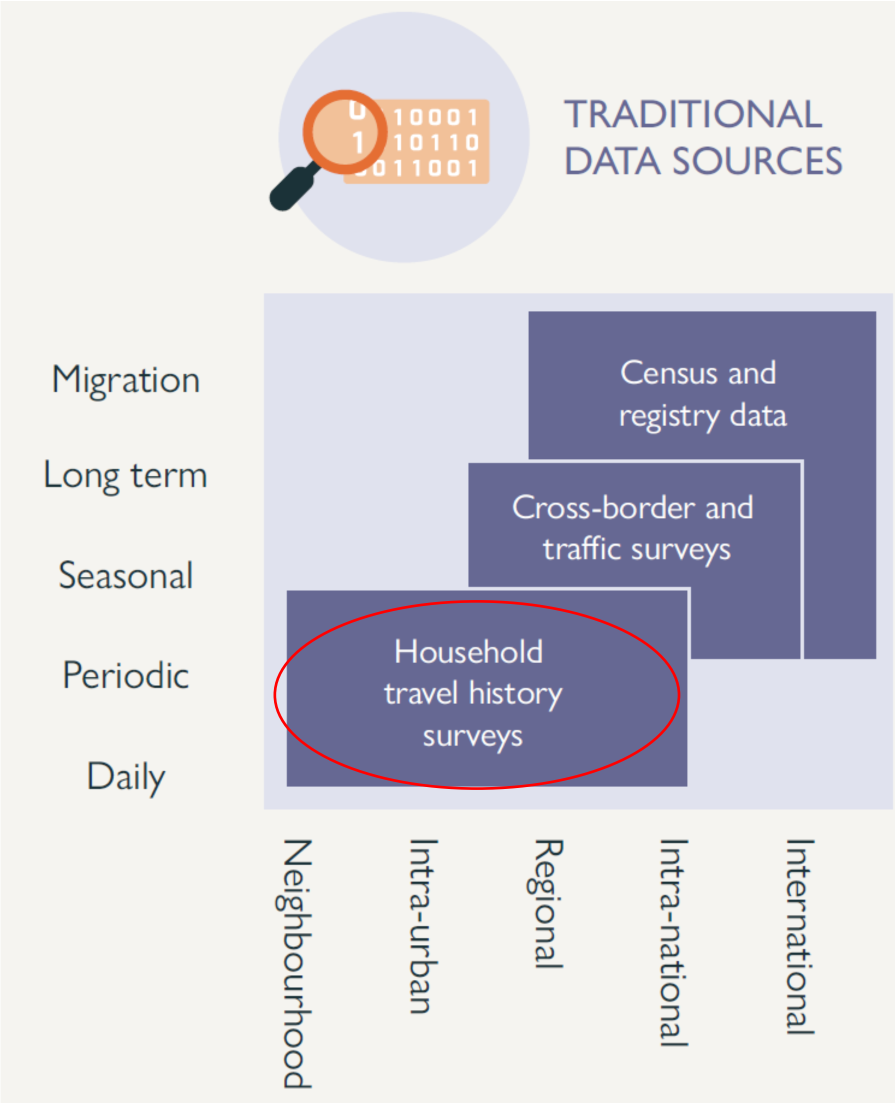

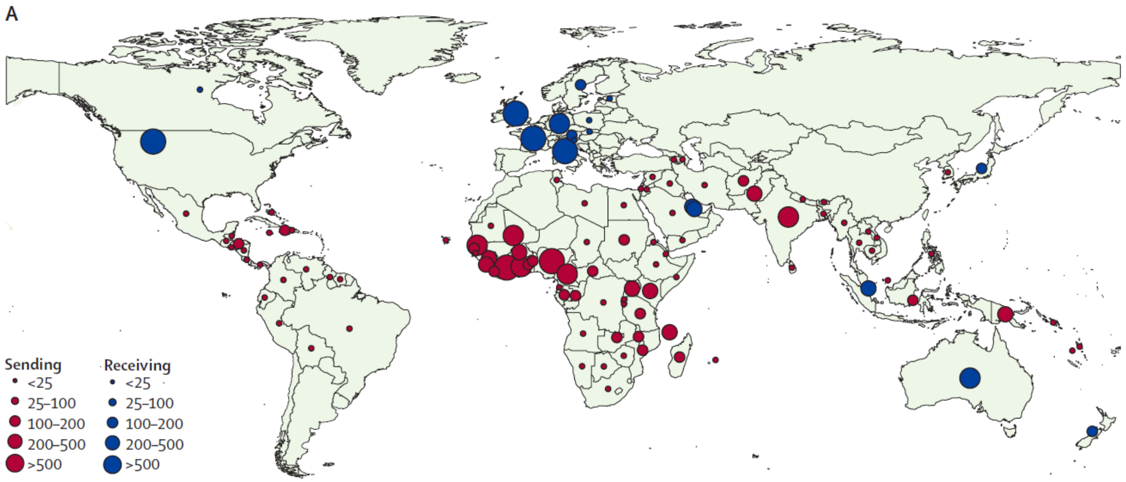

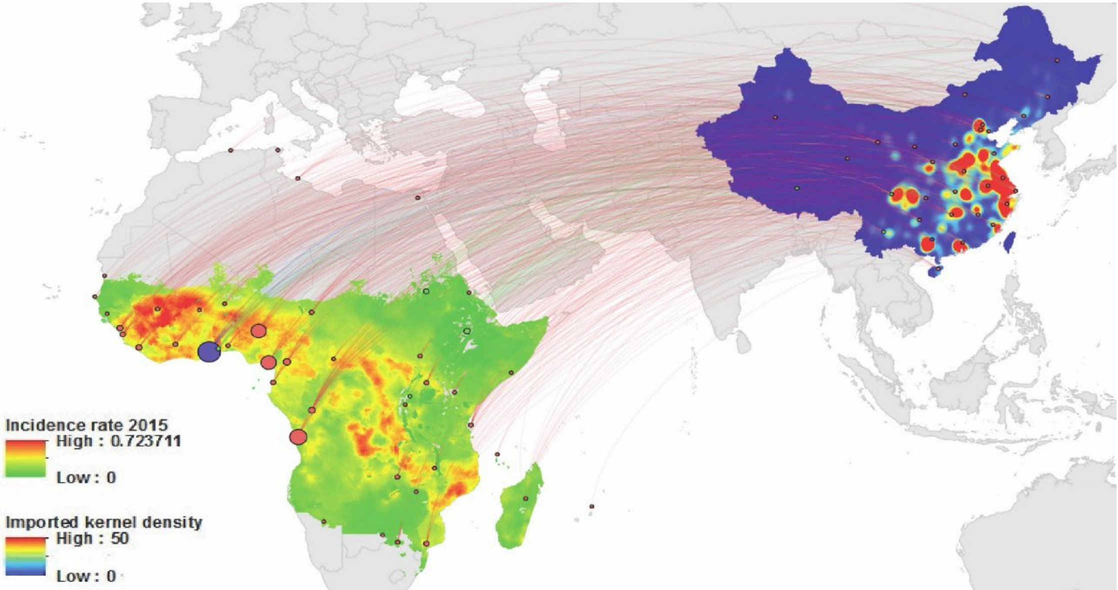

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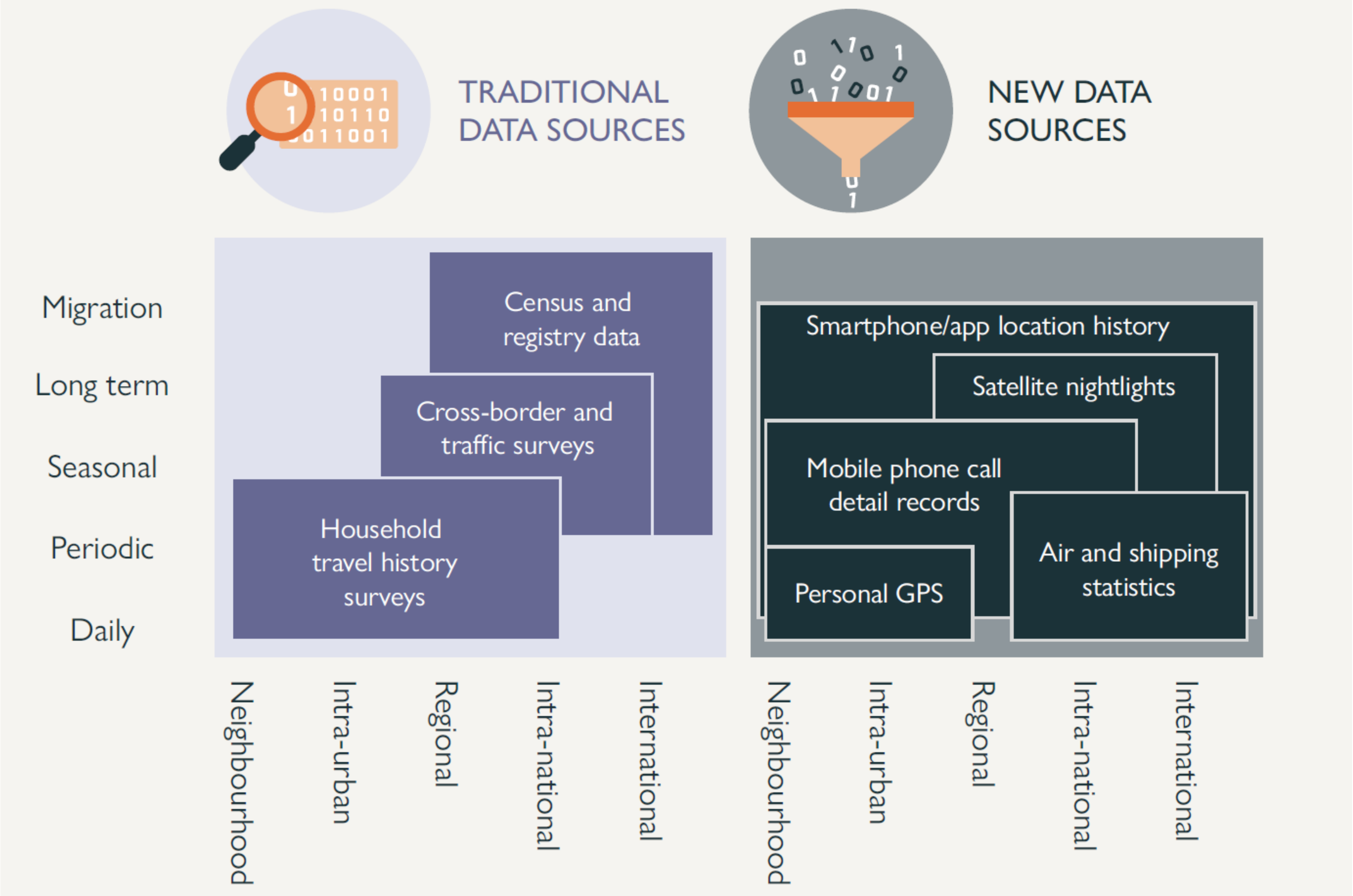

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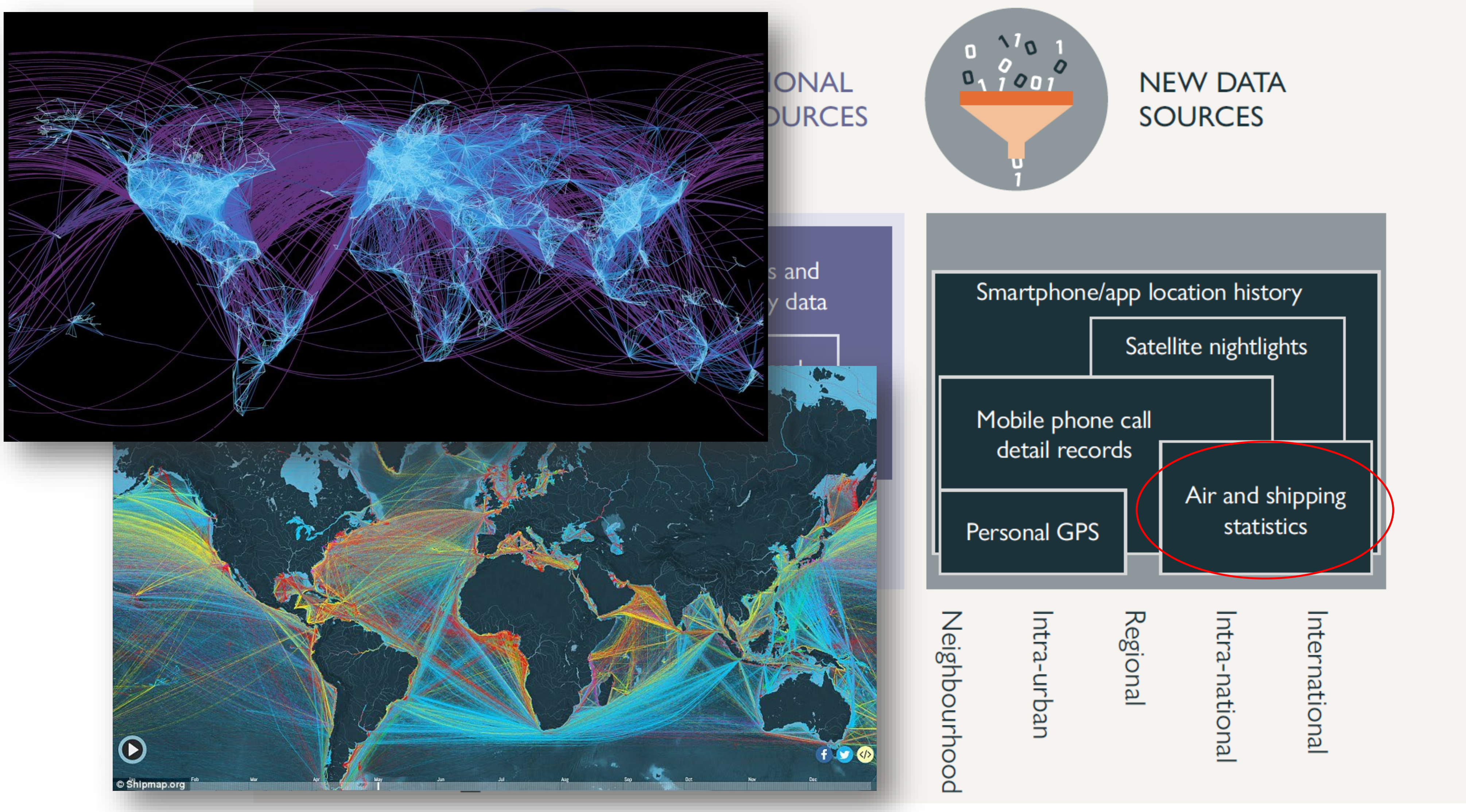

Tatem, Int Health 2015; Ruktanonchai et al, IJHG 2018; Lai et al, JTM 2019; Tatem et al, IOM Practitioners Handbook 2023

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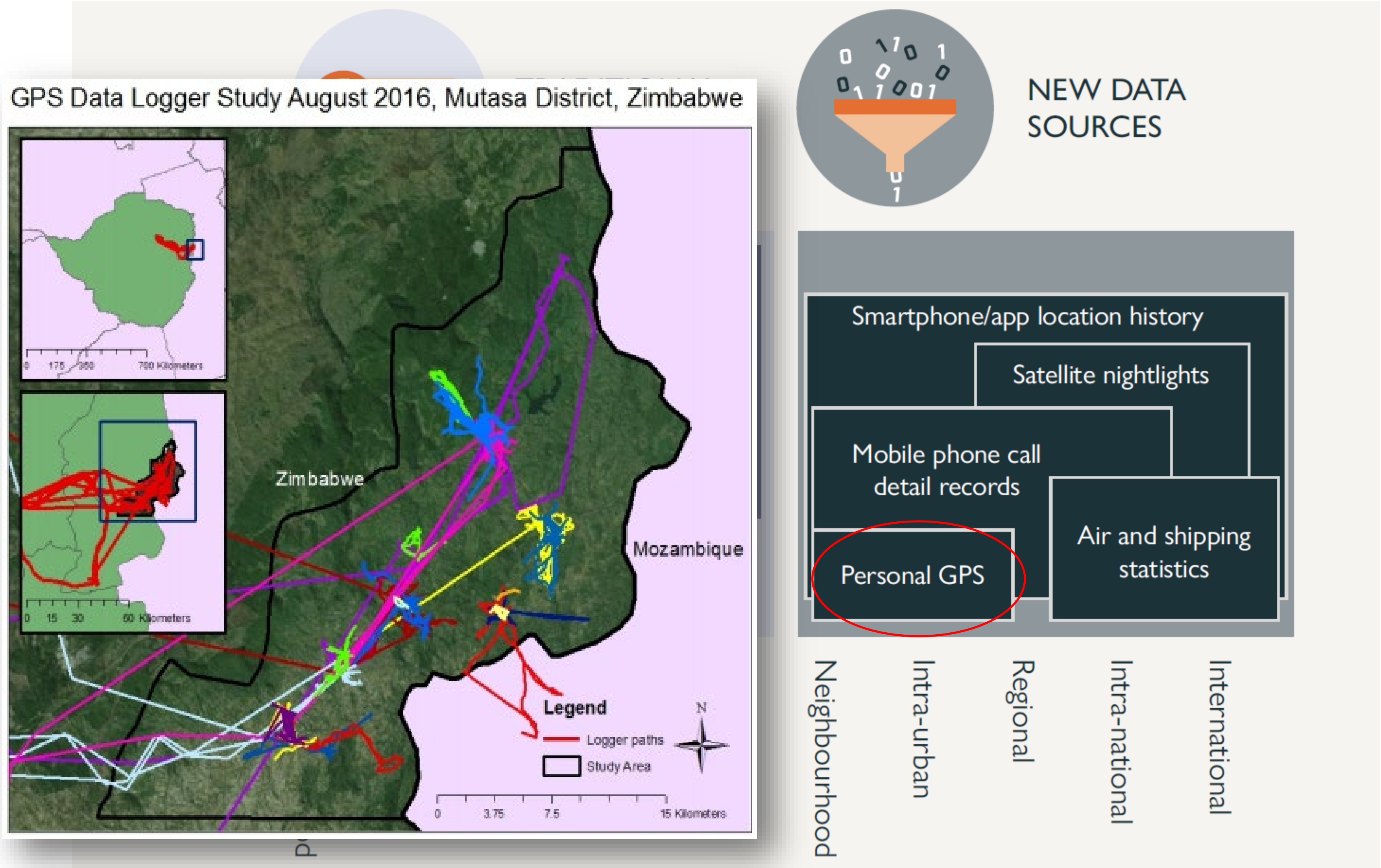

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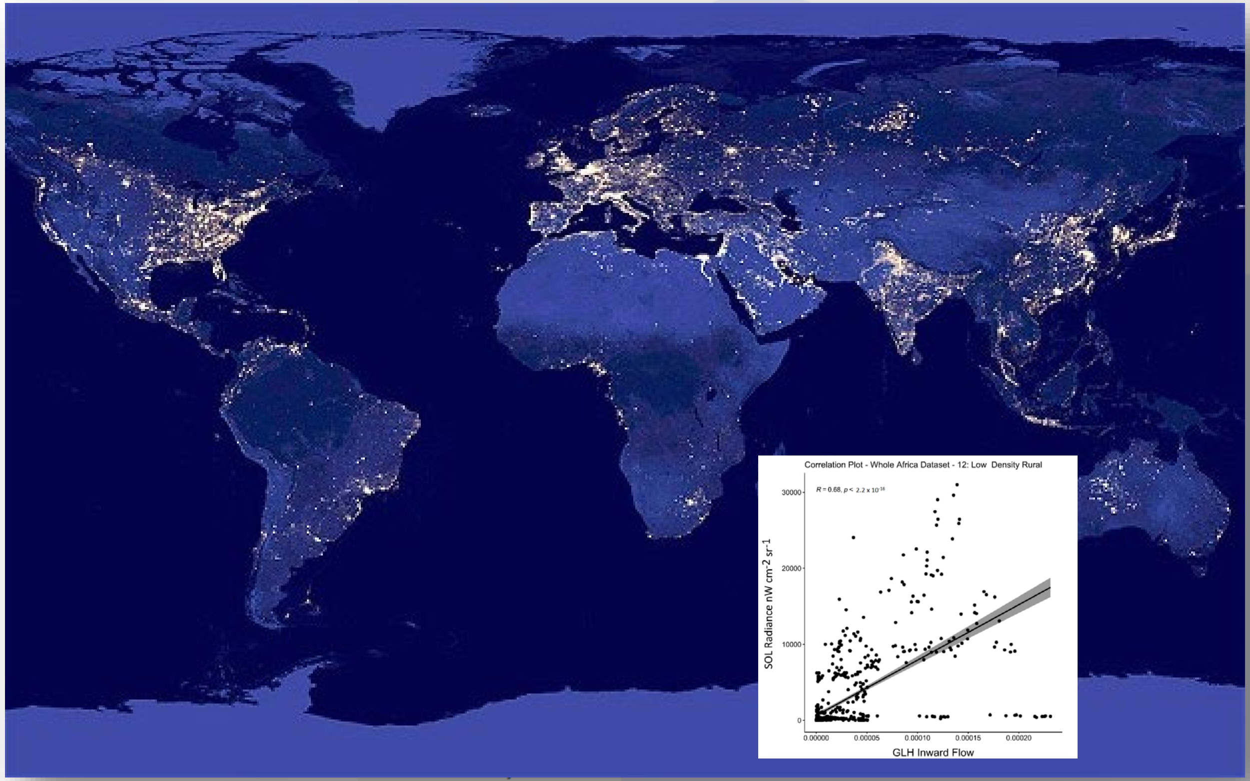
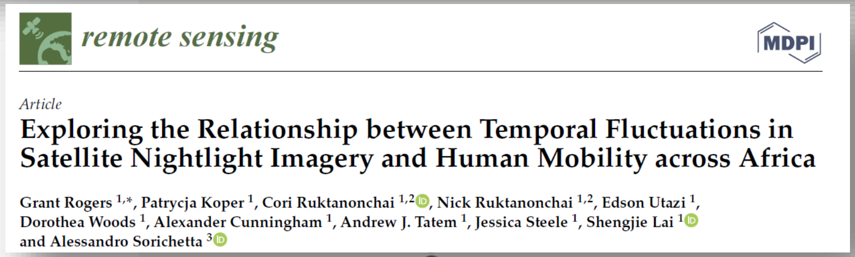
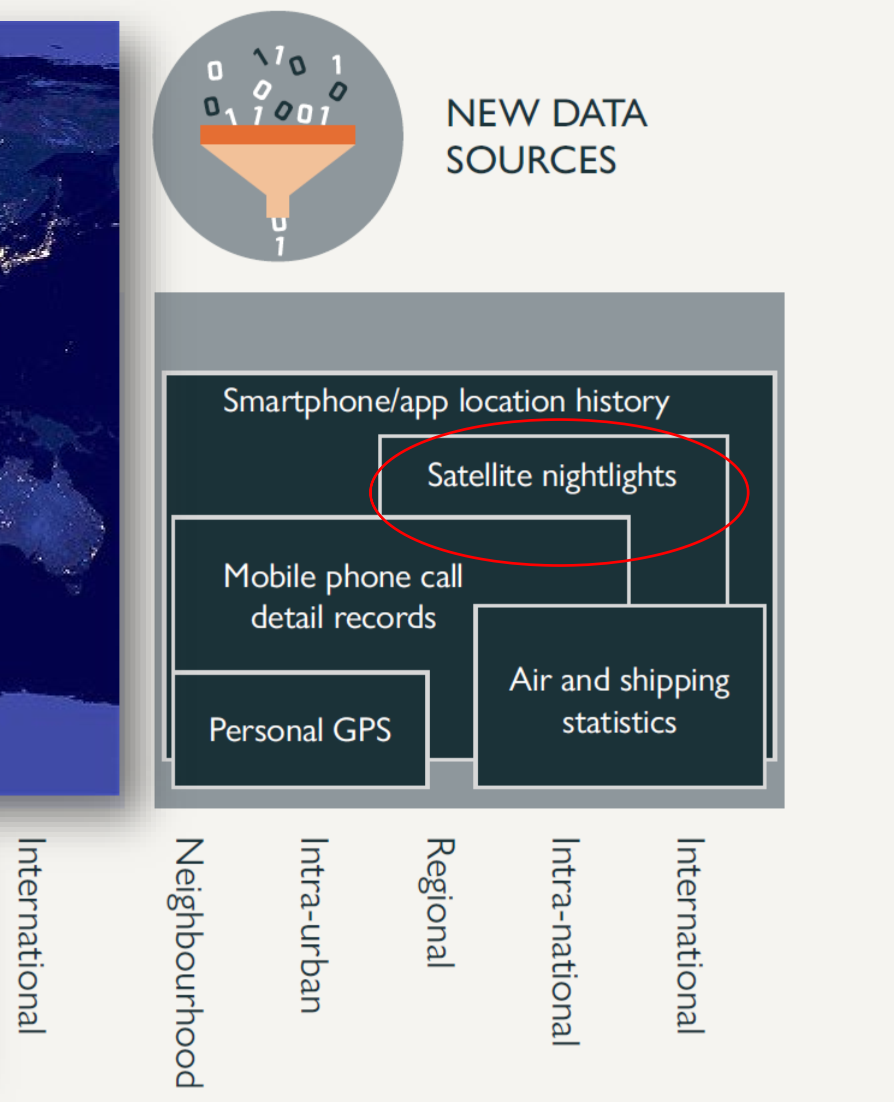



remote sensing
MDPI
Article
Exploring the Relationship between Temporal Fluctuations in Satellite Nightlight Imagery and Human Mobility across Africa
Grant Rogers [1,*], Patrycja Koper [1], Cori Ruktanonchai [1,2], Nick Ruktanonchai [1,2], Edson Utazi [1], Dorothea Woods [1], Alexander Cunningham [1], Andrew J. Tatem [1], Jessica Steele [1], Shengjie Lai [1] and Alessandro Sorichetta [3]



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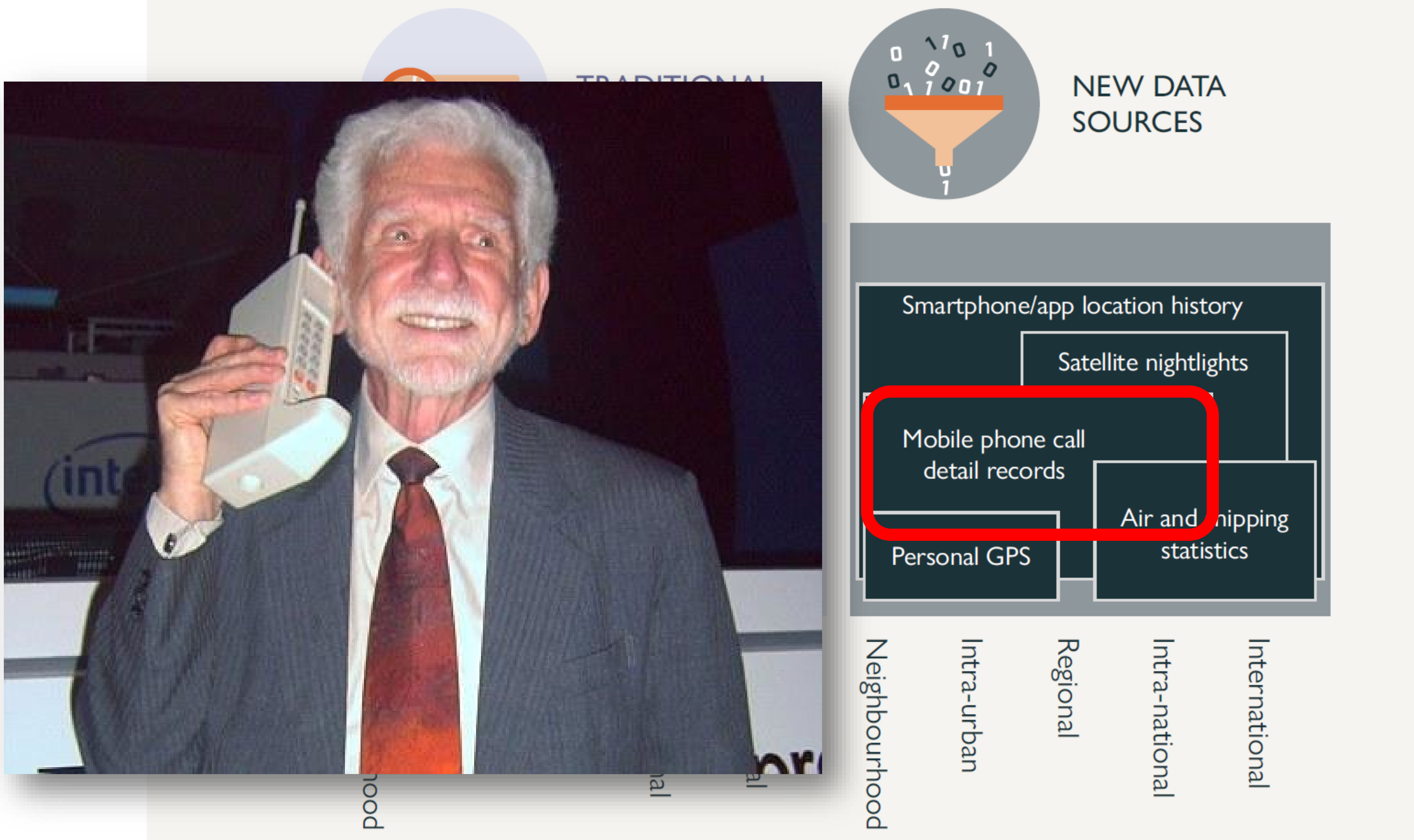


Tatem, Int Health 2015; Ruktanonchai et al, IJHG 2018; Lai et al, JTM 2019; Tatem et al, IOM Practitioners Handbook 2023

Mobile phone call detail records (CDRs)

X

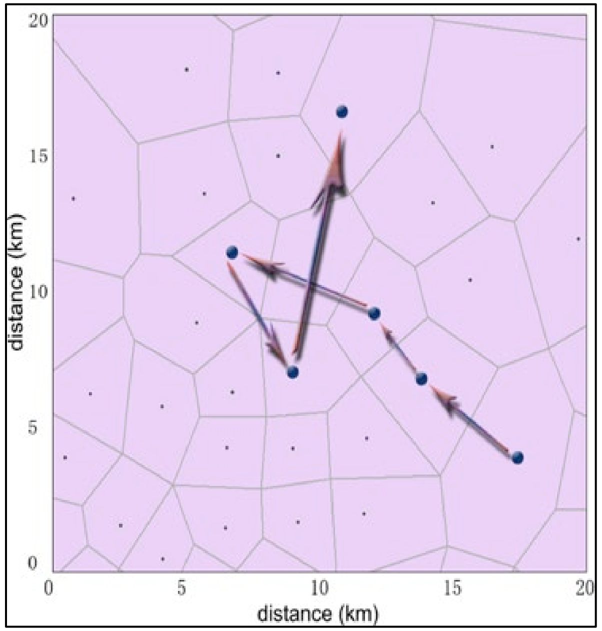
User makes a call
from location X

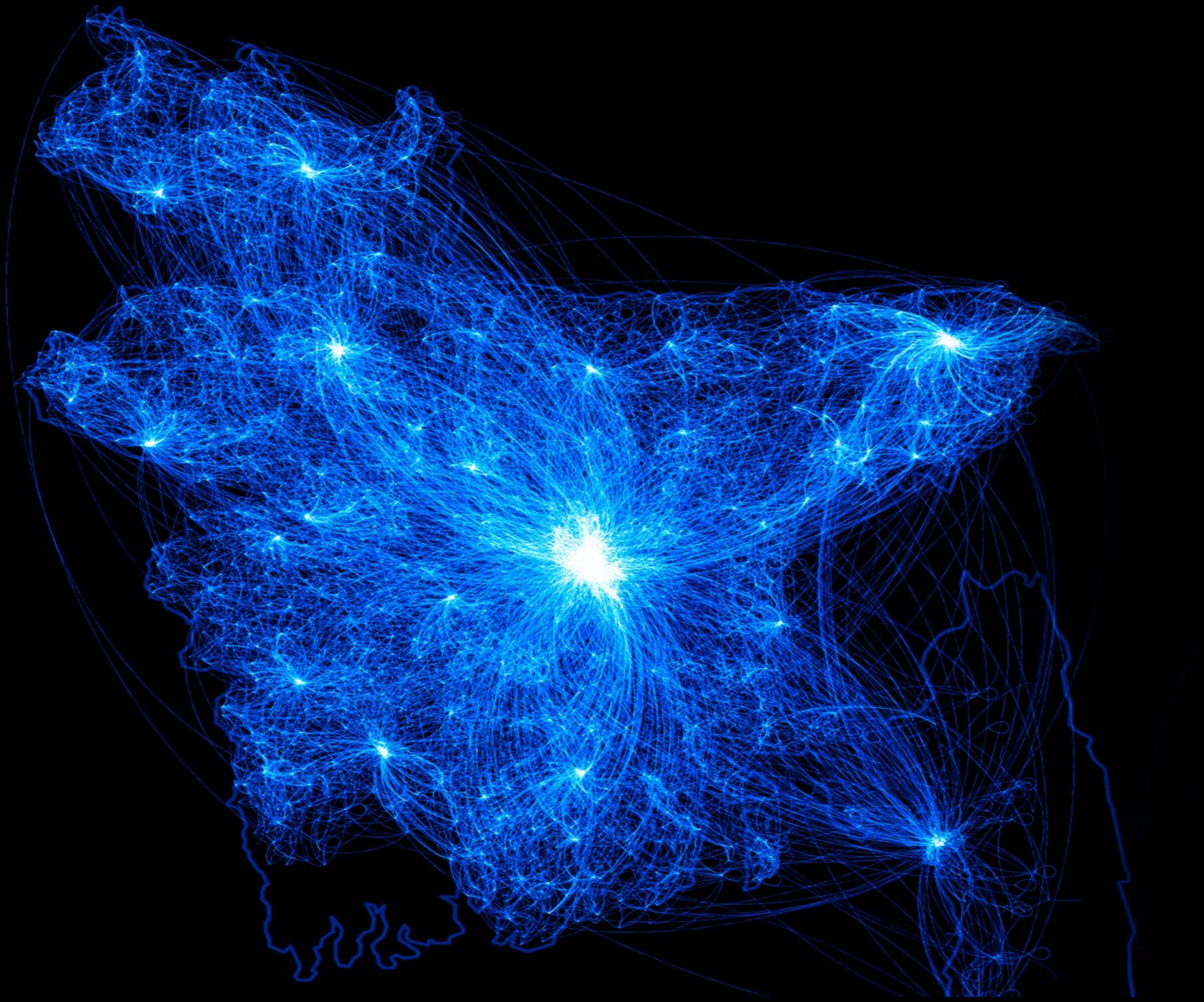
Call routed through
nearest tower

Y

User travels to Y
and makes a call

Network operator records time
and tower of call for billing

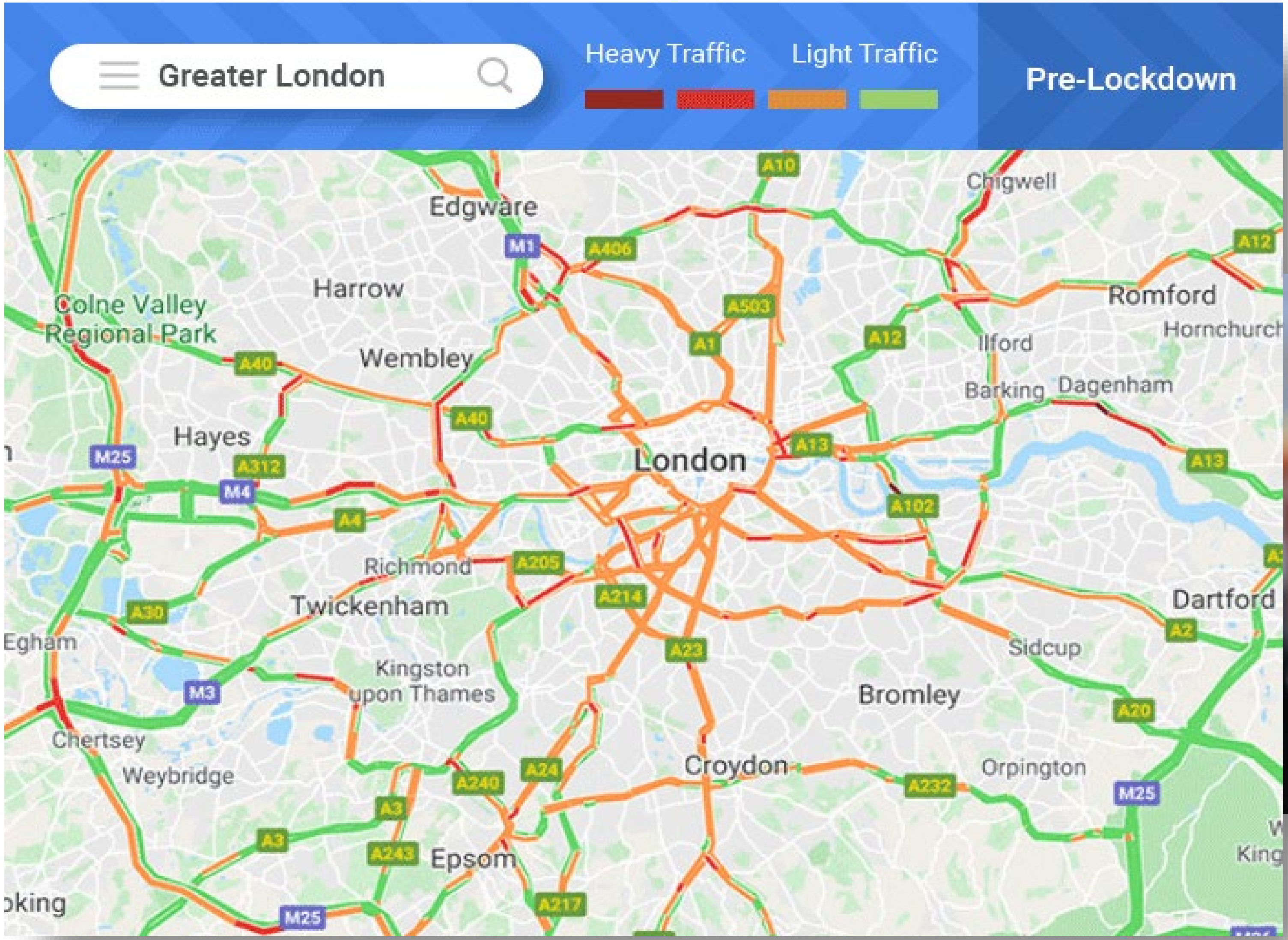




Sources of data for measuring population mobility

Tatem, Int Health 2015; Ruktanonchai et al, IJHG 2018; Lai et al, JTM 2019; Tatem et al, IOM Practitioners Handbook 2023

Smartphone/app location histories

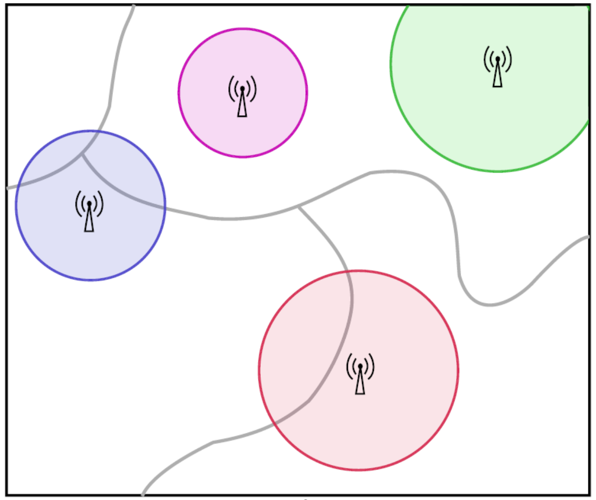


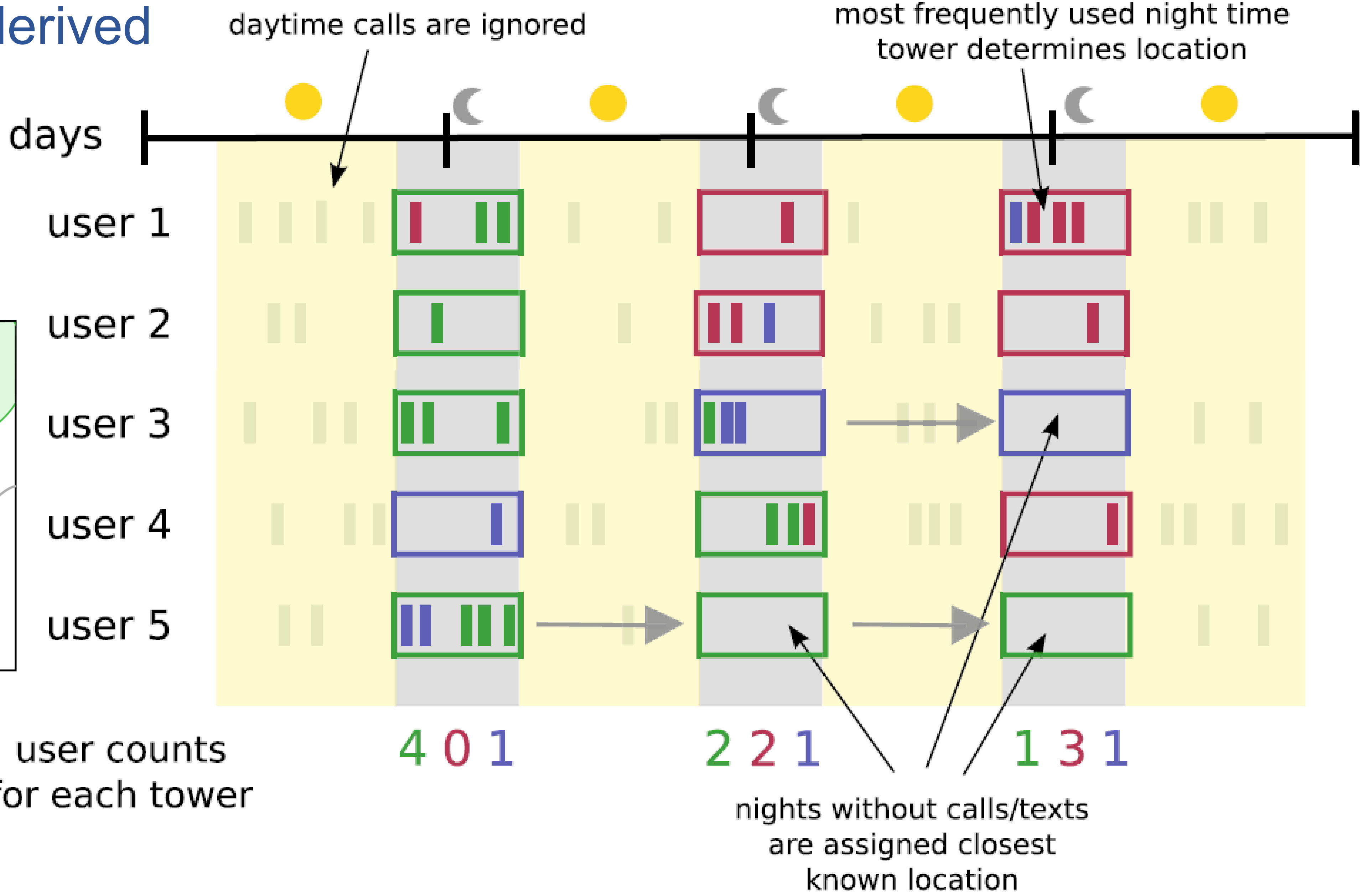
Ruktanonchai et al (2018) IJHG

Case studies: mobile phone data-based population and mobility mapping

Mobile phone-derived home locations

Signal towers/locations

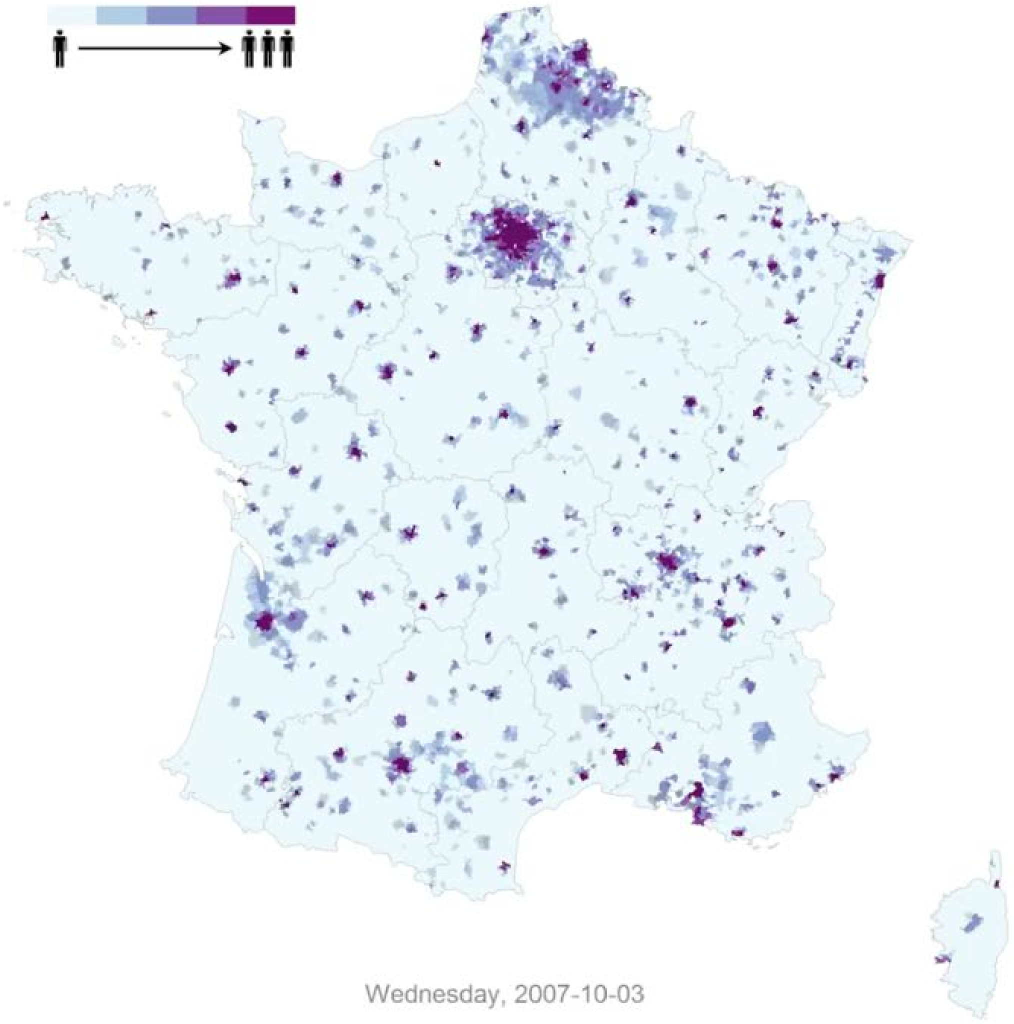




Deville et al (2014); zu Erbach-Schoenberg et al (2016); Lai et al (2019)

Dynamic population mapping using mobile phone data

Pierre Deville[a,b,c,1], Catherine Linard[c,d,1,2], Samuel Martin[e], Marius Gilbert[c,d], Forrest R. Stevens[f], Andrea E. Gaughan[f], Vincent D. Blondel[a], and Andrew J. Tatem[g,h,i]

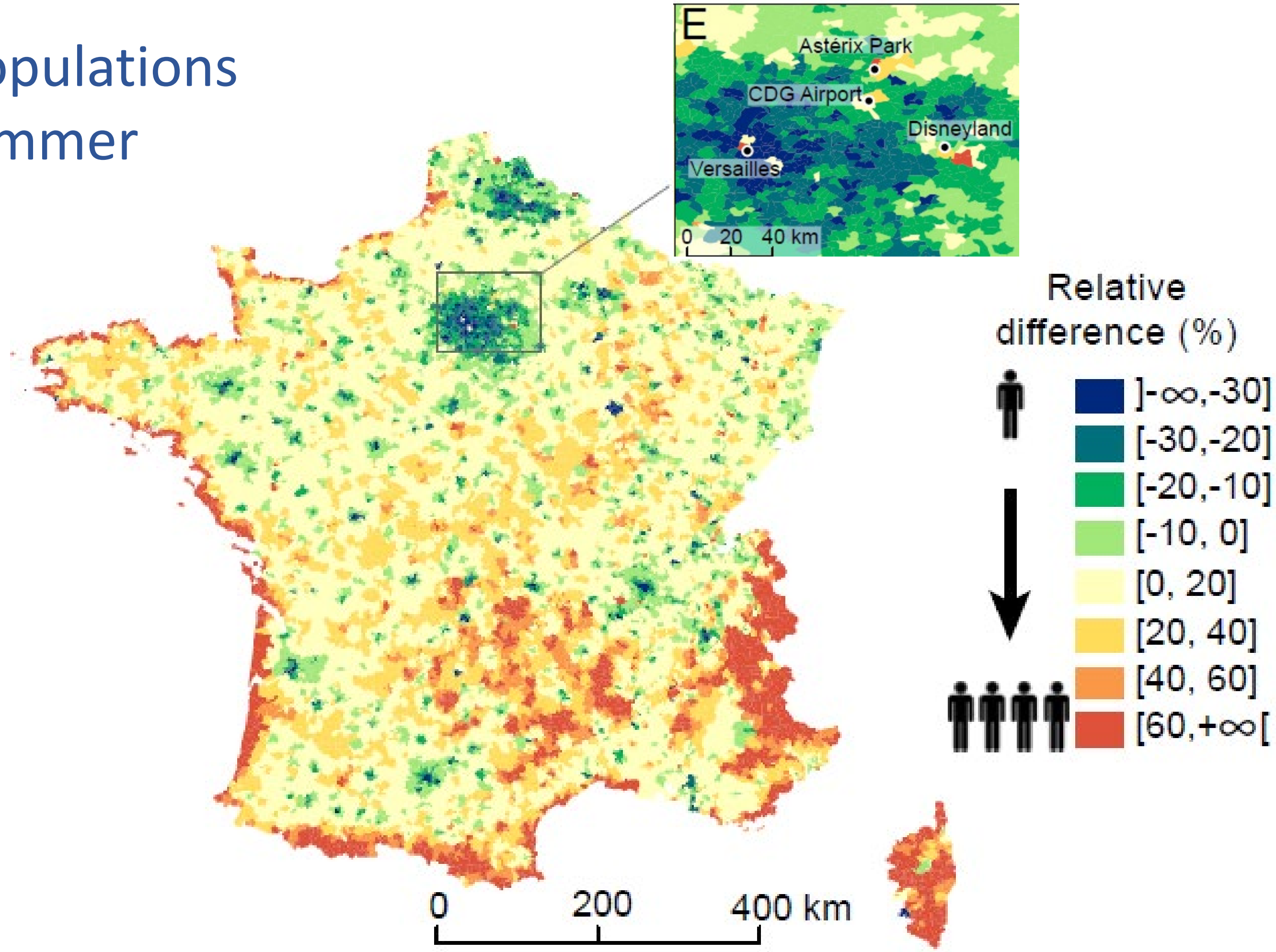


Deville et al (2014) PNAS

Dynamic population mapping using mobile phone data

Pierre Deville[a,b,c,1], Catherine Linard[c,d,1,2], Samuel Martin[e], Marius Gilbert[c,d], Forrest R. Stevens[f], Andrea E. Gaughan[f], Vincent D. Blondel[a], and Andrew J. Tatem[g,h,i]

Changes in populations during the summer



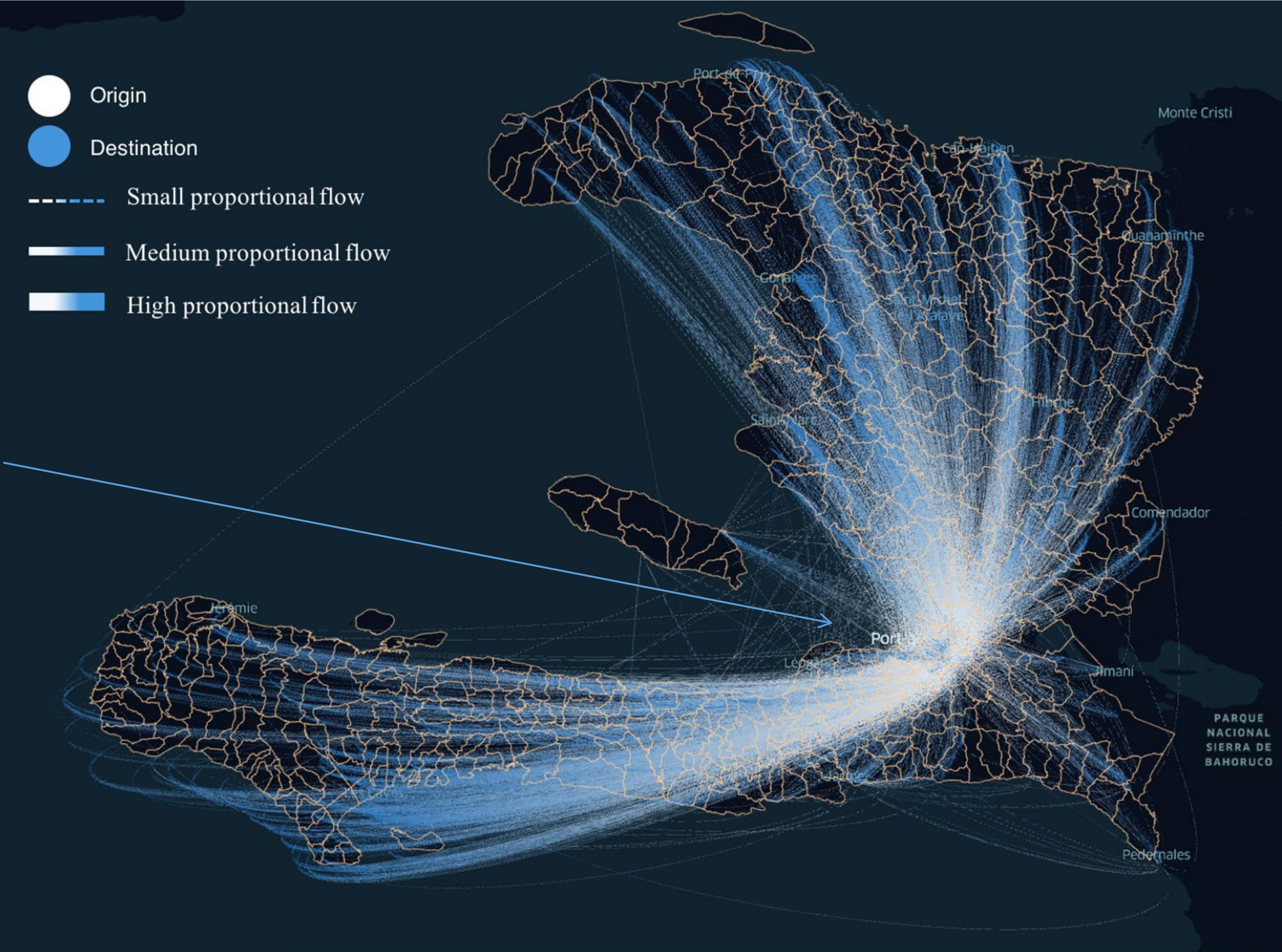
Deville et al (2014) PNAS

Internal displacements observed from CDRs

Following the Haiti earthquake (2010)

About 40% of displaced phone users left Port-au-Prince and the areas affected by the earthquake to stay at many different destinations across Haiti (up to 100km away) in the week following the earthquake.

And about 60% of displaced phone users remained within 10 km of their home (not shown).



Jesper Dejby, Tracey Li, Maximilian Albert and Véronique Lefebvre

INTERNATIONAL ORGANIZATION FOR MIGRATION
IOM OIM THE UNITED NATIONS MIGRATION AGENCY
Digicel
Funded by European Union Civil Protection and Humanitarian Aid
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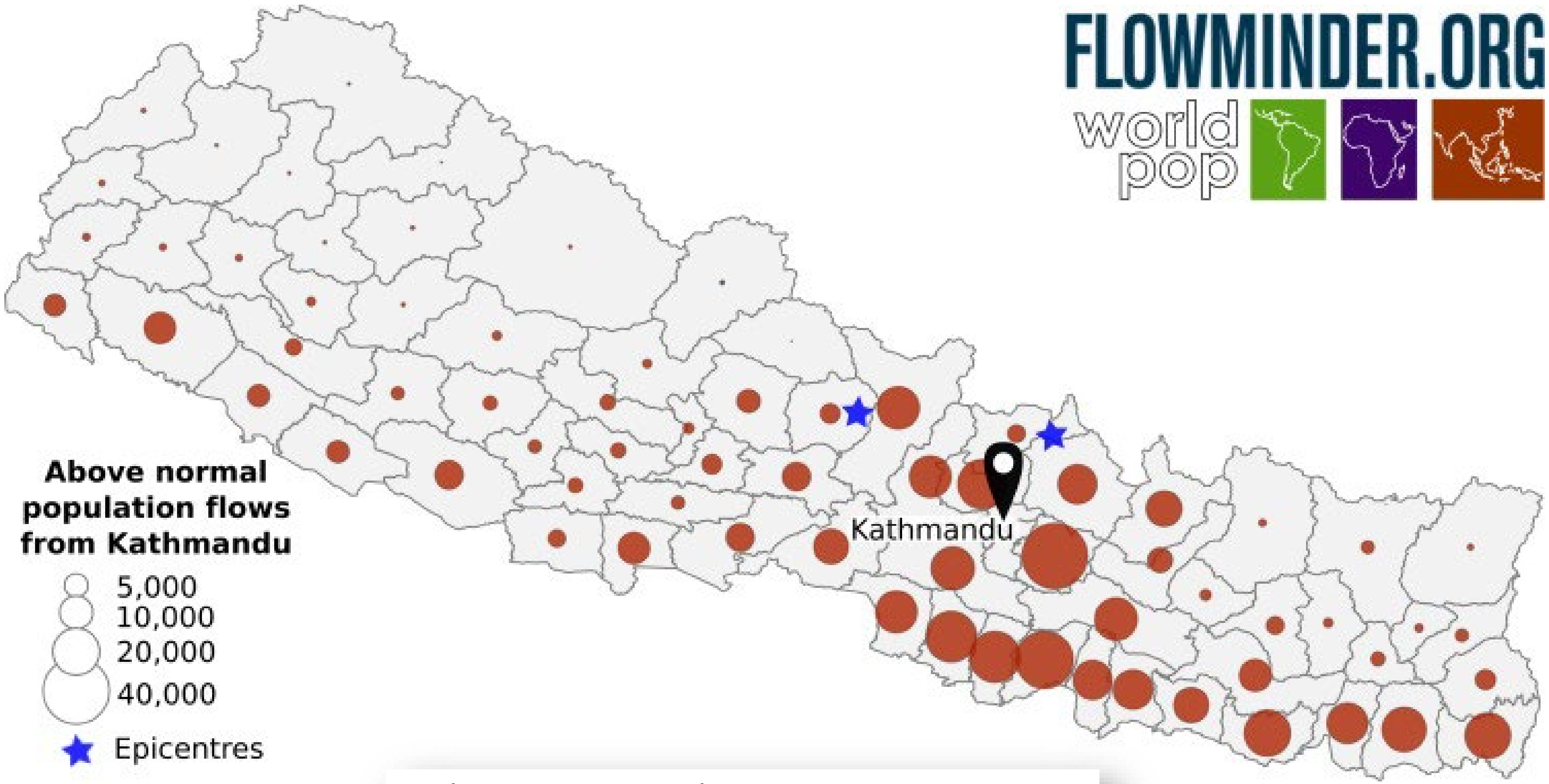


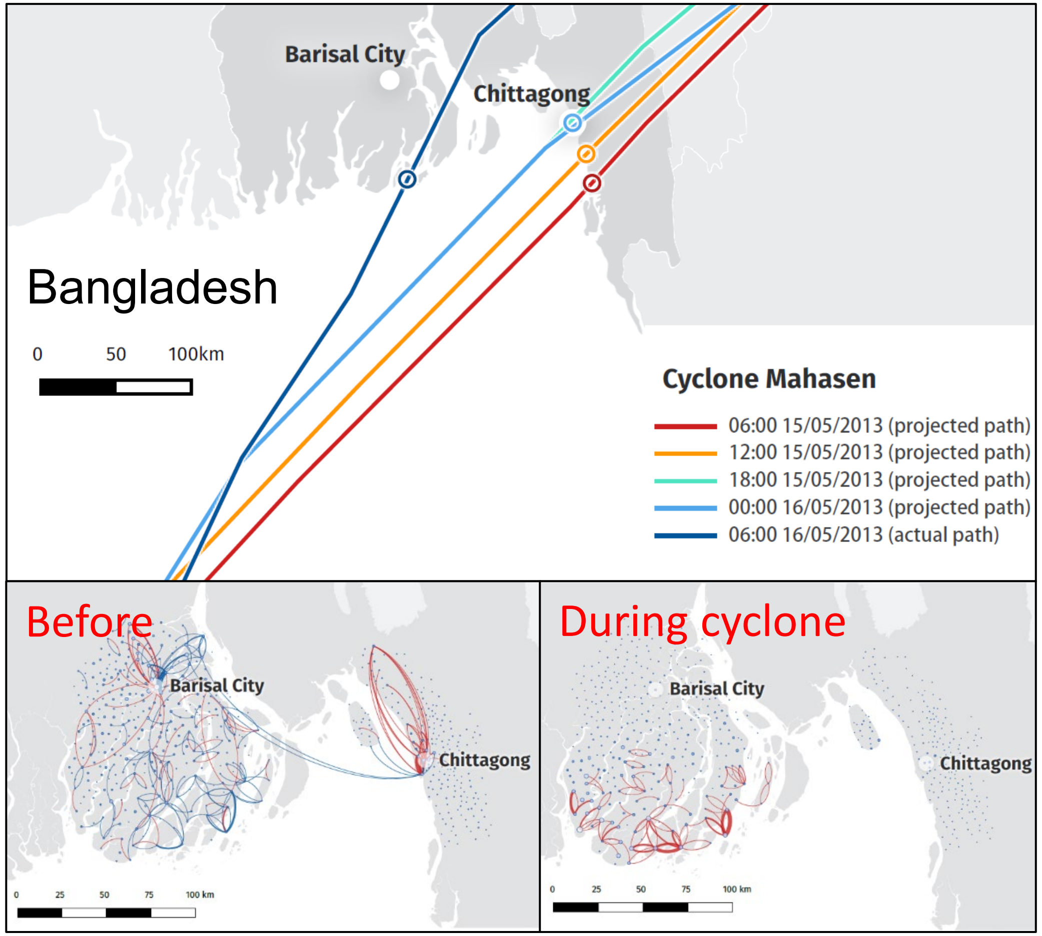
FLOWMINDER.ORG

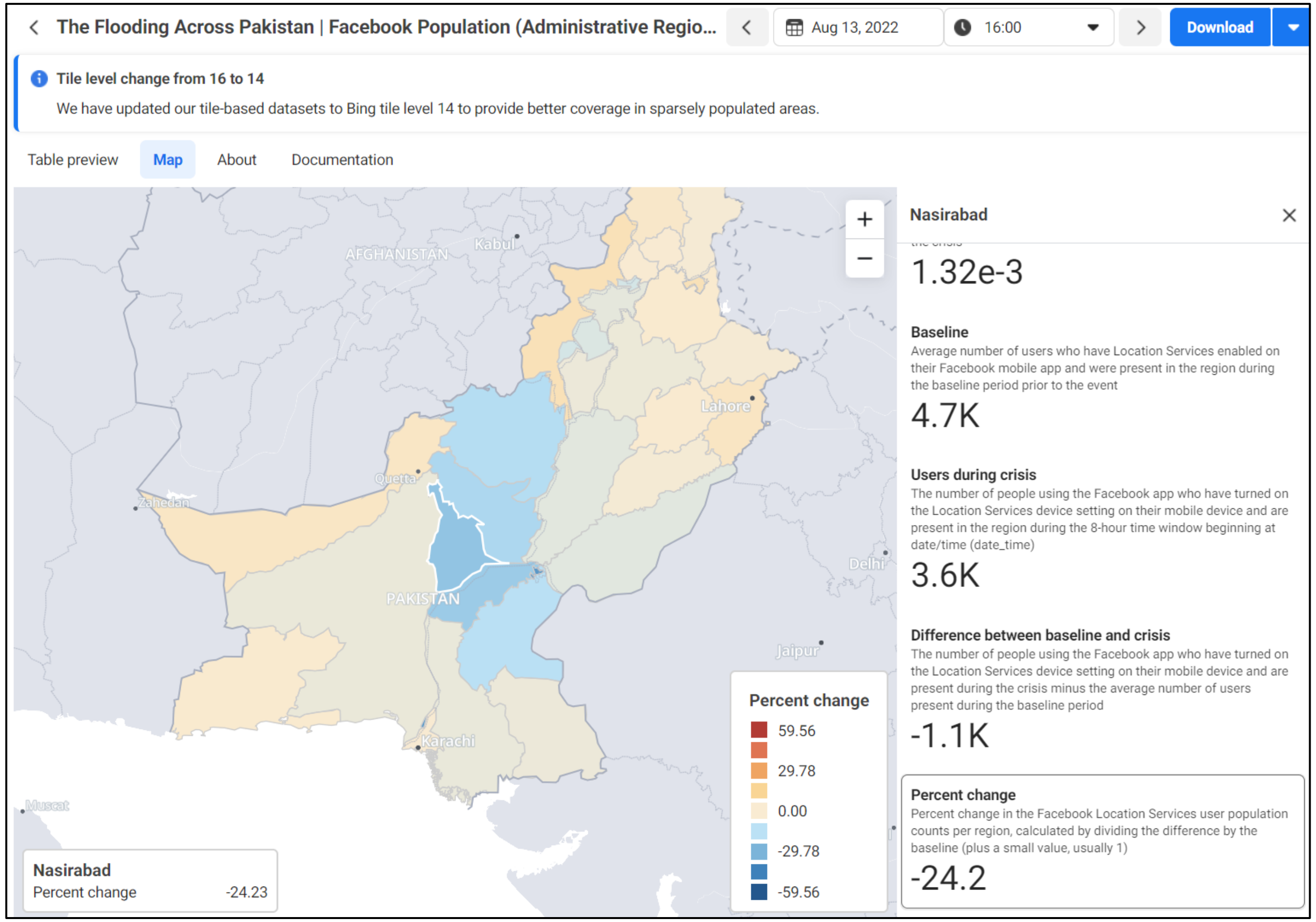
worldpop

Rapid and Near Real-Time Assessments of Population Displacement Using Mobile Phone Data Following Disasters: The 2015 Nepal Earthquake

Robin Wilson [1], Elisabeth Zu Erbach-Schoenberg [1], Maximilian Albert [2], Daniel Power [3], Simon Tudge [3], Miguel Gonzalez [3], Sam Guthrie [4], Heather Chamberlain [1], Christopher Brooks [1], Christopher Hughes [5], Lenka Pitonakova [3], Caroline Buckee [6], Xin Lu [7], Erik Wetter [8], Andrew Tatem [1], Linus Bengtsson [9]

Understanding mobility patterns in climate stressed regions





Lu X et al. Global Environmental Change 2016.

Mobile phone data for migration statistics

ARTICLE

https://doi.org/10.1057/s41599-019-0242-9 OPEN

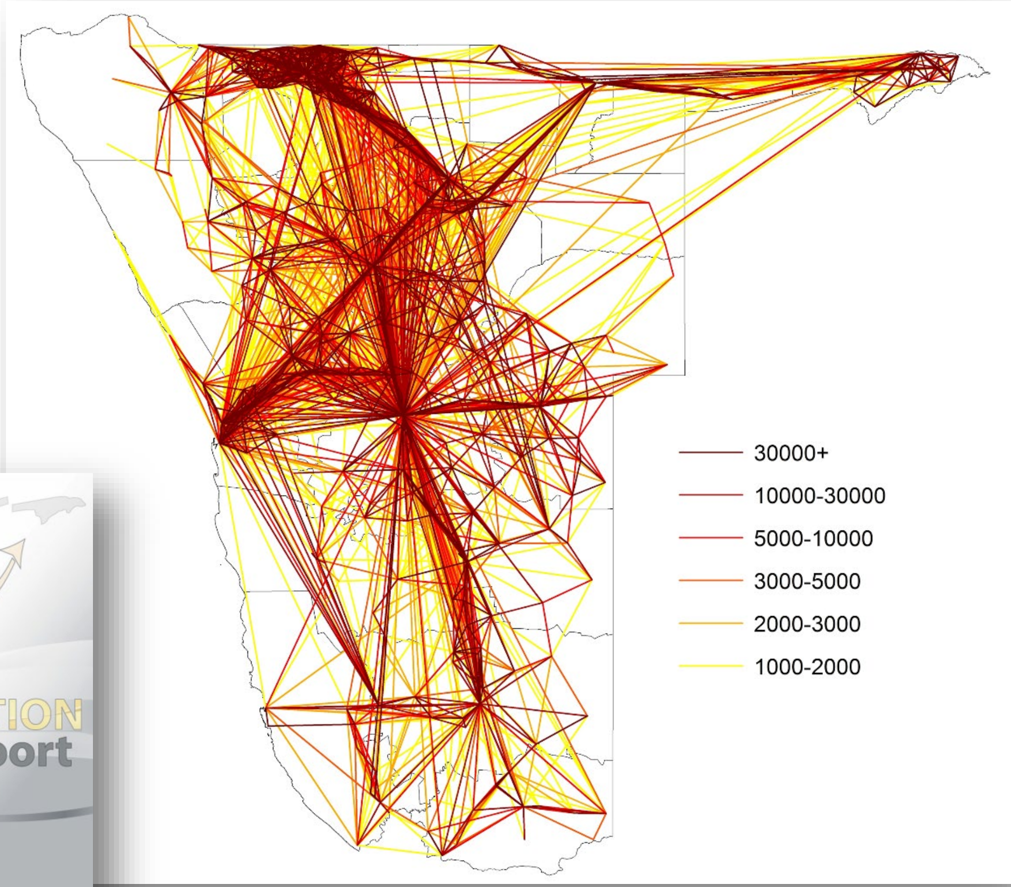
Exploring the use of mobile phone data for national migration statistics

Shengjie Lai[1,2,3], Elisabeth zu Erbach-Schoenberg[1,2], Carla Pezzulo[1], Nick W. Ruktanonchai[1,2], Alessandro Sorichetta[1,2], Jessica Steele[1], Tracey Li[2], Claire A. Dooley[1,2] & Andrew J. Tatem[1,2]

Mobile phone data:

- Dataset of 72 billion anonimized CDRs between October 2010 and April 2014 from MTC, the leading network operator in Namibia with a 76% market share.
- Processed to match as closely as possible time period and categories/geography of census questions in 2011

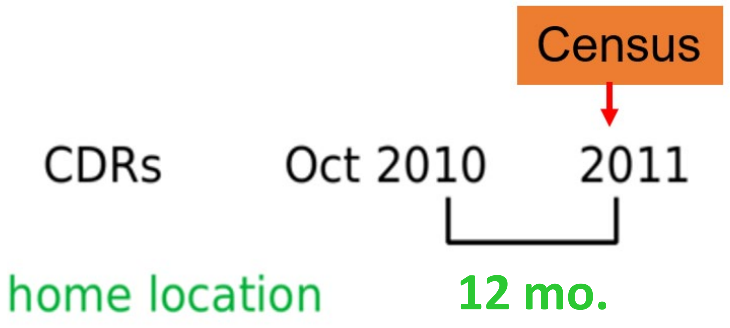
mtc



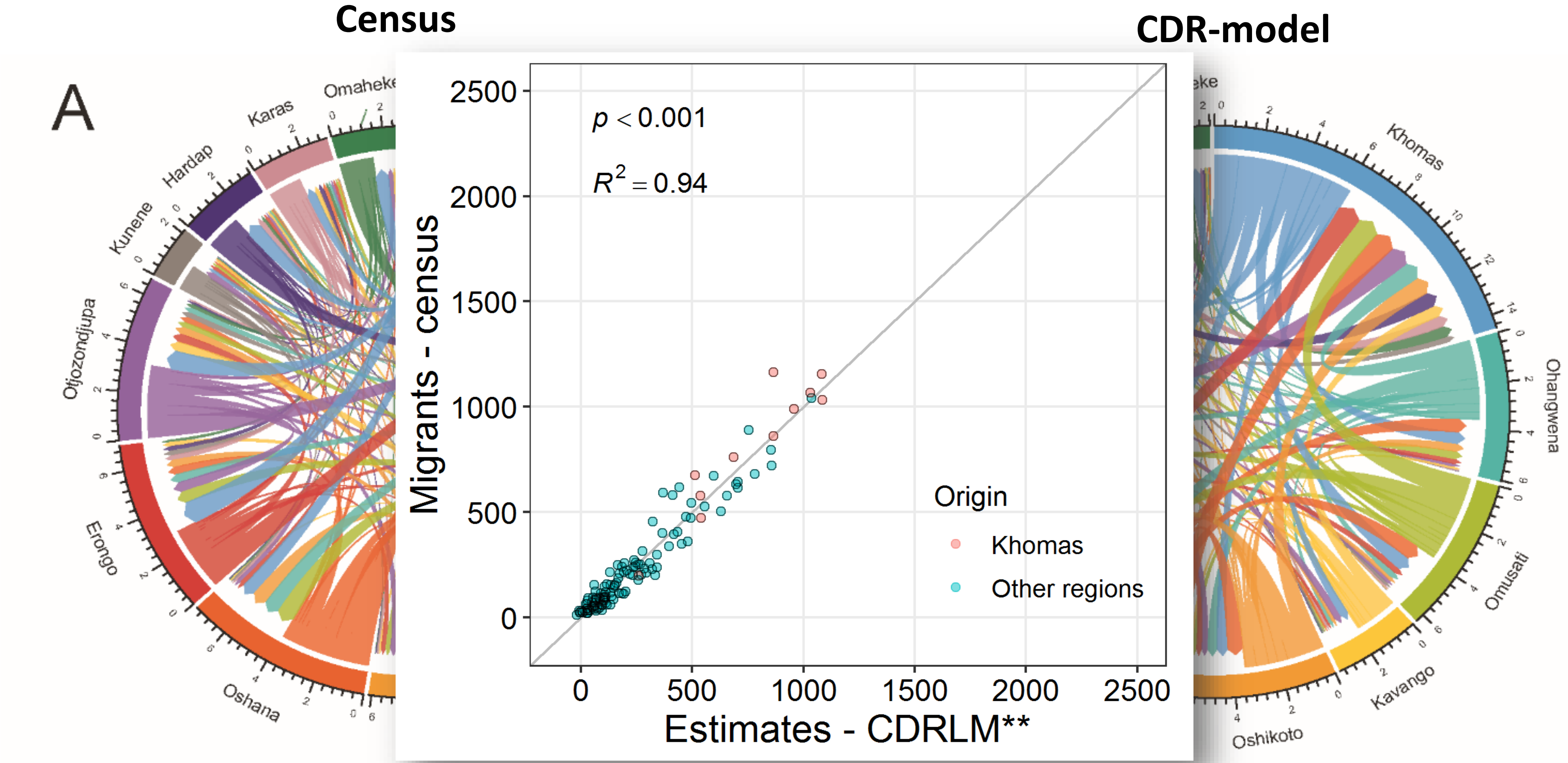
Lai S et al. *Nature Palgrave Communications 2019*

CDR-derived user locations

- **Location** of a mobile/SIM user was defined by the location of the routing mobile phone tower, spatially aggregated to regional level to match the census migration data.
- **Home location:** defined as the region where the user was observed most frequently during 12 months at nighttime
- **Migrant user**: A mobile phone user changed home locations between two years.

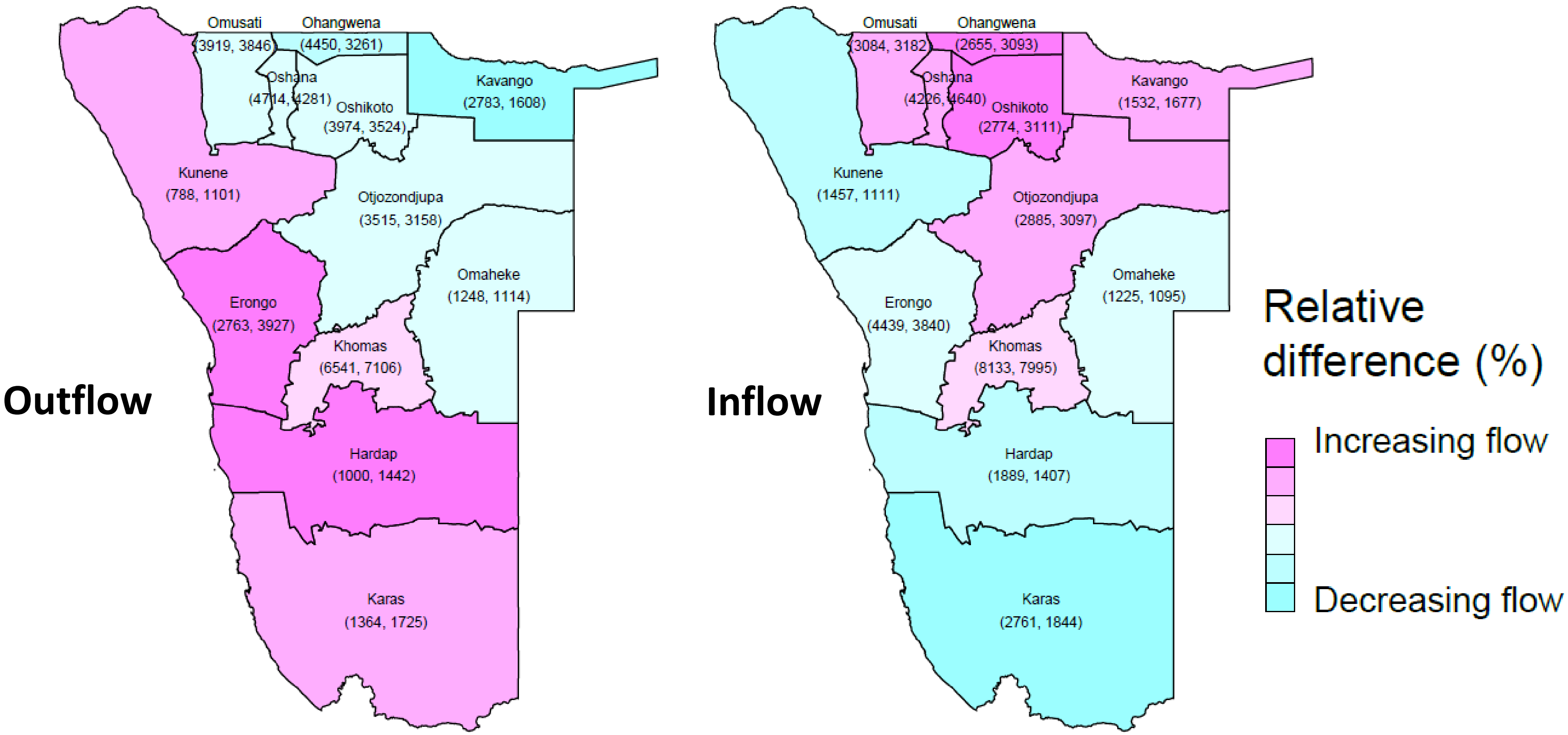


Highly correlation between CDR and census-derived migrations



Note: The Zambezi region as an outliner is excluded.

Updating migration statistics across years

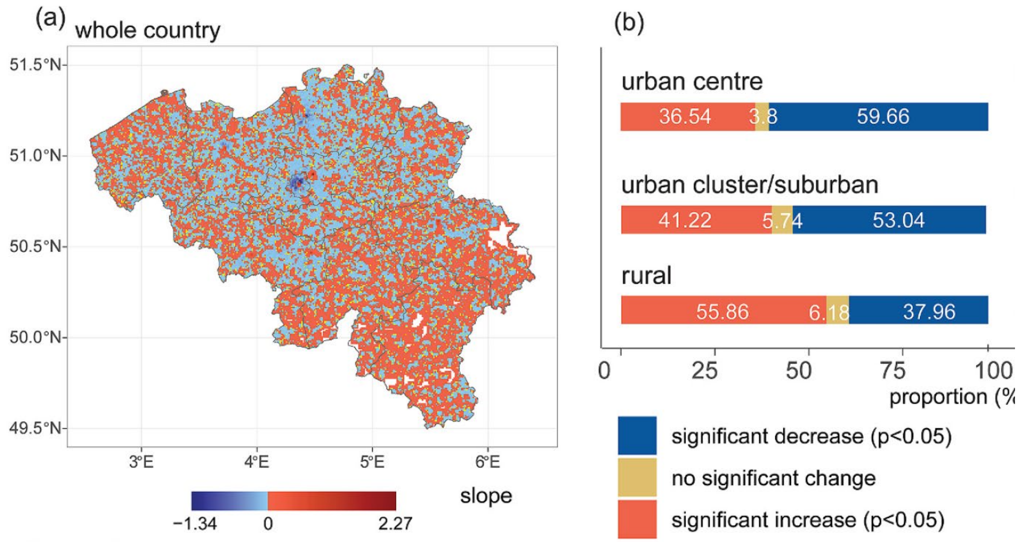


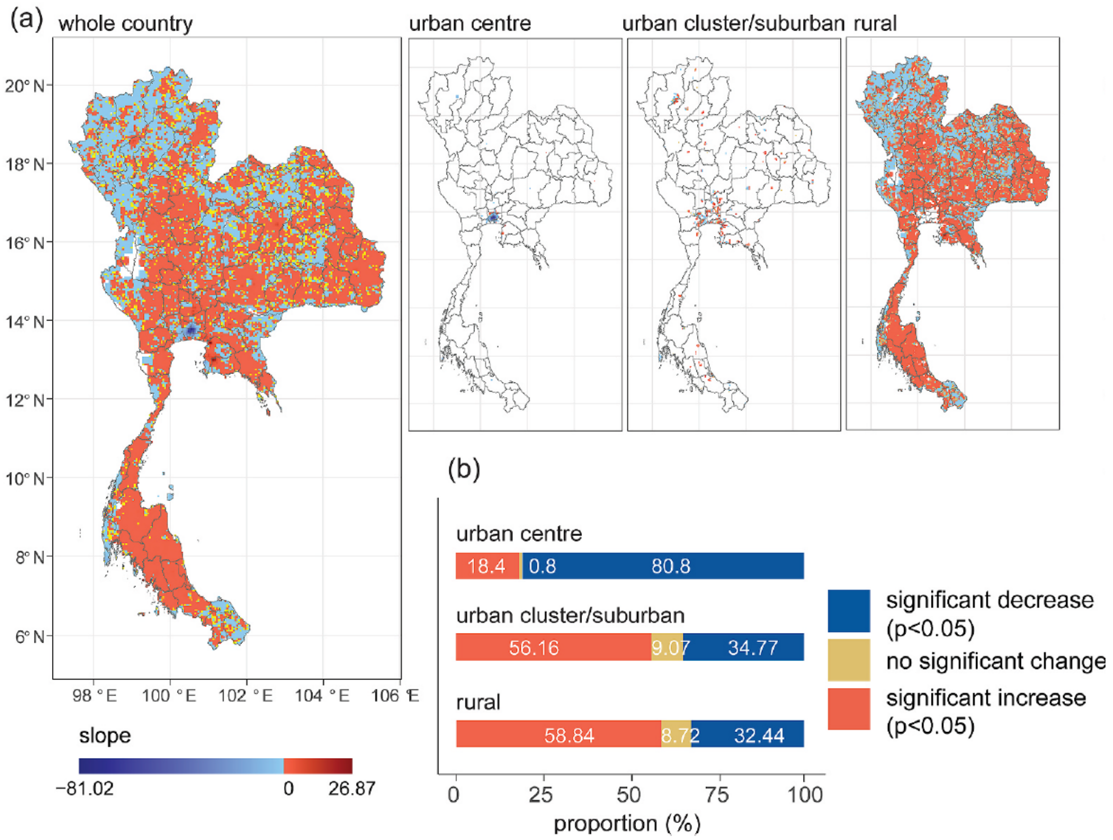
Migrants departing and arriving in 2012 compared to 2011

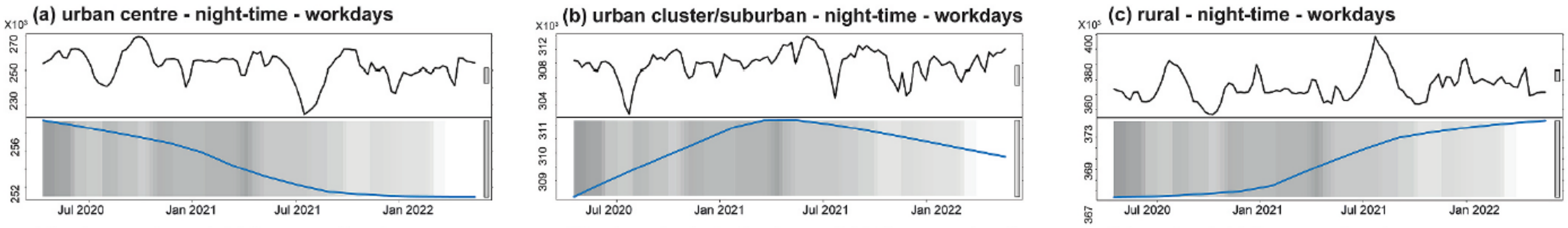
The Zambezi region as an outliner is excluded.

Identifying counter-urbanisation using Facebook's user counts

In Belgium and Thailand, rural residents (night-time user counts) increased by 1.80% and 2.14%, respectively, from March 2020 to May 2022, while urban residents decreased by 3.08% and 5.04%. However, the counter-urbanisation in Thailand appears to be transitory.

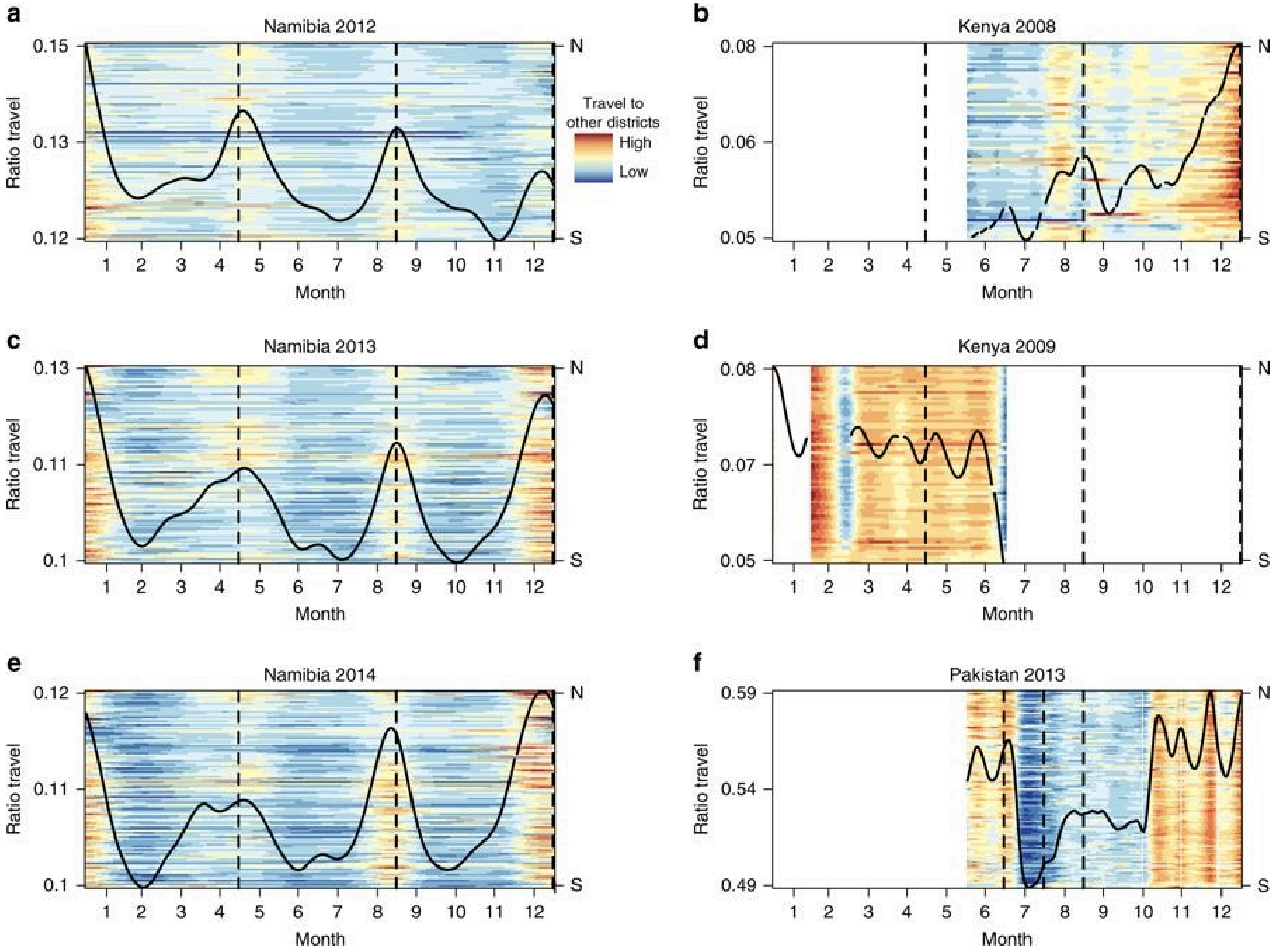


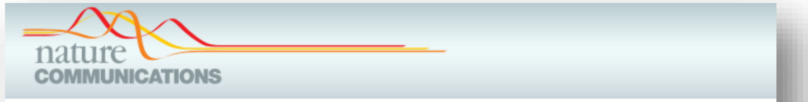




Duan et al. *Habitat Int 2024*

Seasonal movements





ARTICLE

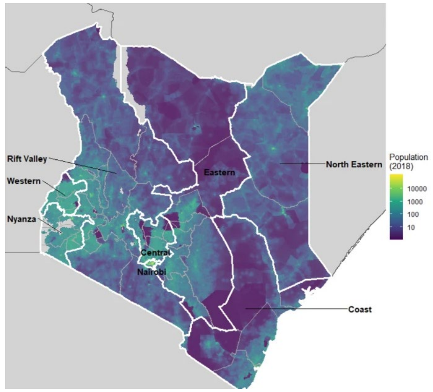
DOI: 10.1038/s41467-017-02064-4 OPEN

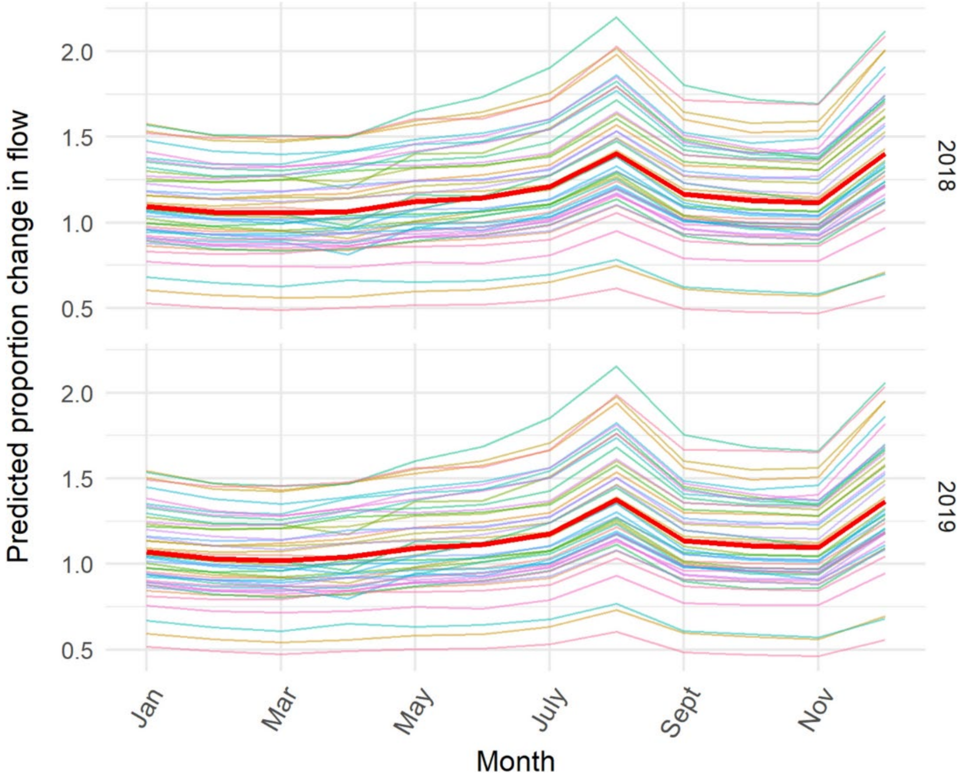
Multinational patterns of seasonal asymmetry in human movement influence infectious disease dynamics

Amy Wesolowski[1], Elisabeth zu Erbach-Schoenberg[2,3], Andrew J. Tatem[2,3], Christopher Lourenço[2,4], Cecile Viboud[5], Vivek Charu[5], Nathan Eagle[6], Kenth Engø-Monsen[7], Taimur Qureshi[7], Caroline O. Buckee[6,8] & C.J.E. Metcalf[9,10]

Article | Open Access | Published: 28 July 2021

Practical geospatial and sociodemographic predictors of human mobility



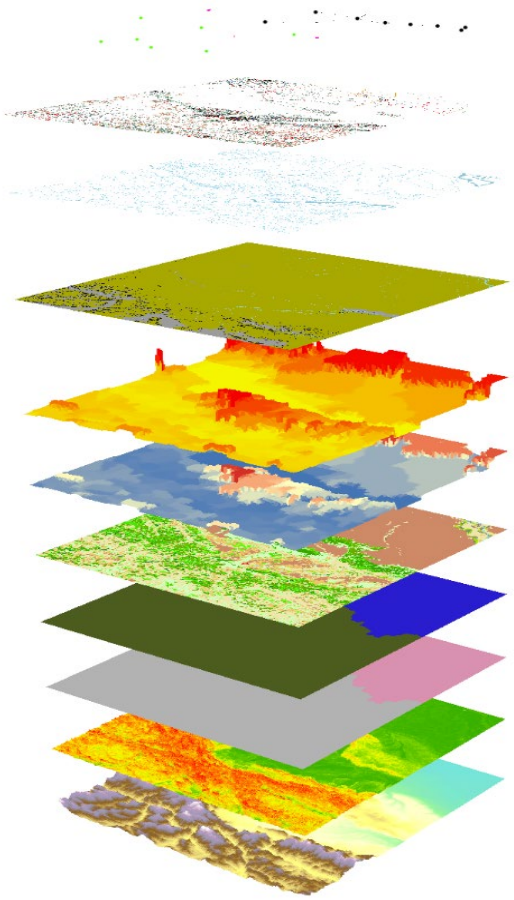


Covariate
% population living in urban extent
% people living in povertyy[1]
% women with no primary education
Travel time (minutes) to the nearest urban centre[2]
school holidays (days)
Aridity index
Enhanced Vegetation Index (EVI)
Precipitation (mm)[3]
Temperature (°C)[3]
VIIRS Night-time lights

Ruktanonchai et al (2021) Nature Sci Reports; Lai et al (2021) Nature Sci Data

Article | Open Access | Published: 28 July 2021

Practical geospatial and sociodemographic predictors of human mobility



Change in mobility for district *i* in month *t*

Temporal fixed effects component

Spatially and temporally varying covariates

$$\log(y_{it}) = \beta_0 + A_i + B_t + C_{it} + X'_{it}\beta + \epsilon_{it}$$

Spatial autocorrelation component

Spatial and temporal interactions

Ruktanonchai et al (2021) Nature Sci Reports; Lai et al (2021) Nature Sci Data

Seasonal mobility's health impacts: Health metrics

RESEARCH Open Access

Dynamic denominators: the impact of seasonally varying population numbers on disease incidence estimates

Elisabeth zu Erbach-Schoenberg[1,2*], Victor A. Alegana[1,2], Alessandro Sorichetta[1,2], Catherine Linard[3,4], Christoper Lourenço[1,5], Nick W. Ruktanonchai[1,2], Bonita Graupe[6], Tomas J. Bird[1,2], Carla Pezzulo[1,2], Amy Wesolowski[2,7,8] and Andrew J. Tatem[1,2,9]

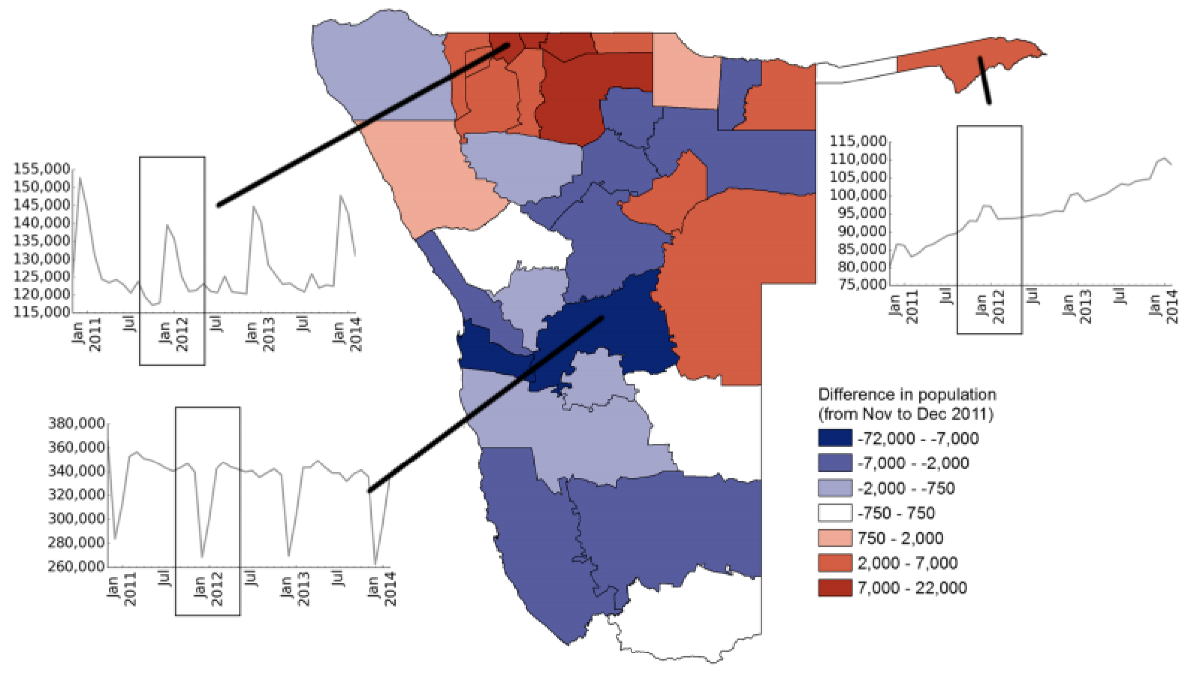
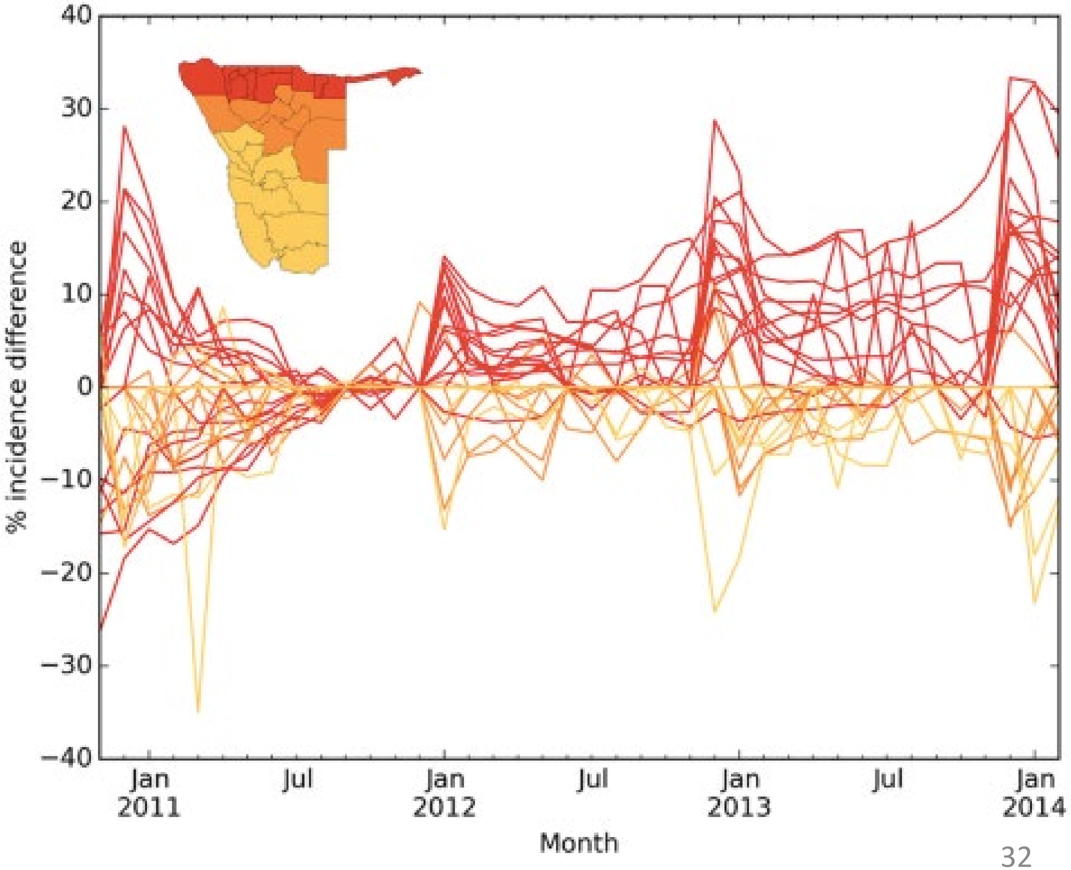
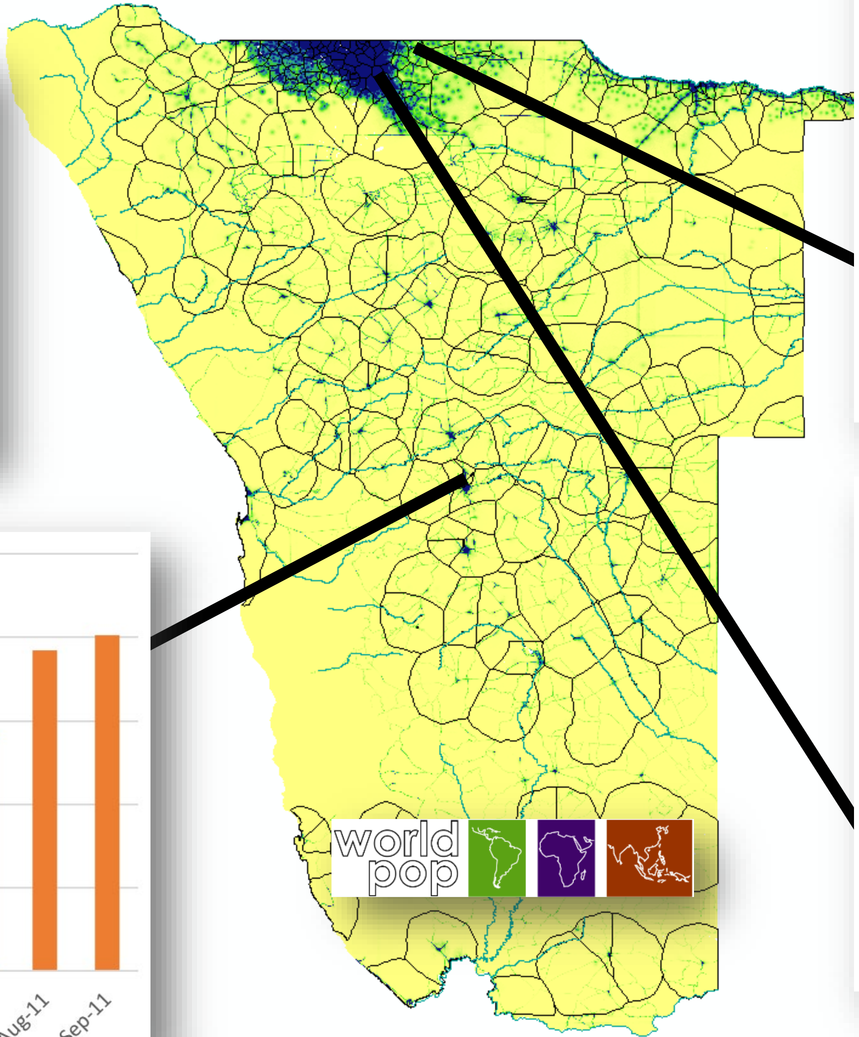


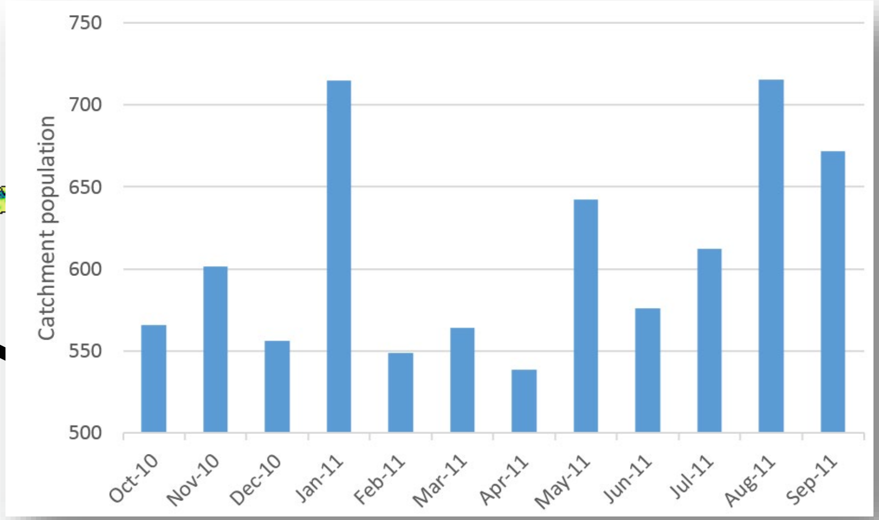
Fig. 4 Seasonal changes in population numbers: Difference in predicted population number between November and December 2011 for each health district. Insets show predicted population number for selected health districts over the whole study period

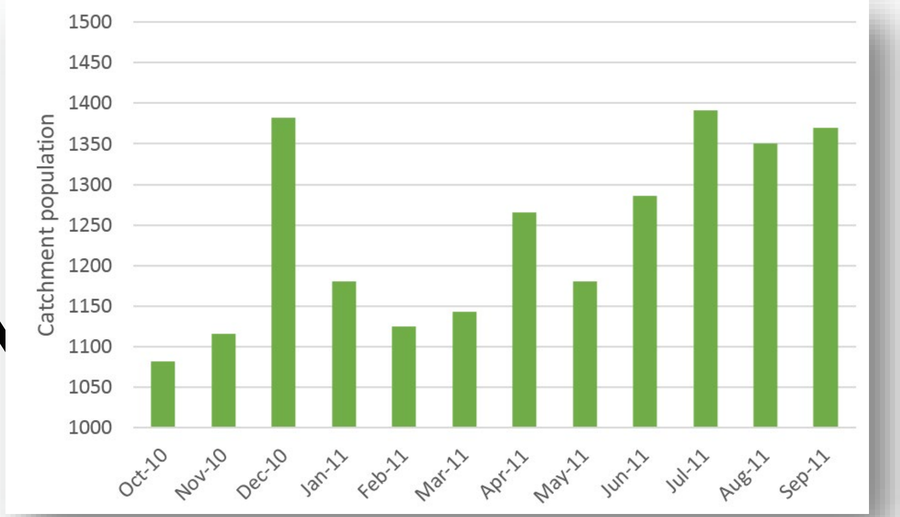
% incidence difference by district

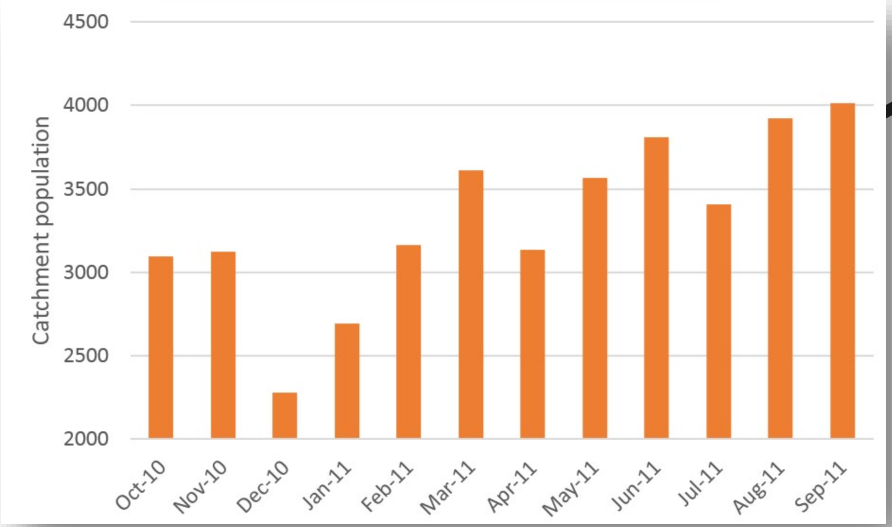


Seasonal mobility's health impacts:
Intervention/Healthcare demands









Erbach-Schoenberg et al (2016) Pop Health Metrics; Alegana et al (2012) IJHG

Case studies: Assessing the spread risk and intervention effects for emerging infectious diseases

Spread of infectious diseases

nature

https://doi.org/10.1038/s41586-022-04788-w

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Climate change increases cross-species viral

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Volume 26, Issue 3
2019

EDITOR'S CHOICE

Measuring mobility, disease connectivity and individual risk: a review of using mobile phone data and mHealth for travel medicine FREE

Shengjie Lai, MD PhD, Andrea Farnham, MPH PhD, Nick W Ruktanonchai, PhD, Andrew J Tatem, PhD

Journal of Travel Medicine, Volume 26, Issue 3, 2019, taz019, https://doi.org/10.1093/jtm/taz019
Published: 14 March 2019 **Article history** ▾

https://covid19.apple.com/mobility

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 doesn't associate your data with your Apple ID, and Apple doesn't keep a history of where you've been.

Google COVID-19 Community Mobility Reports

https://www.google.com/covid19/mobility/

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

As global communities respond to COVID-19, we've heard from public health officials that the same type of aggregated, anonymized insights we use in products such as Google Maps could be helpful as they make critical decisions to combat COVID-19.

These Community Mobility Reports aim to provide insights into what has changed in response to policies aimed at combating COVID-19. The reports chart movement trends over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential.

FACEBOOK Data for Good   Public Datasets   Tools for Nonprofits   Impact   Approach

https://dataforgood.fb.com/

We use data to address some of the world's greatest humanitarian issues.

Flattening the COVID-19 curve is a challenge that takes all of us. People are distancing to protect their communities, healthcare workers are saving lives on the front lines, and public health systems are looking to put the right guidelines in place. To do that, they need better information on whether preventive measures are working and how the virus may spread. We offer maps on population movement that researchers and nonprofits are already using to understand the coronavirus crisis, using aggregated data to protect people's privacy.

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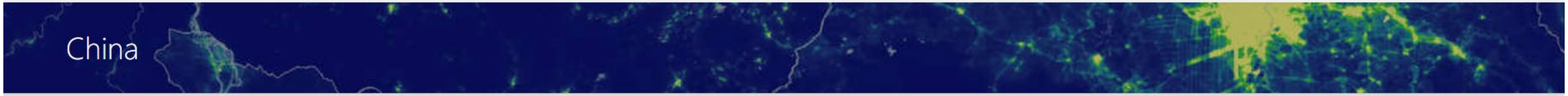
Tencent



January 25th, 2020 (Lunar New Year's Day)

Preliminary risk analysis of 2019 novel coronavirus spread within and beyond China

Shengjie Lai[1*], Isaac I. Bogoch[2], Alexander Watts[3,4], Kamran Khan[2,3,4], Andrew Tatem[1*]

[1]WorldPop, School of Geography and Environmental Science, University of Southampton, UK
[2]Department of Medicine, University of Toronto, Toronto, Canada
[3]Li Ka Shing Knowledge Institute, St. Michael's Hospital, Toronto, Canada
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[*]Email: Shengjie.Lai@soton.ac.uk; A.J.Tatem@soton.ac.uk

Updated version on MedArxiv
Updated on February 5th, 2020

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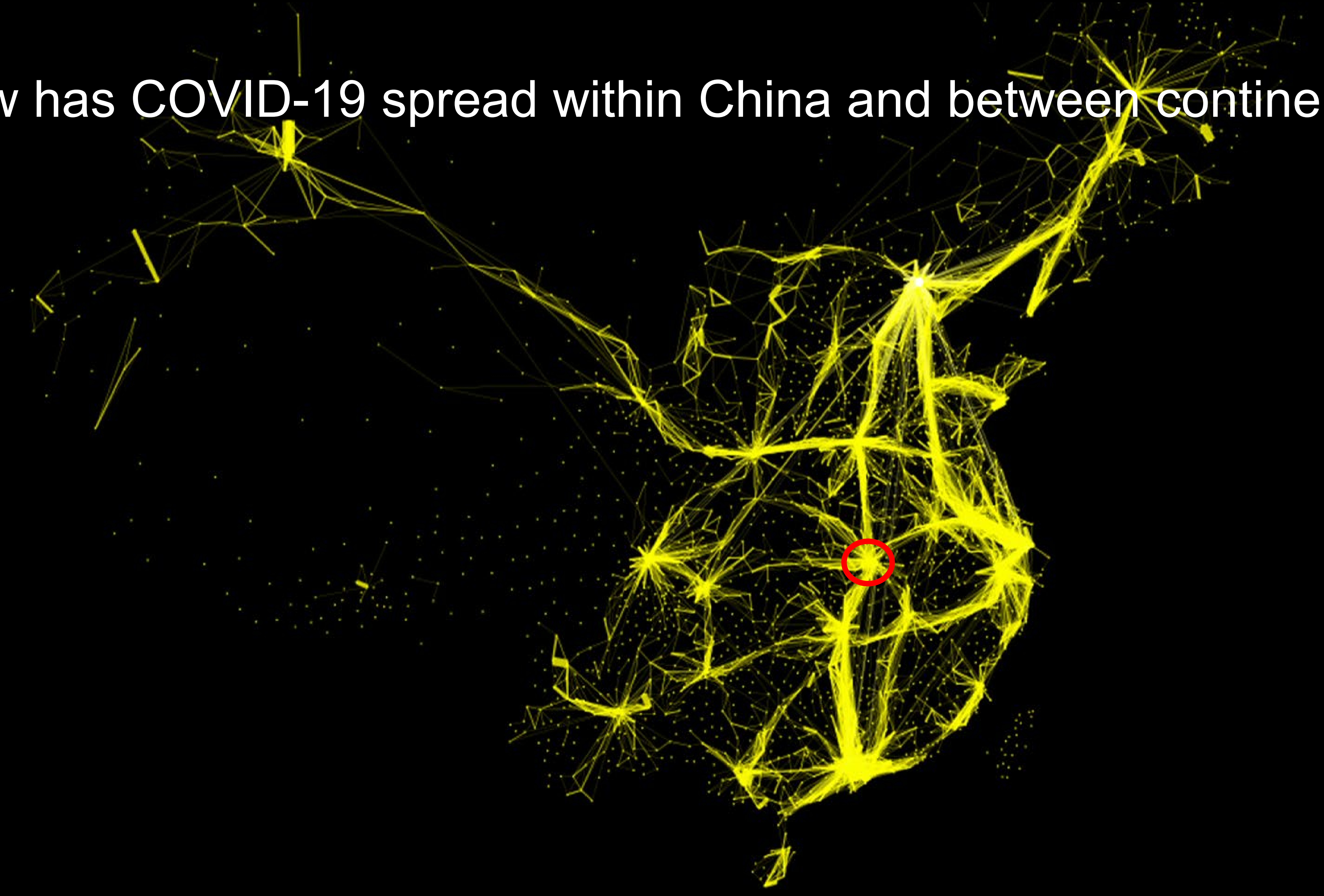
Destinations of airline travellers from 18 high-risk cities in mainland China by continent or region

OXFORD ACADEMIC
JOURNAL of TRAVEL MEDICINE

Uncovering two phases of early intercontinental COVID-19 transmission dynamics FREE

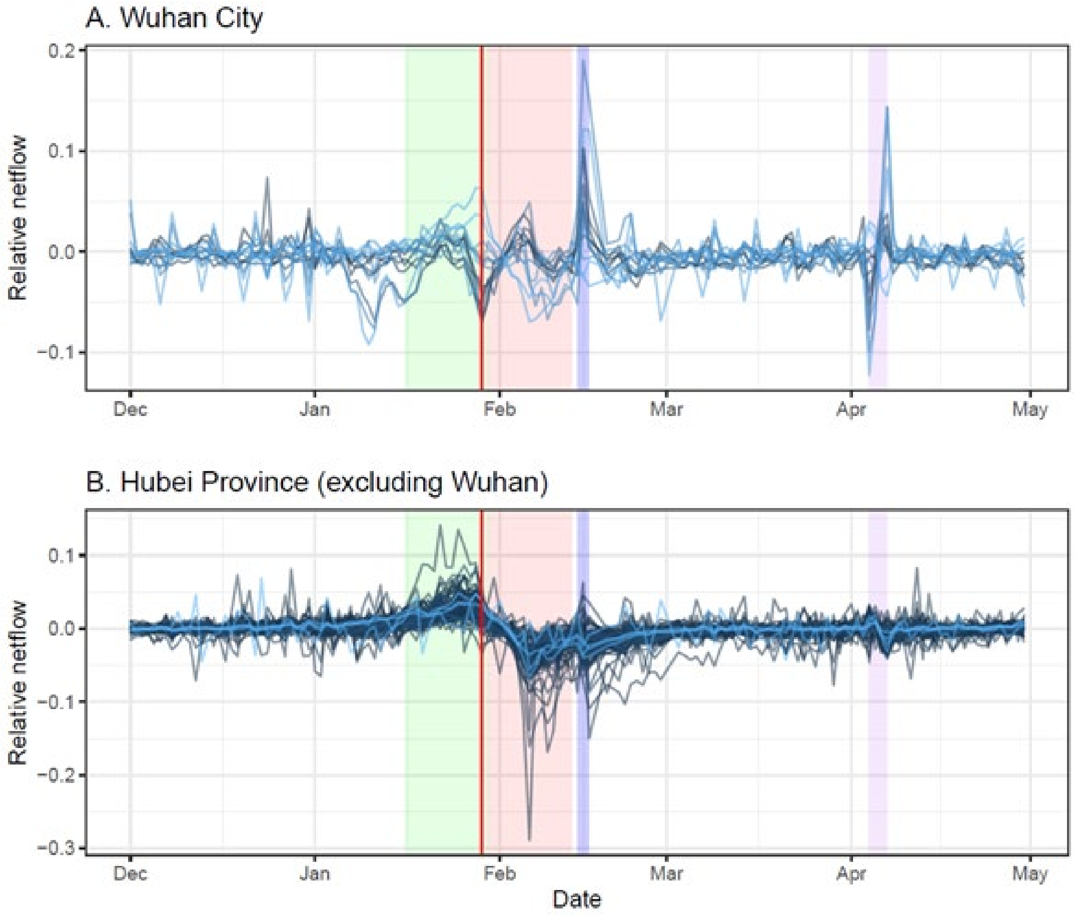
How has COVID-19 spread within China and between continents?



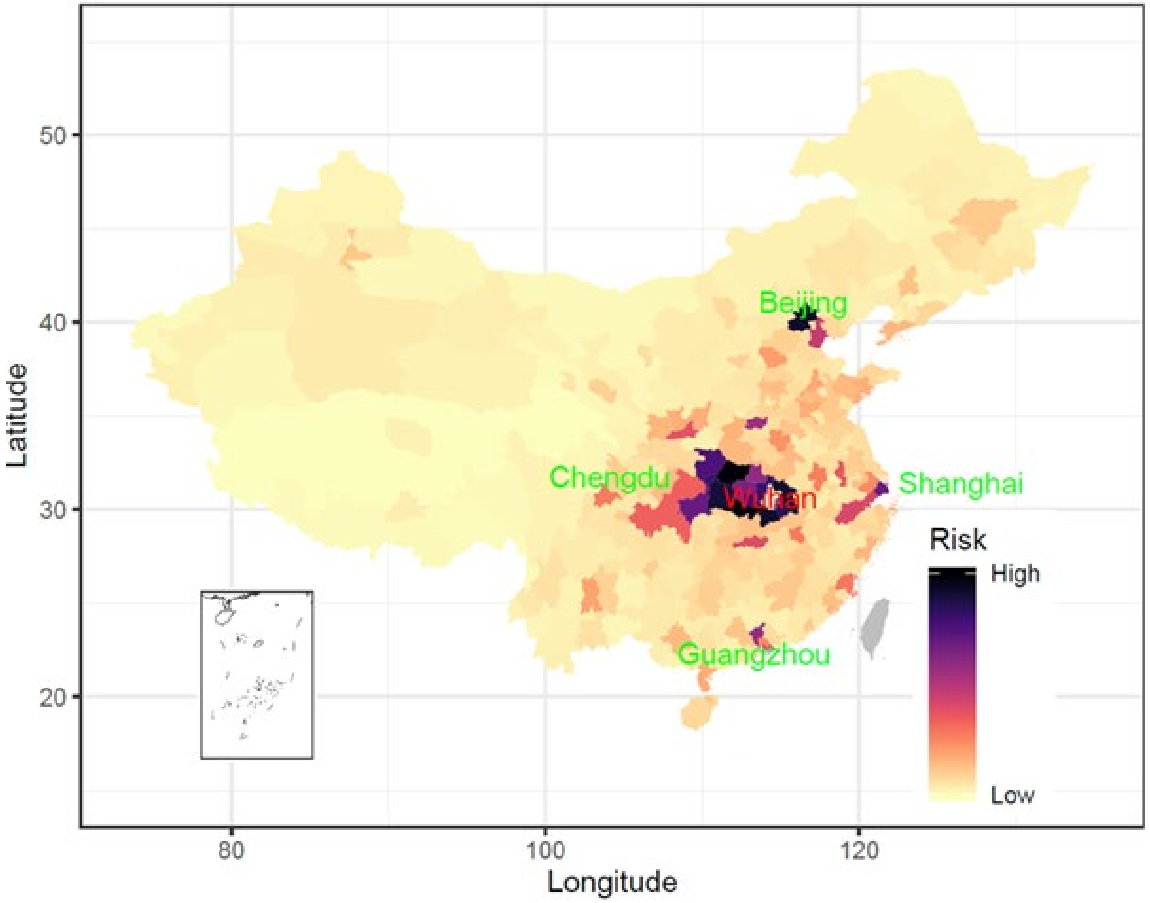
Based on Baidu LBS data, 2013.7-2014.3

COVID-19:

Domestic destinations of 5 million travellers from Wuhan



Historical patterns of daily human movement by county in Wuhan City and Hubei Province before COVID-19
Green/Red colour: 2 weeks before/since LNY's Day



Risk of cities in mainland China receiving travellers with COVID-19 infections from Wuhan during the LNY migration
based on the population movement data

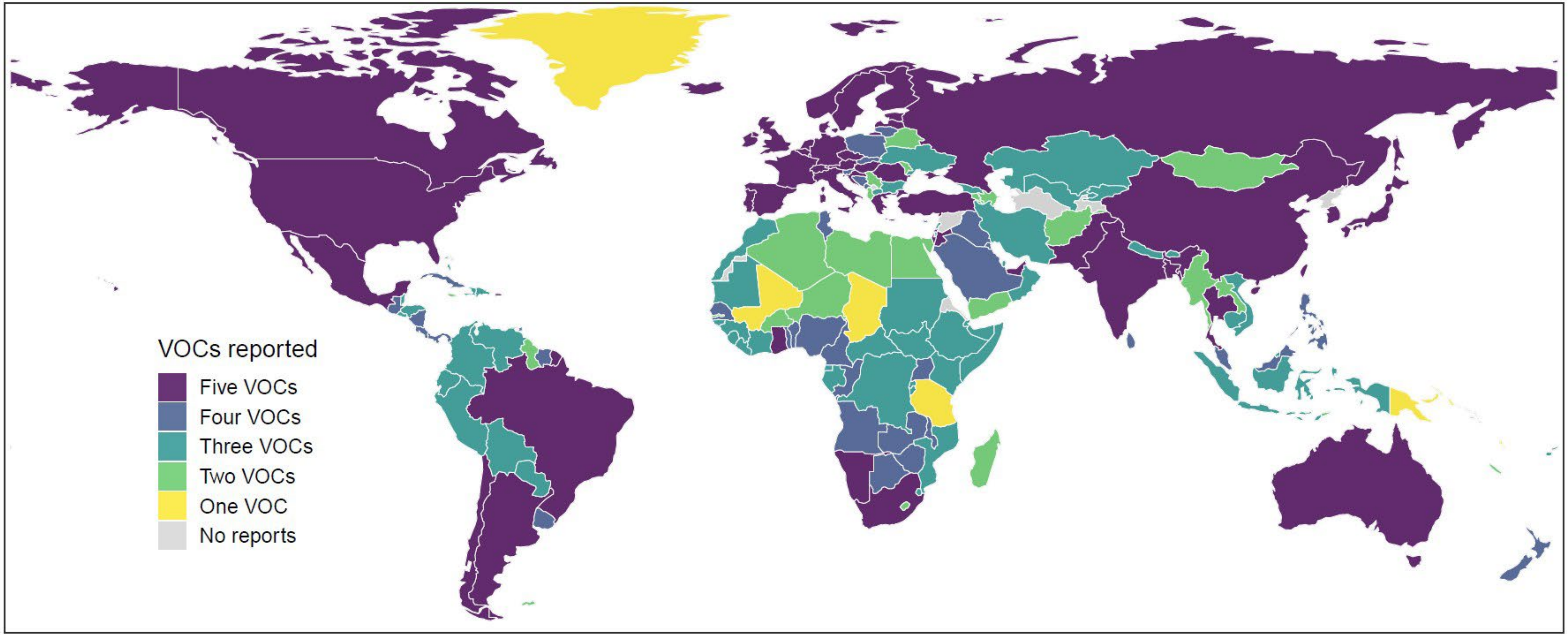
Lai et al. DSM

International destinations of travellers from China

Top 50 ranked cities receiving airline travellers from 18 cities in mainland China over a period of three months, representing 15 days before LNY's Day and 2 and half months following LNY's Day.

Based on air travel data from February to April 2018, obtained from the International Air Travel Association

Variants of concern (VOCs)



Data sources: WHO, as of 14 Dec 2021

Li & Lai , et al. Nature 2021

December 17th, 2021

Exploring international travel patterns and connected communities for understanding the spreading risk of VOC Omicron

Shengjie Lai[1], Zhenlong Li[2], Eimear Cleary[1], Maksym Bondarenko[1] and Andrew Tatem[1]

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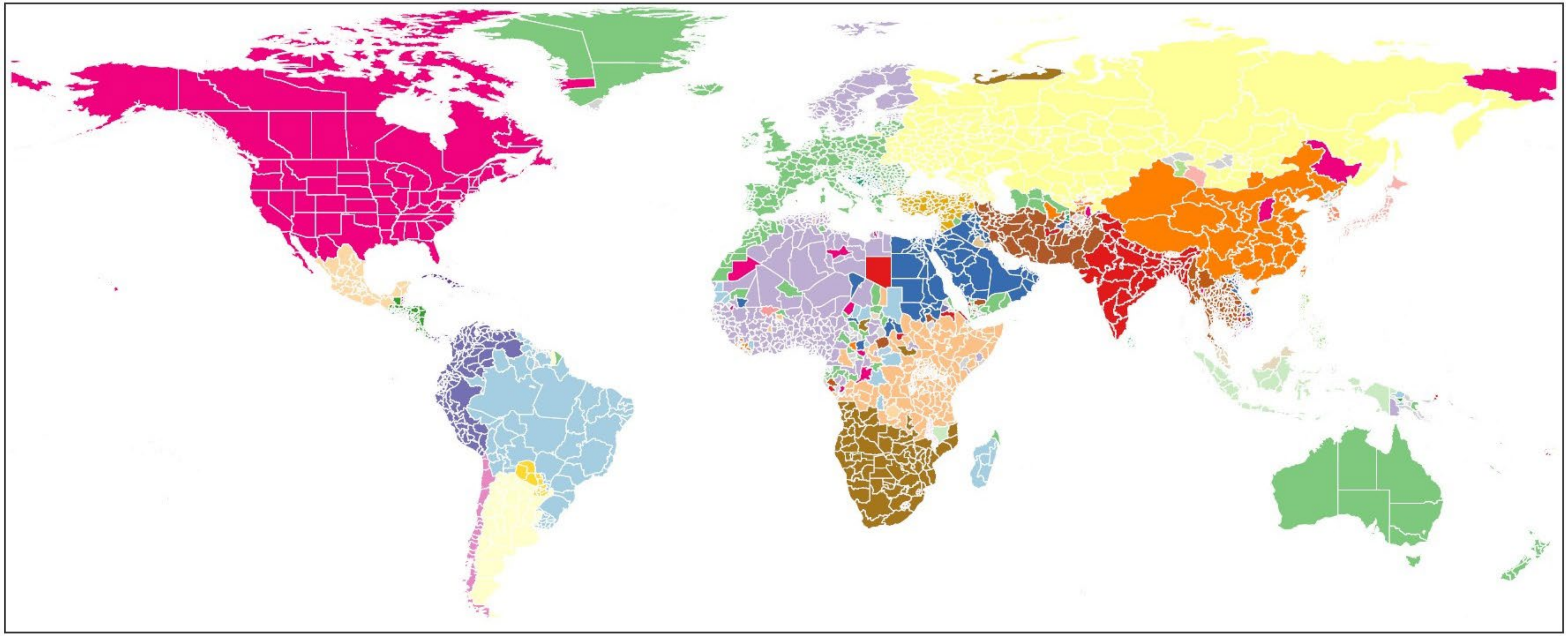


nature
https://doi.org/10.1038/s41586-021-03754-2
Accelerated Article Preview

Untangling introductions and persistence in COVID-19 resurgence in Europe

Received: 4 February 2021
Accepted: 22 June 2021
Accelerated Article Preview Published online 30 June 2021

Philippe Lemey, Nick Ruktanonchai, Samuel L. Hong, Vittoria Colizza, Chiara Poletto, Frederik Van den Broeck, Mandev S. Gill, Xiang Ji, Anthony Levasseur, Bas B. Oude Munnink, Marion Koopmans, Adam Sadilek, Shengjie Lai, Andrew J. Tatem, Guy Baele, Marc A. Suchard & Simon Dellicour

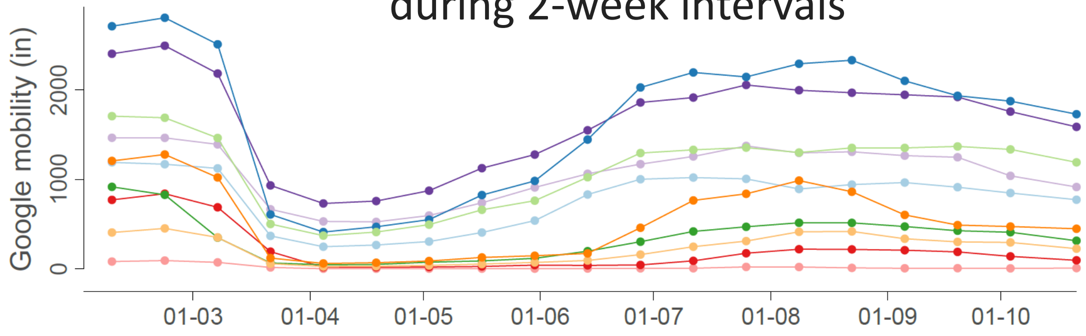
10 European countries

- Google aggregated mobility data
- ~4000 genomes sampled from GISAID datasets between 29 Jan and 31 Oct 2020

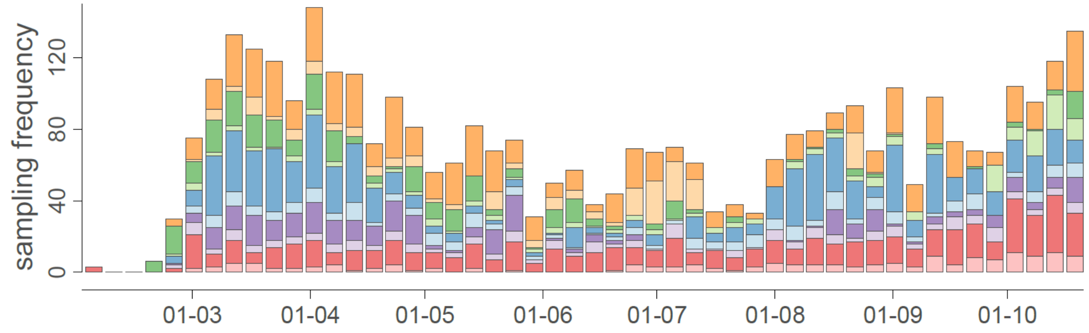
KU LEUVEN

GISAID

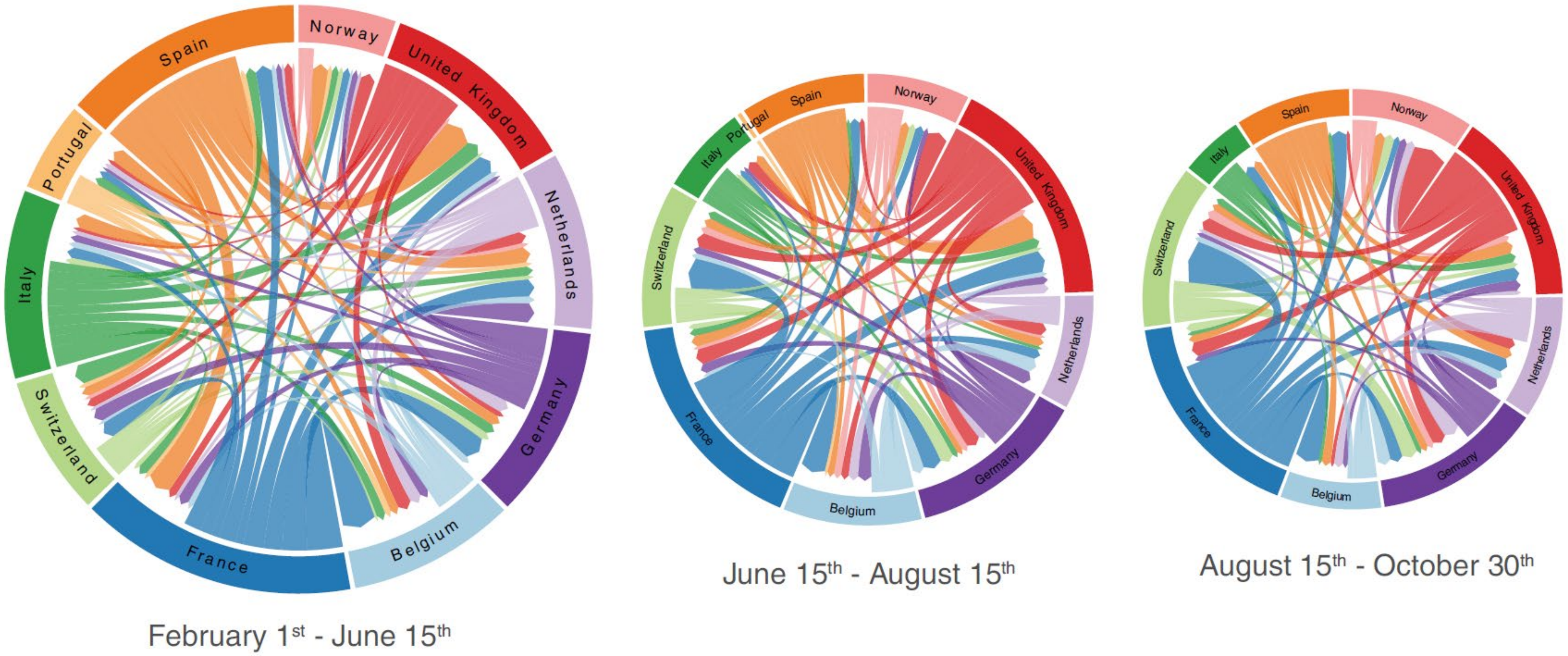
Google mobility in the 10 countries during 2-week intervals



weekly genome sampling by country

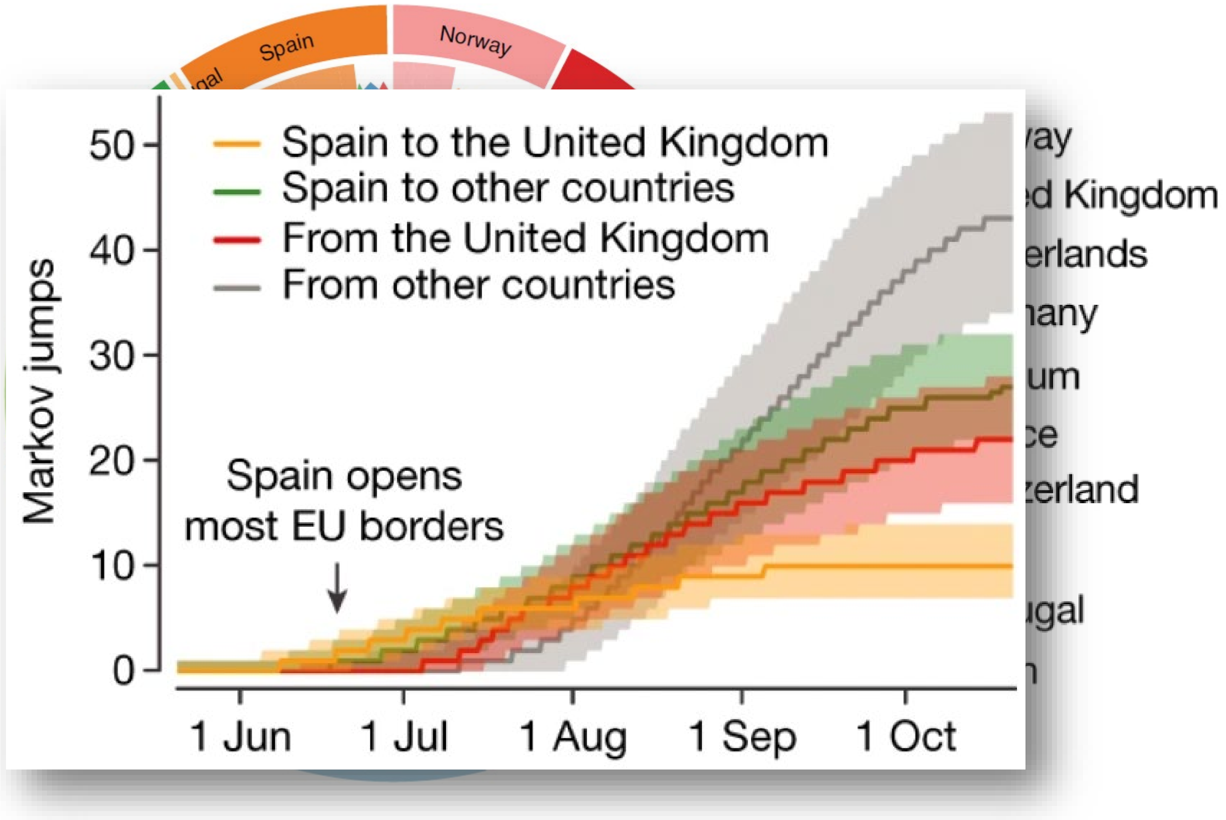


Estimated introductions between the countries for different time intervals throughout the SARS-CoV-2 evolutionary history

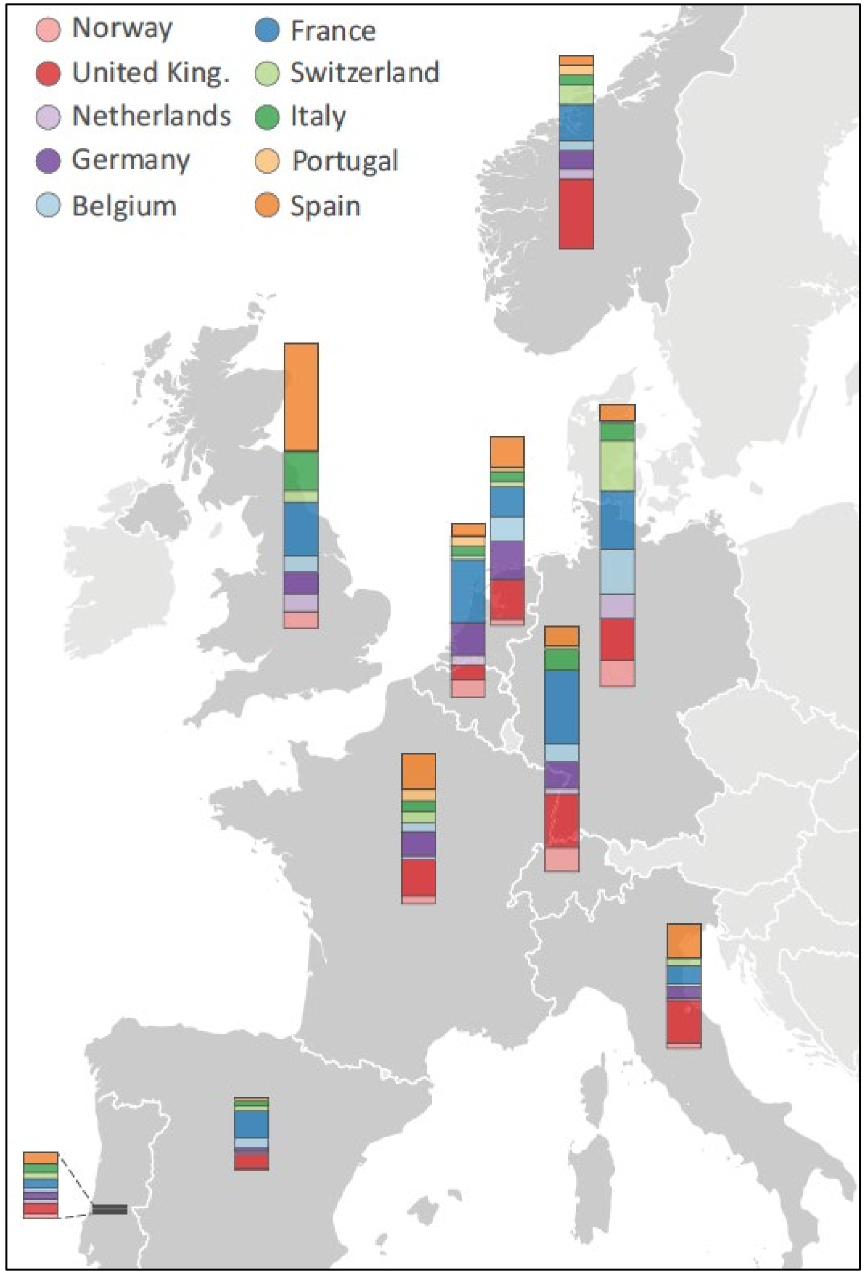


15 June 2020: many EU and Schengen-area countries opened their borders to other countries
15 August 2020: before which the majority of holiday return travel is expected for many countries

Estimated geographical origin of viral influx of lineage B.1.177 over the summer in Europe

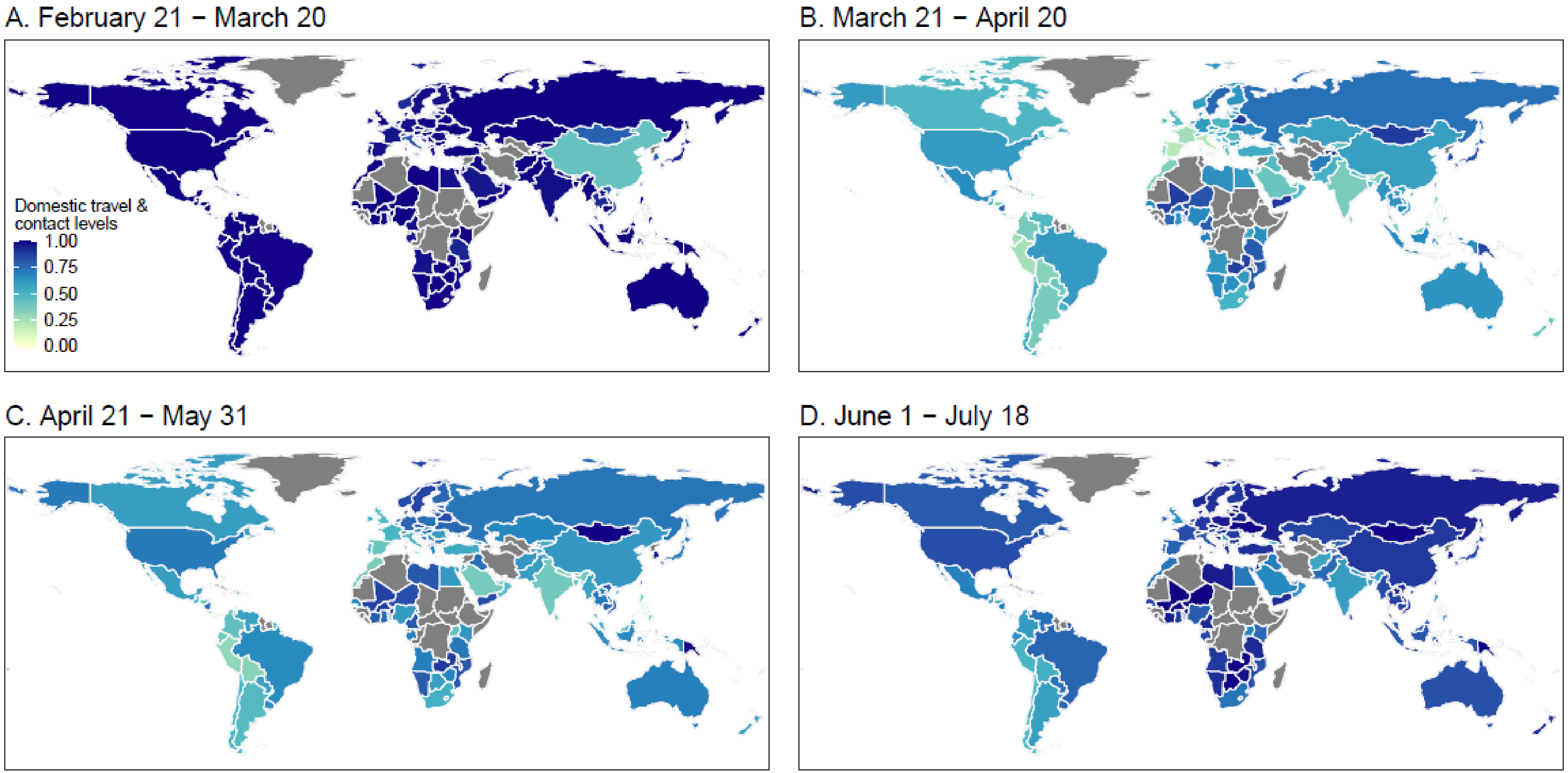


15 June–15 August 2020



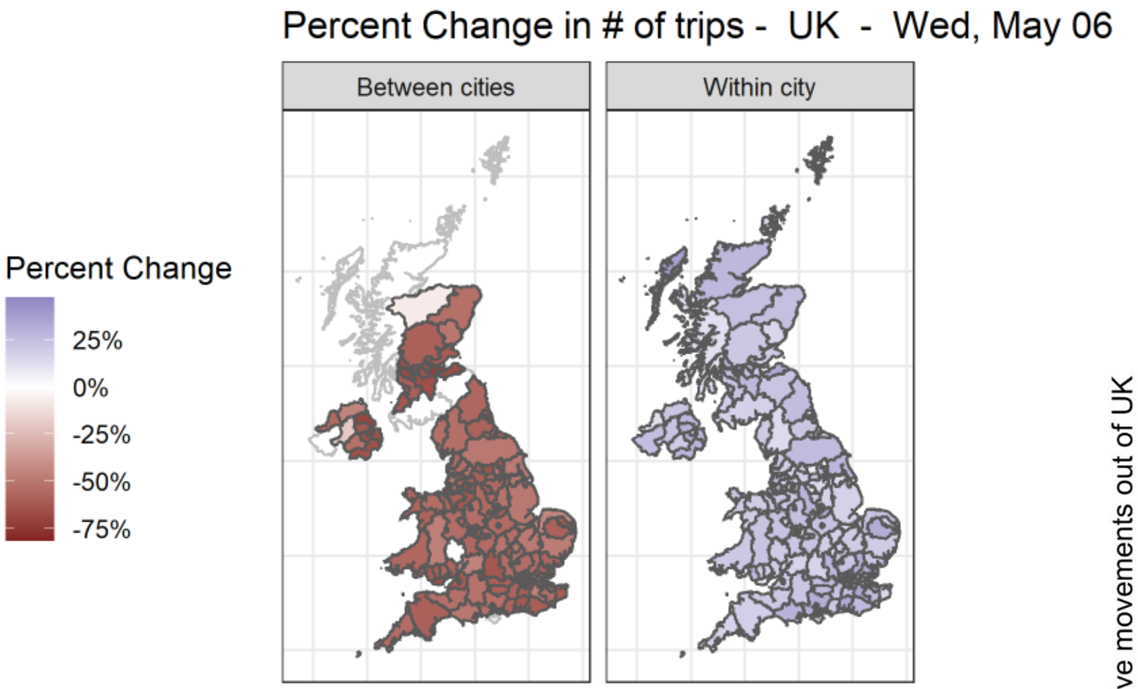
The effects of non-pharmaceutical interventions (NPIs) in containing COVID-19 at the early stage

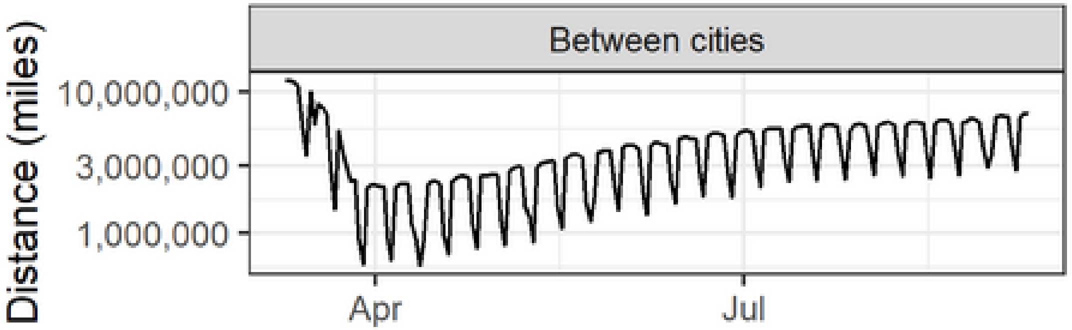
Domestic mobility changes during the first wave of pandemic

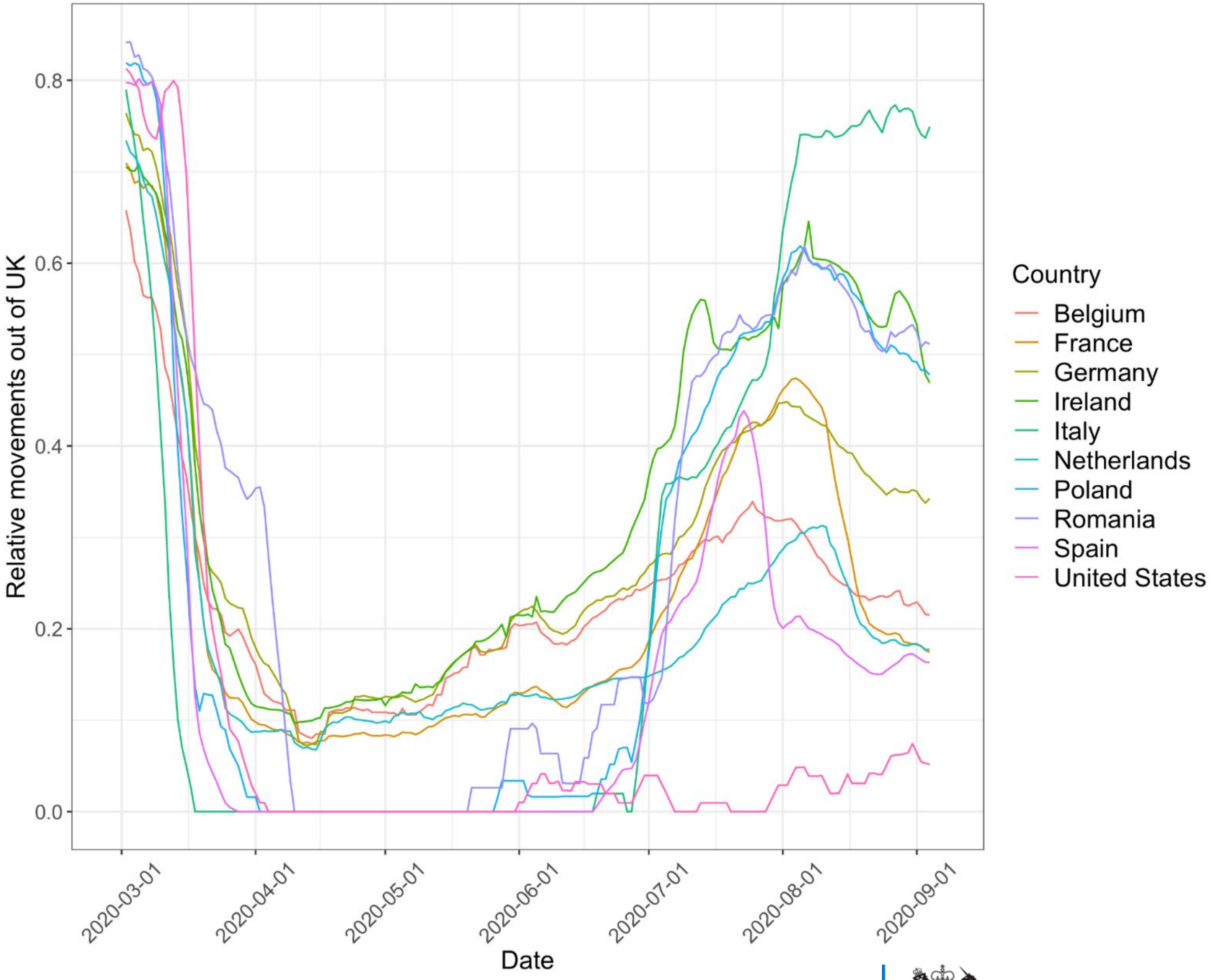


Mainland China used Baidu data, taking Jan 5 – 22, 2020 as a baseline.
All other 134 countries/territories/areas used Google data, taking Jan 5 – Feb 15, 2020 as a baseline

Lai S et al. Engineering 2021.







Office for National Statistics

FACEBOOK Data for Good

Cabinet Office

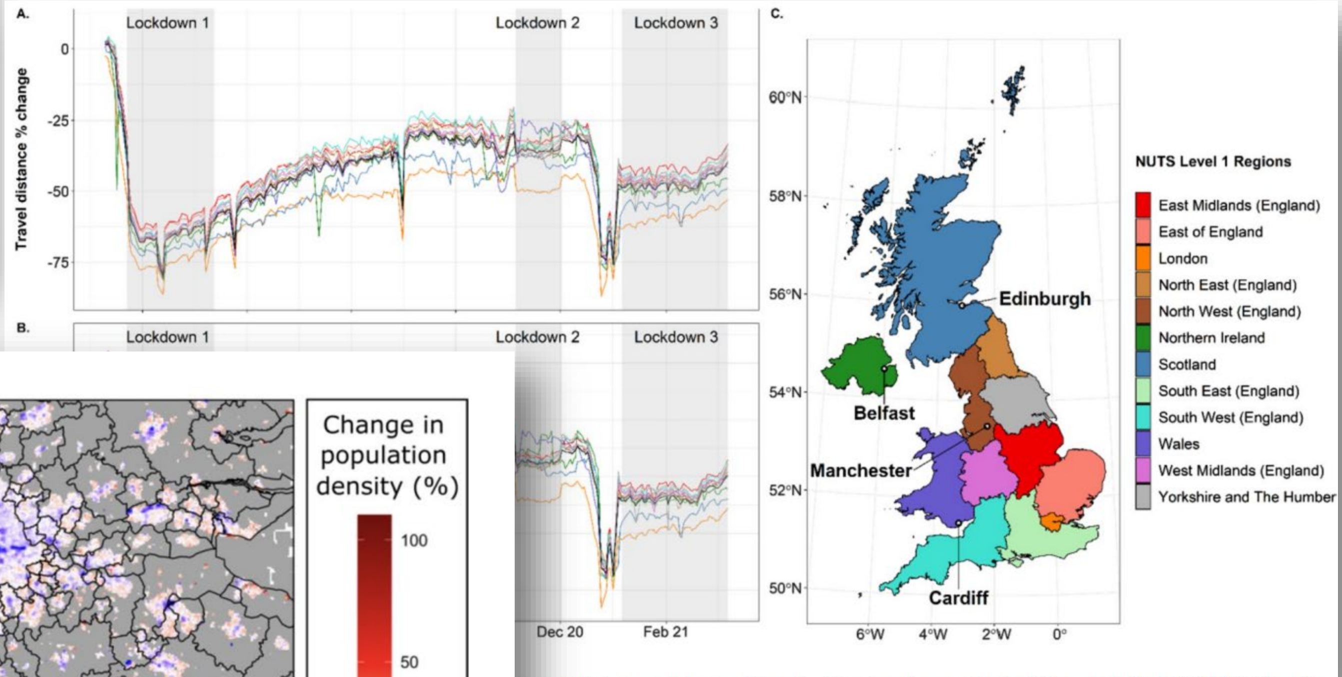
Shepherd *et al.*
International Journal of Health Geographics (2021) 20:46
https://doi.org/10.1186/s12942-021-00299-5

International Journal of Health Geographics

RESEARCH **Open Access**

Domestic and international mobility trends in the United Kingdom during the COVID-19 pandemic: an analysis of facebook data

Harry E. R. Shepherd[1], Florence S. Atherden[2], Ho Man Theophilus Chan[3], Alexandra Loveridge[2] and Andrew J. Tatem[4*]



B population movement (flows) of Facebook users in the UK and within **C** UK NUTS level 1

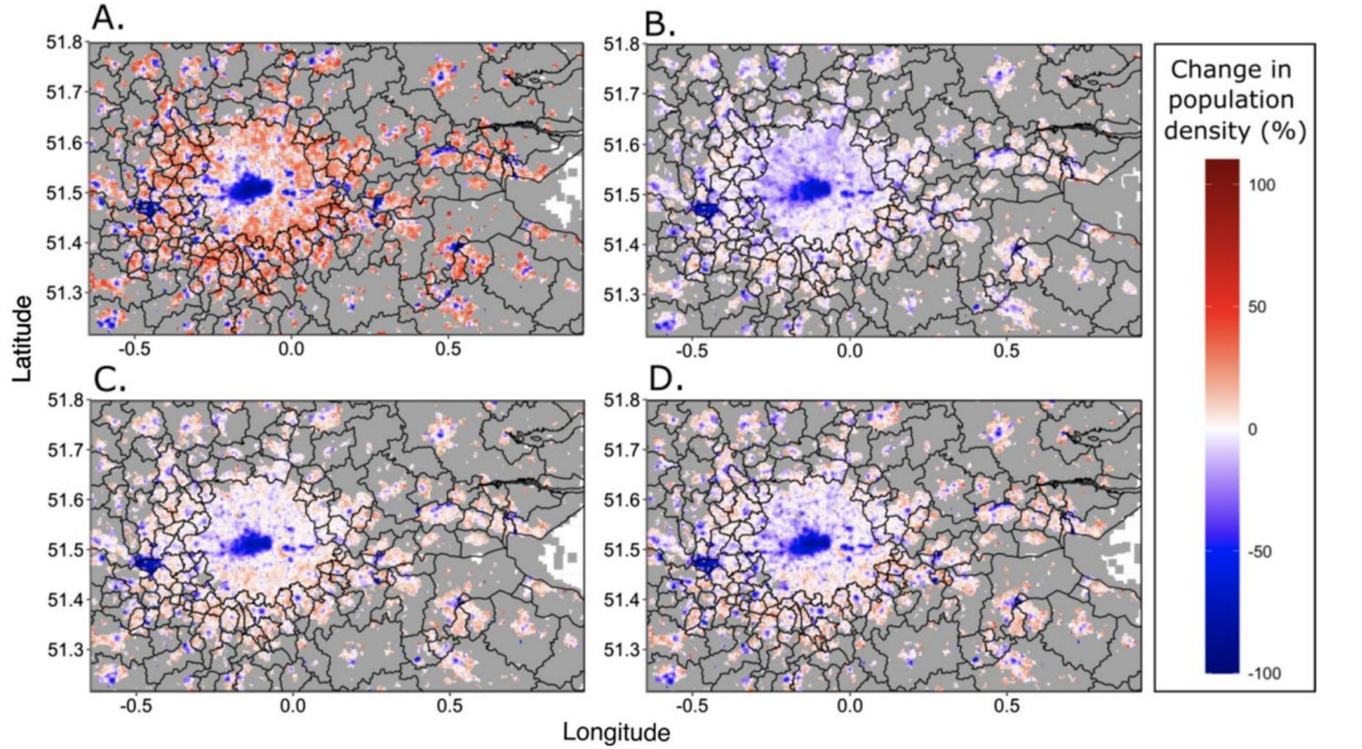
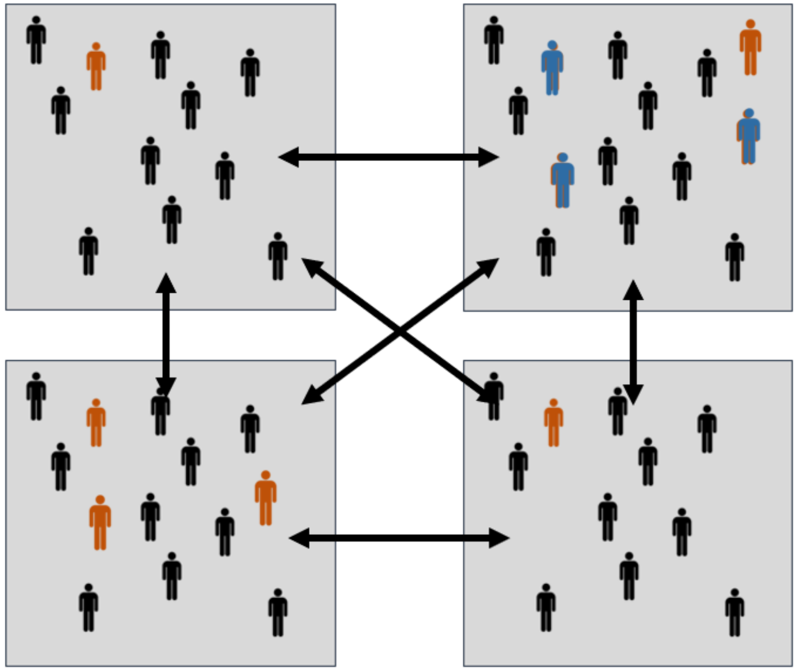


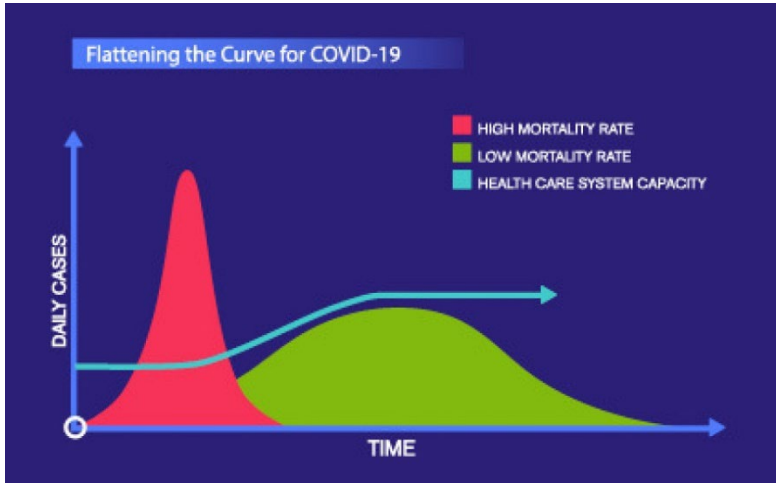
Fig. 4 Relative changes in the average population density of daytime Facebook users within London under different mobility restrictions. **A** Lockdown one (05/04/2020–12/05/2020). **B** Summer 2020 (05/07/2020–31/08/2020). **C** Lockdown two (05/11/2020—01/12/2020). **D** Lockdown three (05/01/2021–08/03/2021). Time period is between 08:00—16:00 UTC. Data does not coincide with the beginning of lockdown one as data

Integrating mobility data and covariates for assessing intervention effects

- Mechanistic transmission models
  - Compartmental model
  - Agent-based model
  - …
- Statistical models
  - Generalised linear model
  - Generalised additive model
  - …
- Geospatial/spatiotemporal model
- Age/gender-stratified model
- Travel network-based model
- Bayesian inference
- Machine learning
- …

Mobility data helps define rates of movement within and between patches





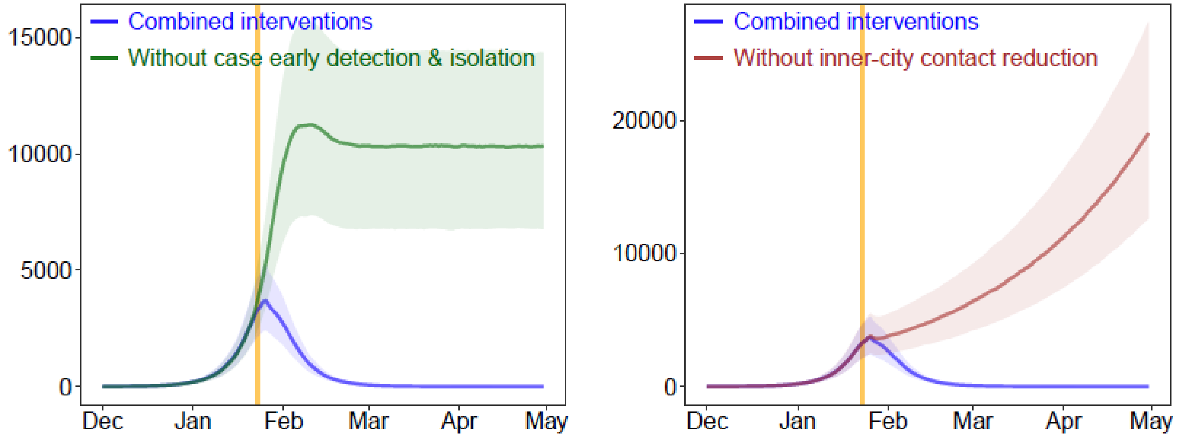
NPI effectiveness + Coordinated strategies?

nature

Article | Published: 04 May 2020

Effect of non-pharmaceutical interventions to contain COVID-19 in China

Shengjie Lai, Nick W. Ruktanonchai, Liangcai Zhou, Olivia Prosper, Wei Luo, Jessica R. Floyd, Amy Wesolowski, Mauricio Santillana, Chi Zhang, Xiangjun Du, Hongjie Yu & Andrew J. Tatem

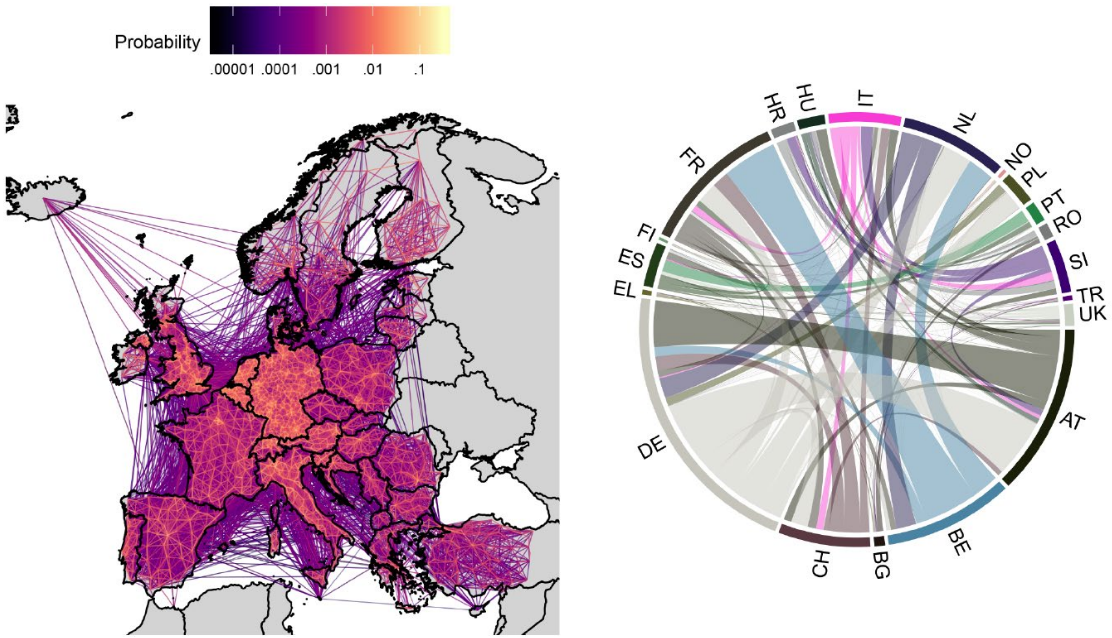


Science RESEARCH ARTICLES

Cite as: N. W. Ruktanonchai *et al.*, *Science* 10.1126/science.abc5096 (2020).

Assessing the impact of coordinated COVID-19 exit strategies across Europe

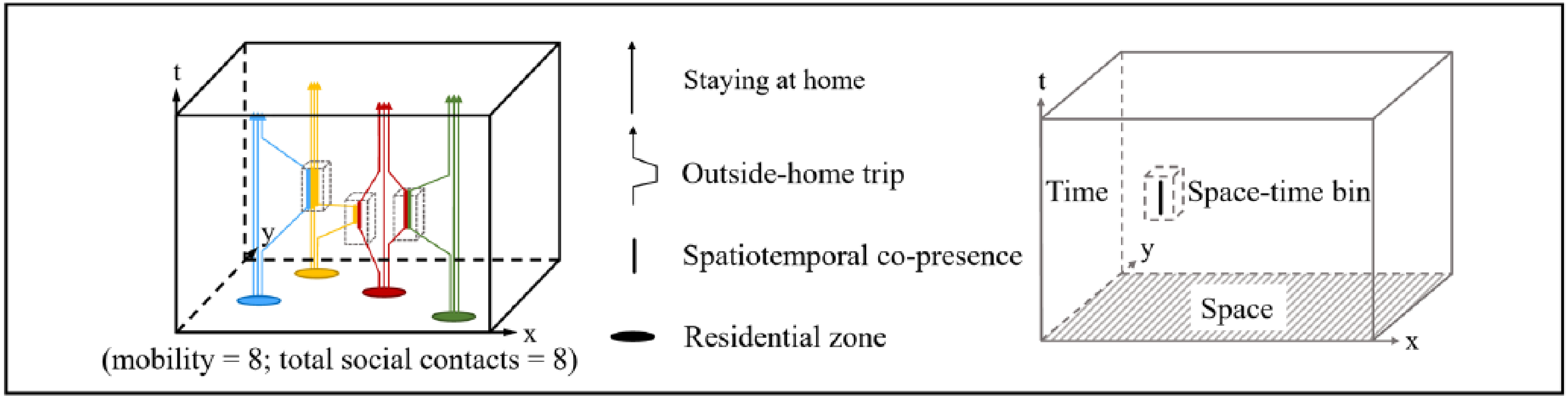
N. W. Ruktanonchai[1,2*†], J. R. Floyd[1*†], S. Lai[1*†], C. W. Ruktanonchai[1†], A. Sadilek[3], P. Rente-Lourenco[4], X. Ben[3], A. Carioli[1], J. Gwinn[5], J. E. Steele[1], O. Prosper[6], A. Schneider[3], A. Oplinger[3], P. Eastham[3], A. J. Tatem[1]

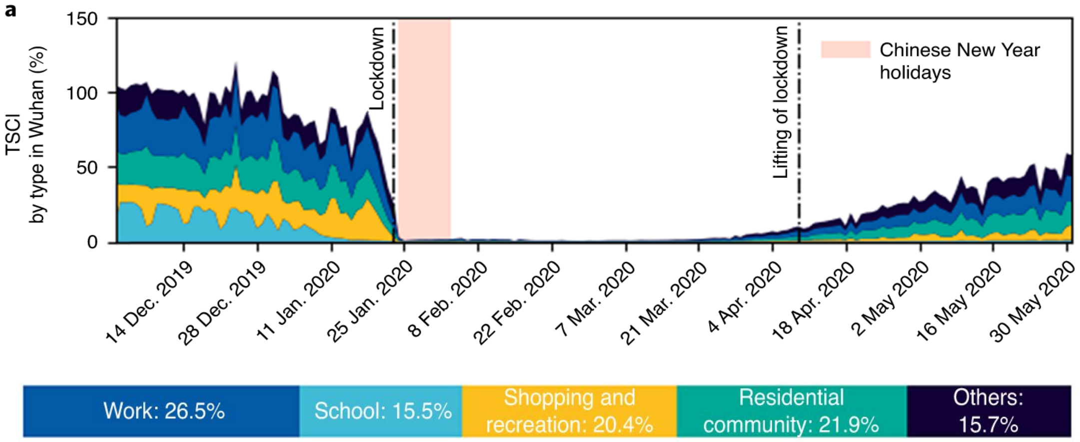


mHealth for COVID-19 interventions

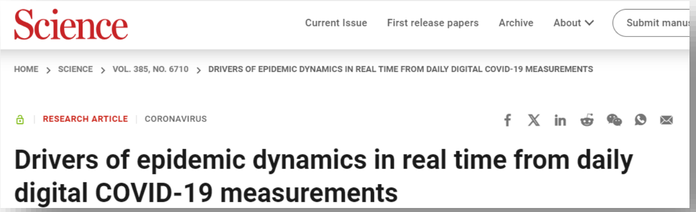

nature human behaviour
ARTICLES
https://doi.org/10.1038/s41562-021-01063-2
Check for updates
Integrated vaccination and physical distancing interventions to prevent future COVID-19 waves in

Mobile phone-derived contact patterns in the form of spatiotemporal co-presence





Change in total social contact index (TSCI) in Wuhan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HOME › SCIENCE › VOL. 385, NO. 6710 › DRIVERS OF EPIDEMIC DYNAMICS IN REAL TIME FROM DAILY DIGITAL COVID-19 MEASUREMENTS
RESEARCH ARTICLE CORONAVIRUS
Drivers of epidemic dynamics in real time from daily digital COVID-19 measurements


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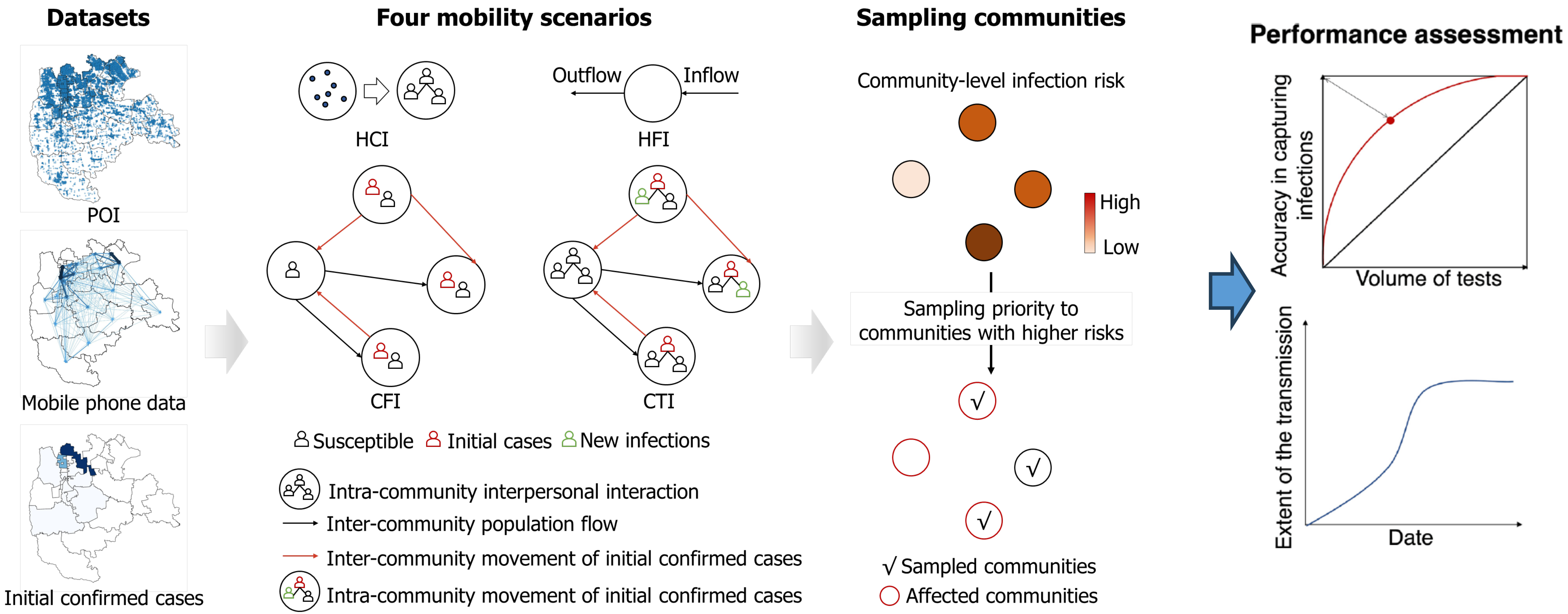
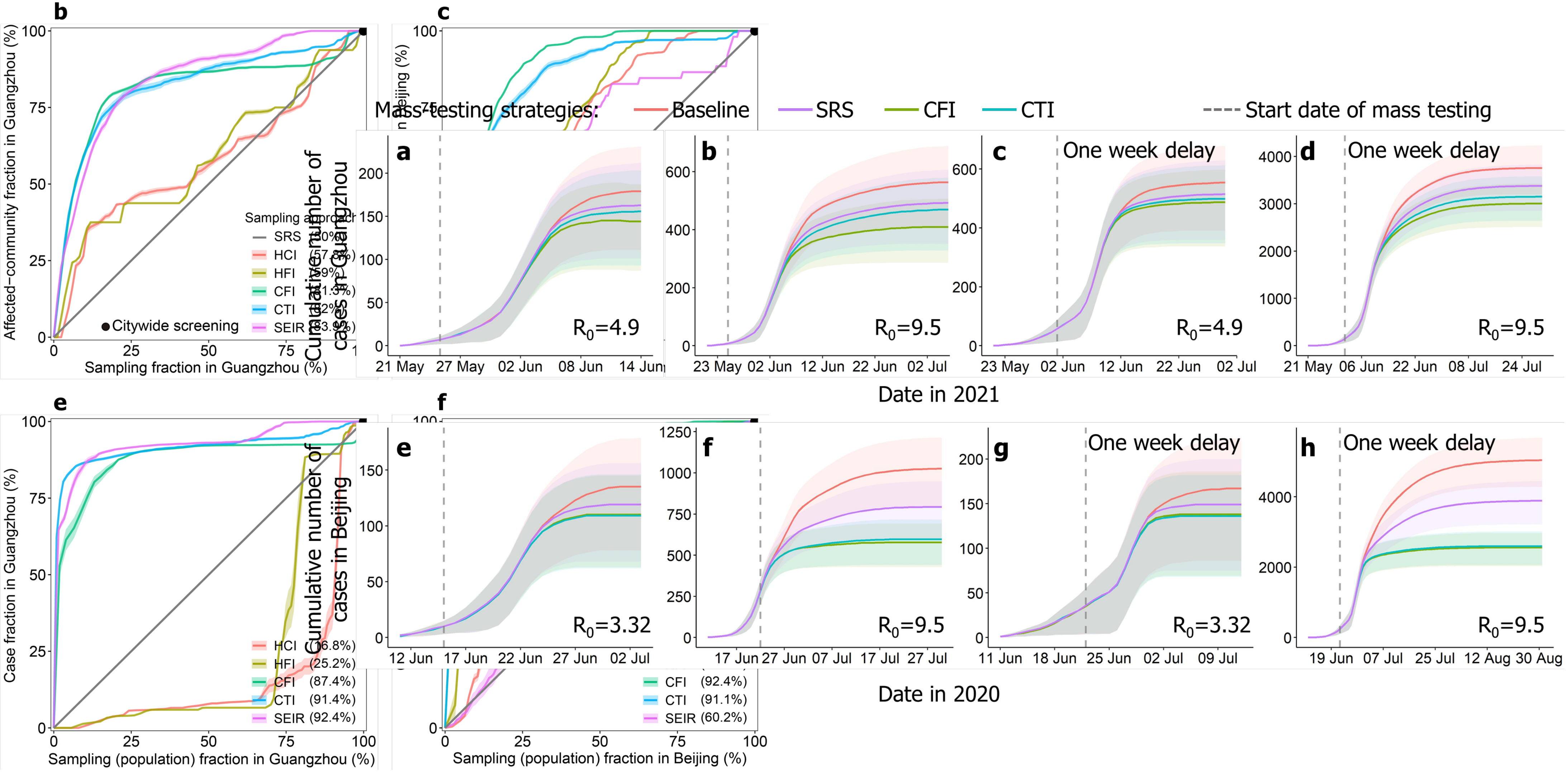
Article | Published: 12 May 2021
The epidemiological impact of the NHS COVID-19 app

Mobility-based spatial sampling improves detection of emerging infections



Zhang D, et al. JAG. 2024

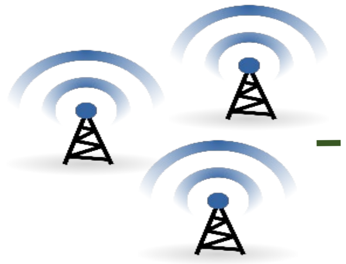
Mobility-based spatial sampling improves detection of emerging infections in testing

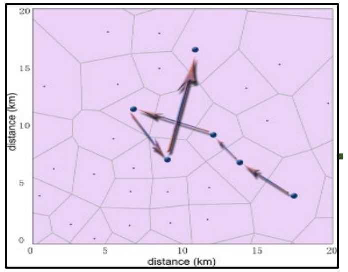


Limitations & challenges

Preserving confidentiality

Data Protection Act 2018

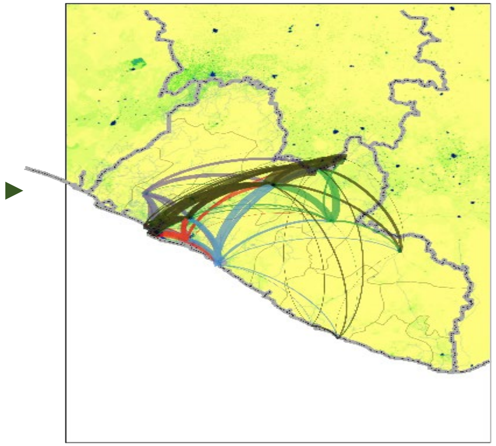




Operators Call Detail Records' (CDRs) including low-resolution location data (nearest tower location) anonymized on separate server hosted by operator.

We conduct analyses under operator supervision, anonymous raw data always behind operator firewall

Mobile operator firewall



Aggregated mobility estimates are exported and made open access - can be used with other mobility estimates, epidemiological data

Raw data never leaves mobile operator's system to avoid any privacy, commercial concerns.

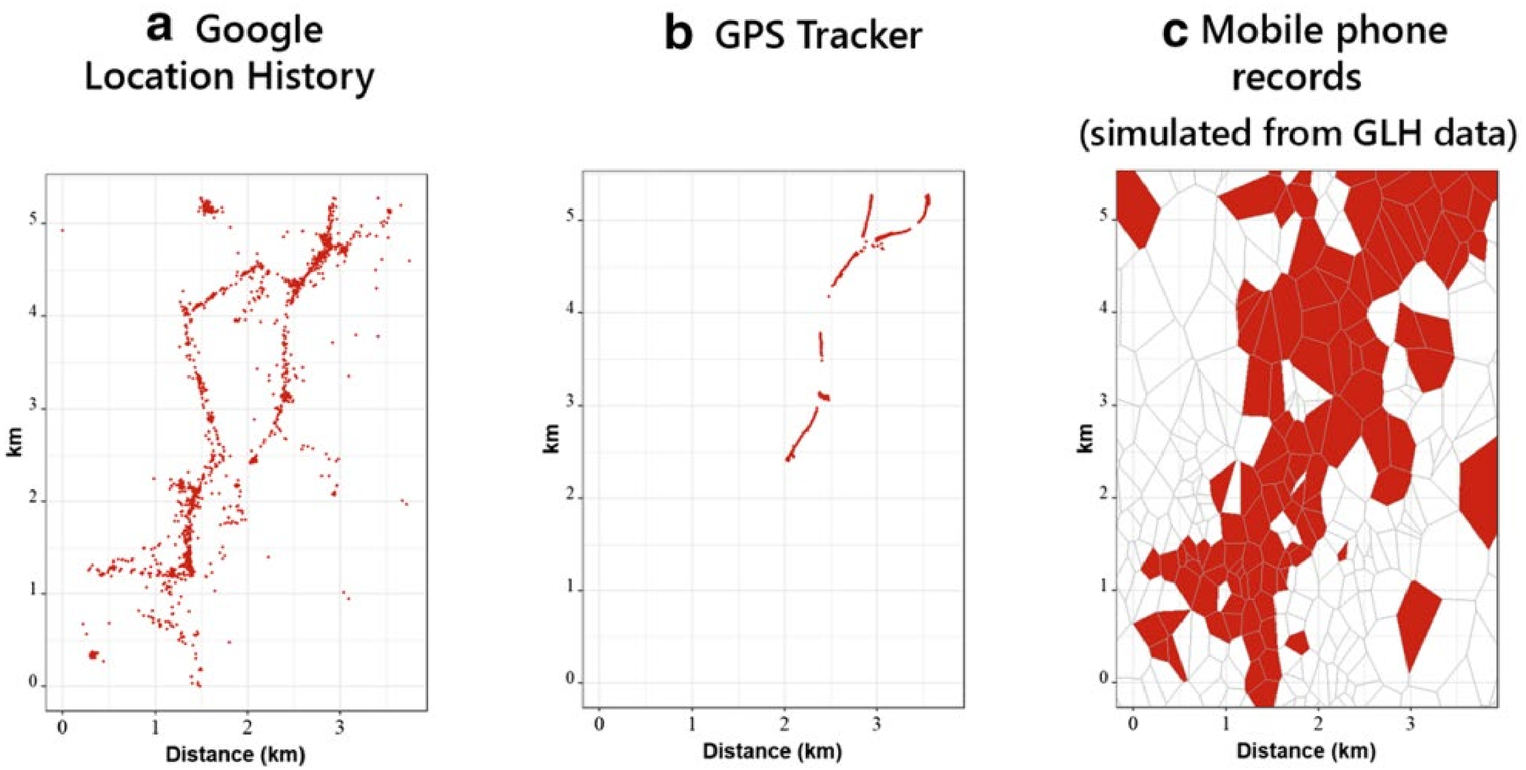
Smartphone/App-based data for measuring mobility

RESEARCH Open Access

Using Google Location History data to quantify fine-scale human mobility

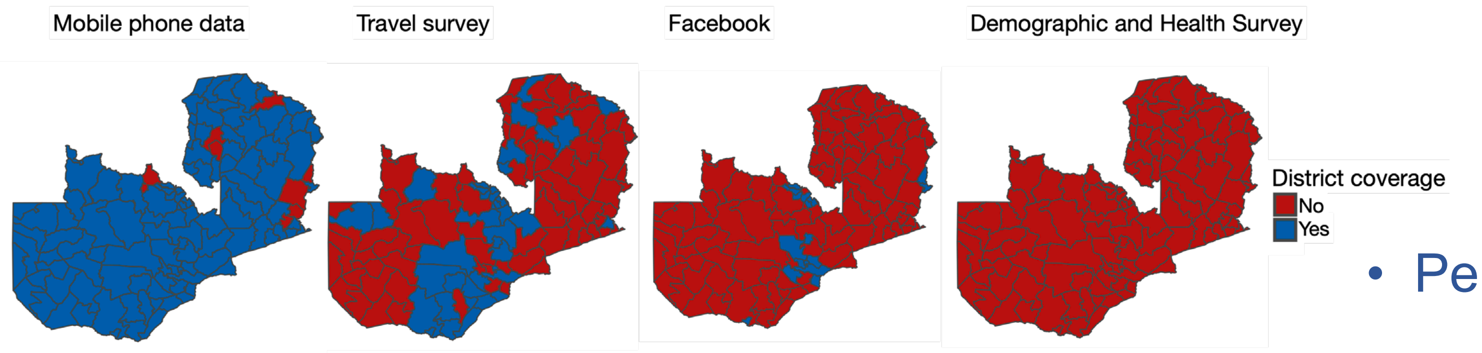
Nick Warren Ruktanonchai[1,2*], Corrine Warren Ruktanonchai[1,2], Jessica Rhona Floyd[1,2] and Andrew J. Tatem[1,2]

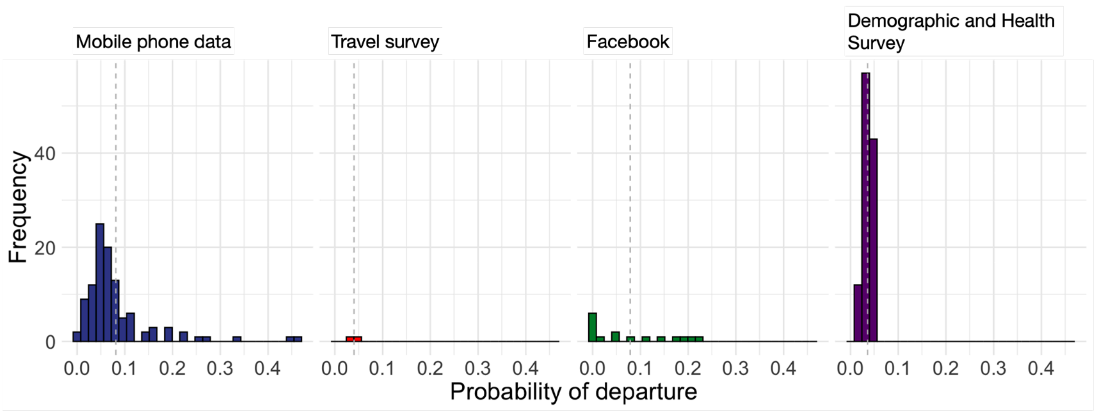
Local mobility (<5km)



Smartphone/App-based data for measuring mobility

Comparing mobility datasets for measles outbreak modelling in Zambia

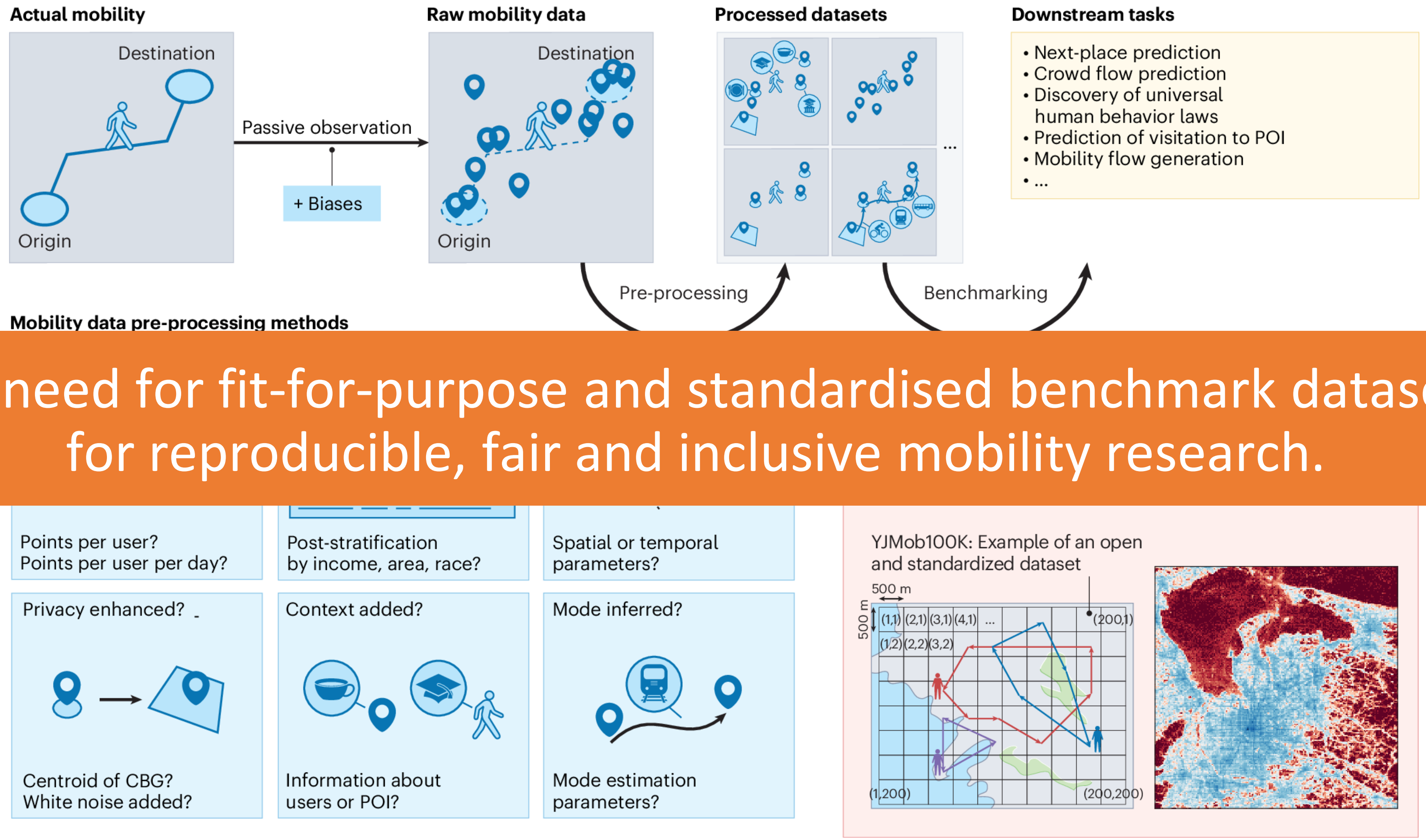




- Penetration of smartphone/internet etc.
- Local history data/APP – Android Phone
- Lack of demographical information
- Privacy protection policy/algorithms – aggregated/relative mobility metrics
- …

Natalya Kostandova, et al (submitted)

Bias introduced by data processing

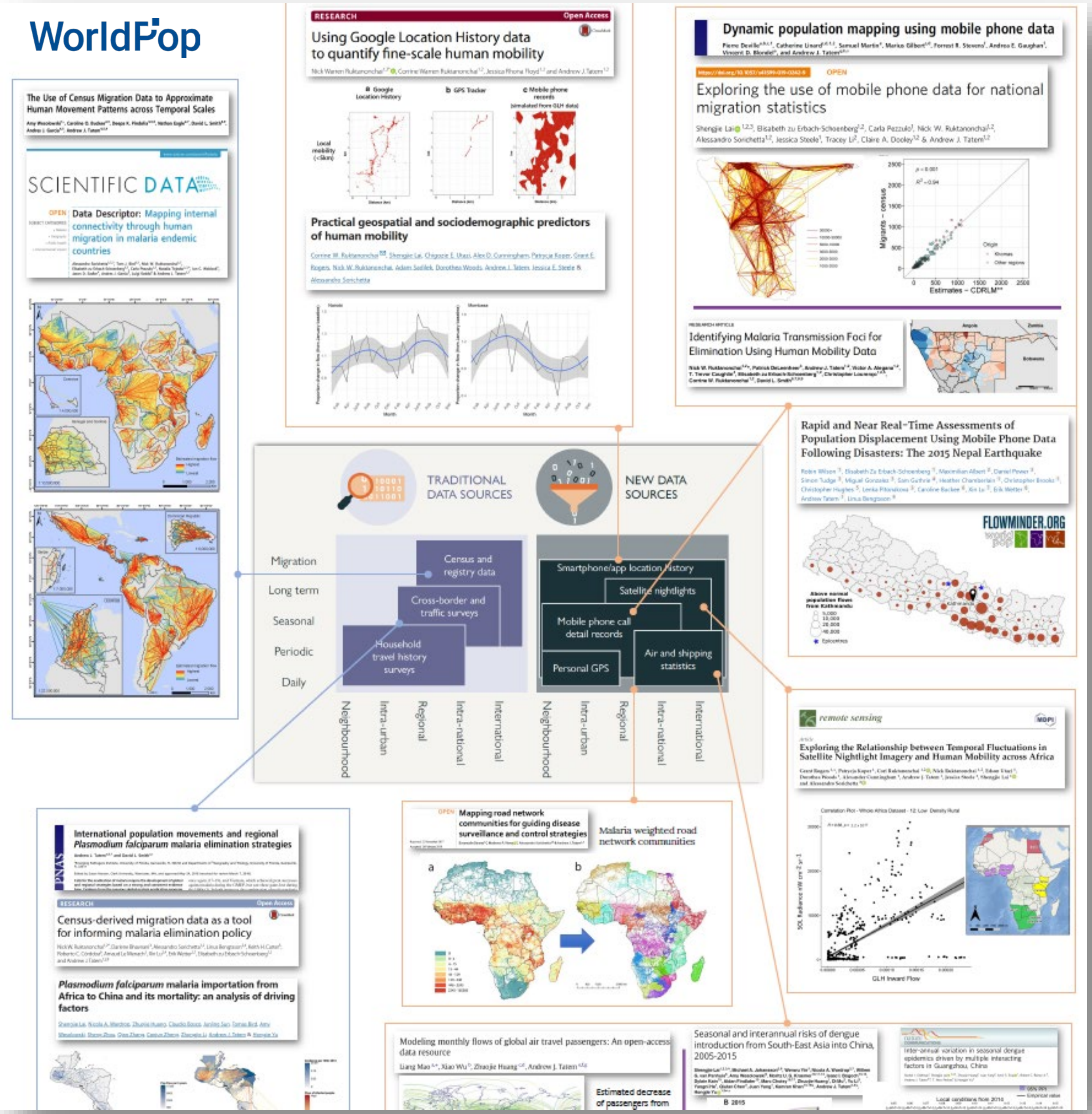


The need for fit-for-purpose and standardised benchmark datasets for reproducible, fair and inclusive mobility research.

Yabe, T *et al.* *Nature Comput Sci* (2024).

Wrap-up

- Mobile device-based geolocation data, covering a wide range of spatial scales and temporal frequencies, are increasingly useful and available for measuring human mobility and population dynamics.
- These datasets from different sources have been used in various applications such as disease control, crisis response, demographics, and development planning.
- It is important to consider privacy, data bias, and standardisation in mobile phone data processing, integration and modelling.



E-mail: Shengjie.Lai@soton.ac.uk

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