UBDC seminar, University of Glasgow

Measuring human mobility, epidemic connectivity, and intervention effectiveness

Shengjie Lai, PhD

Principal Research Fellow

WorldPop, University of Southampton, UK

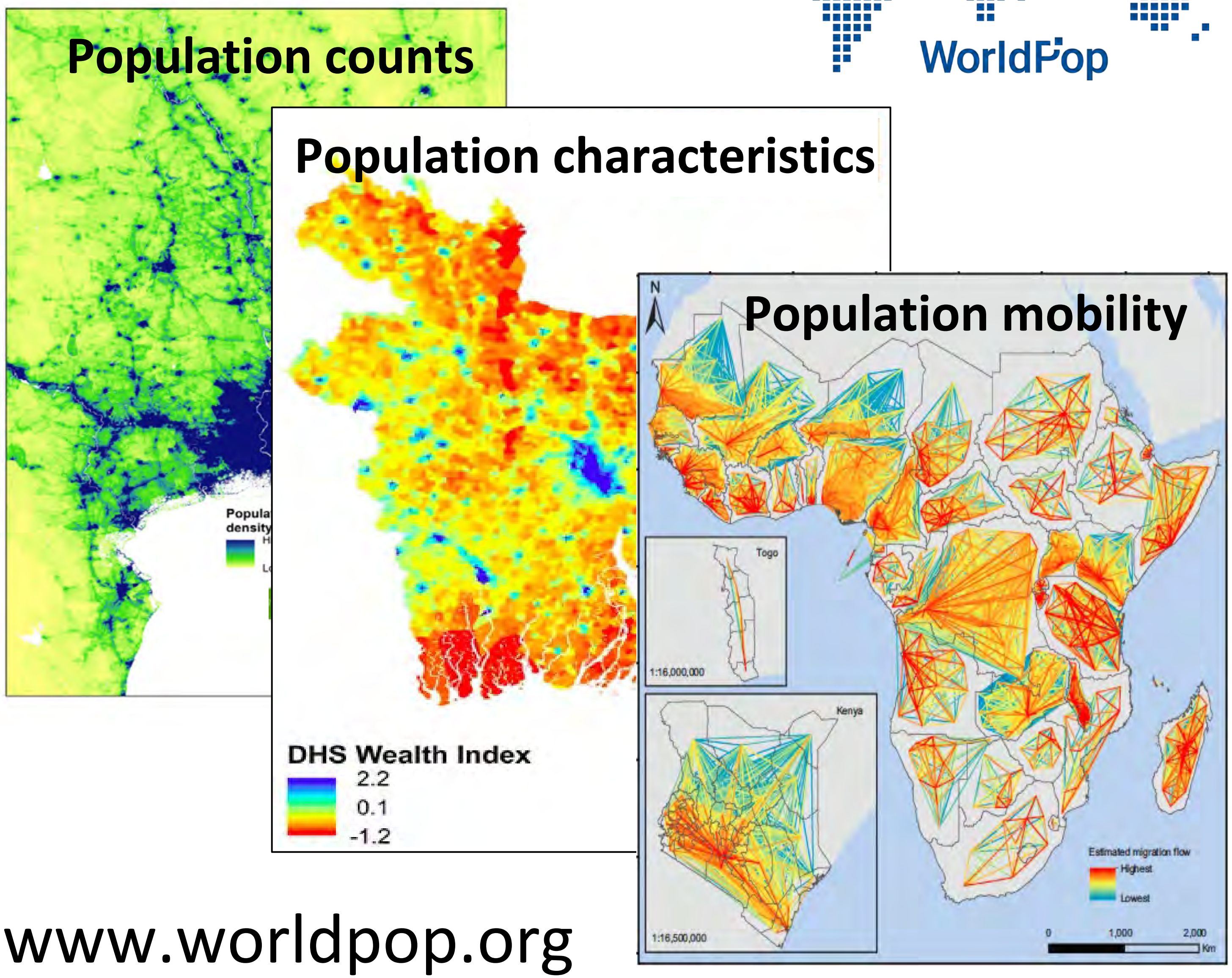
11/10/2022

WorldPop

University of Southampton

WorldPop

UNIVERSITY OF Southampton



Applied research and implementation group

30+ staff 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

www.worldpop.org

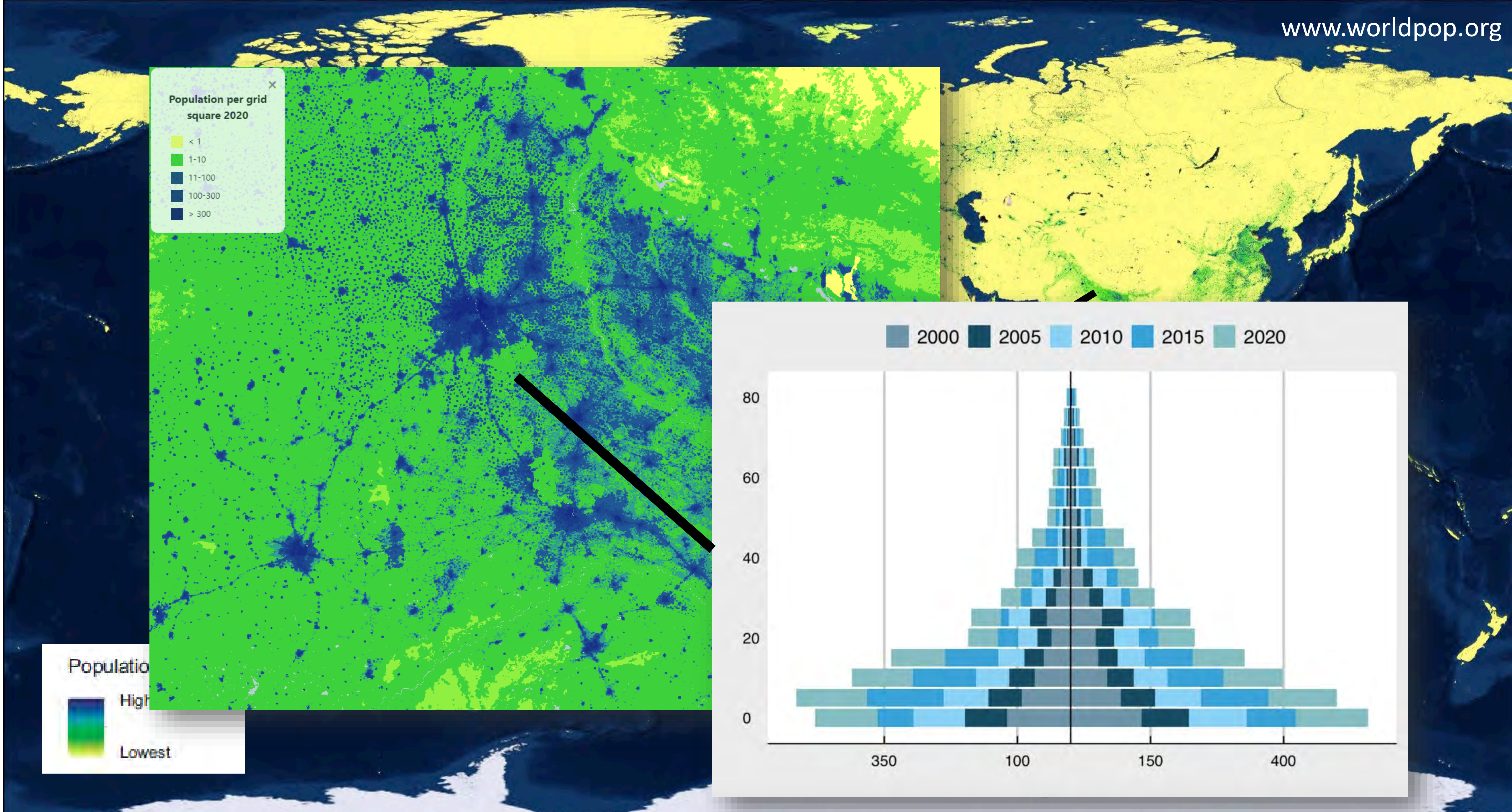
WorldPop www.worldpop.org

ABOUT | METHODS & TOOLS | NEWS | DATA | CONTACT

- POPULATION
- BIRTHS
- PREGNANCIES
- URBAN CHANGE
- AGE AND SEX STRUCTURES
- DEVELOPMENT INDICATORS
- DEPENDENCY RATIOS
- INTERNAL MIGRATION
- DYNAMIC MAPPING
- GLOBAL FLIGHT DATA
- COVARIATES
- GLOBAL SETTLEMENT GROWTH
- GRID-CELL SURFACE AREAS
- ADMINISTRATIVE AREAS

Open Spatial Demographic Data and Res

WorldPop develops peer-reviewed research and methods for the construction of open and high-resolution geosp population distributions, demographic and dynamics, with a focus on low and middle income countries.



Sorichetta et al (2017) Nature Sci Data; Gaughan et al (2017) Nature Sci Data

People don’t stay still….

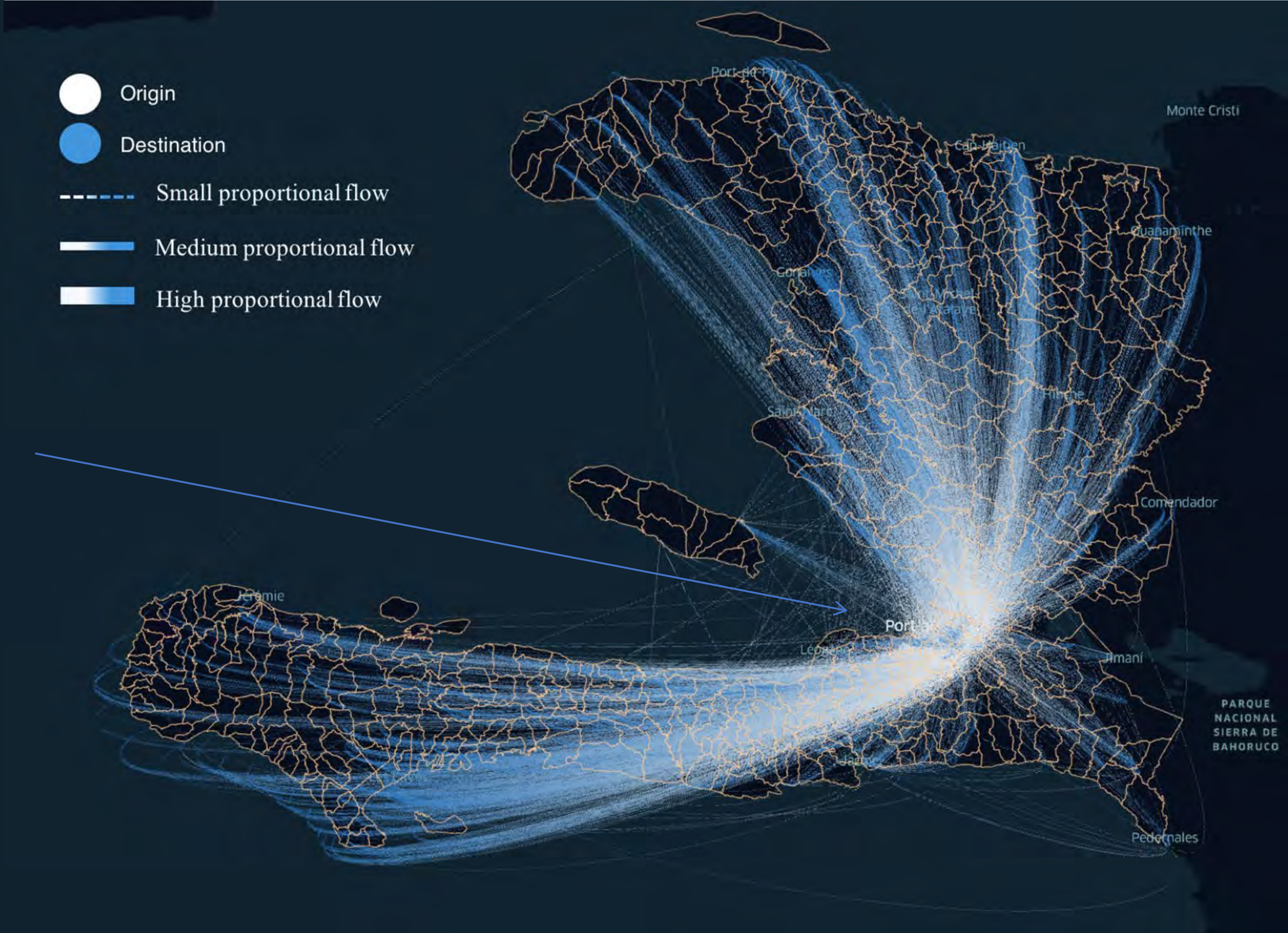
Movements via air travel in 21st century

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).

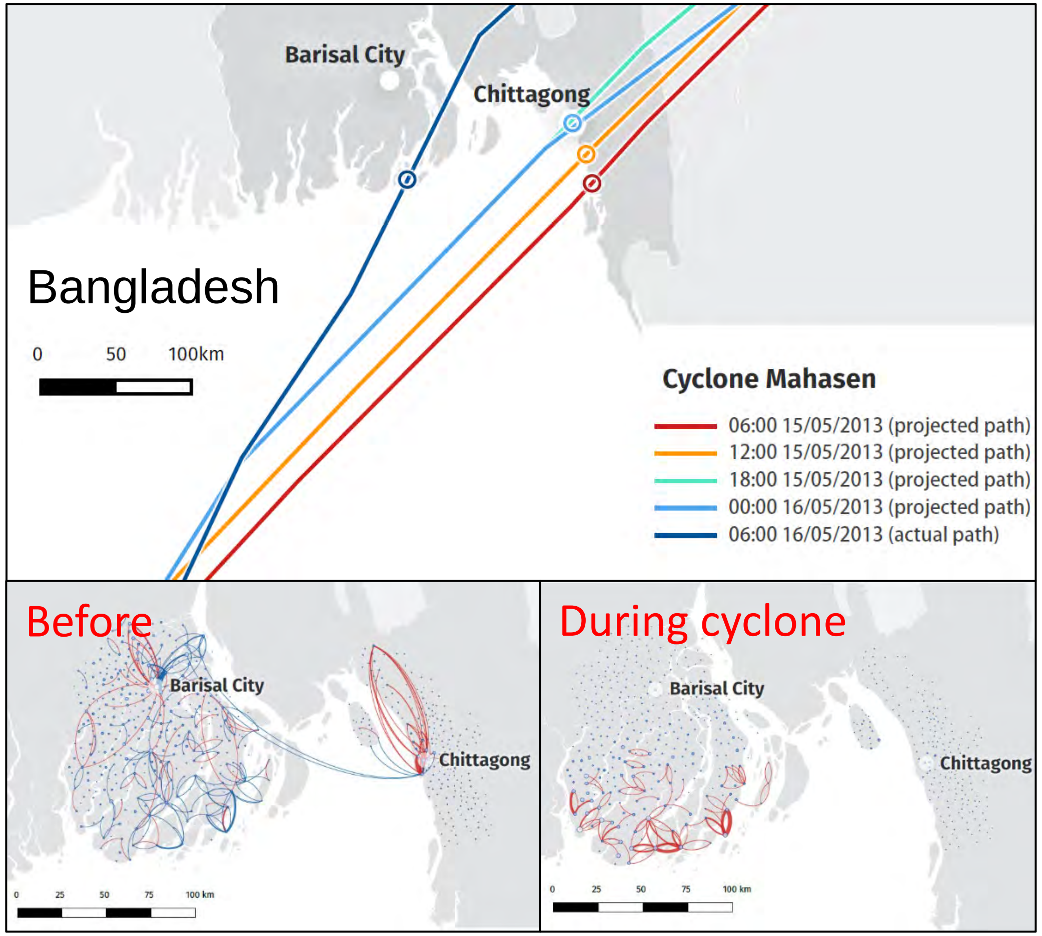


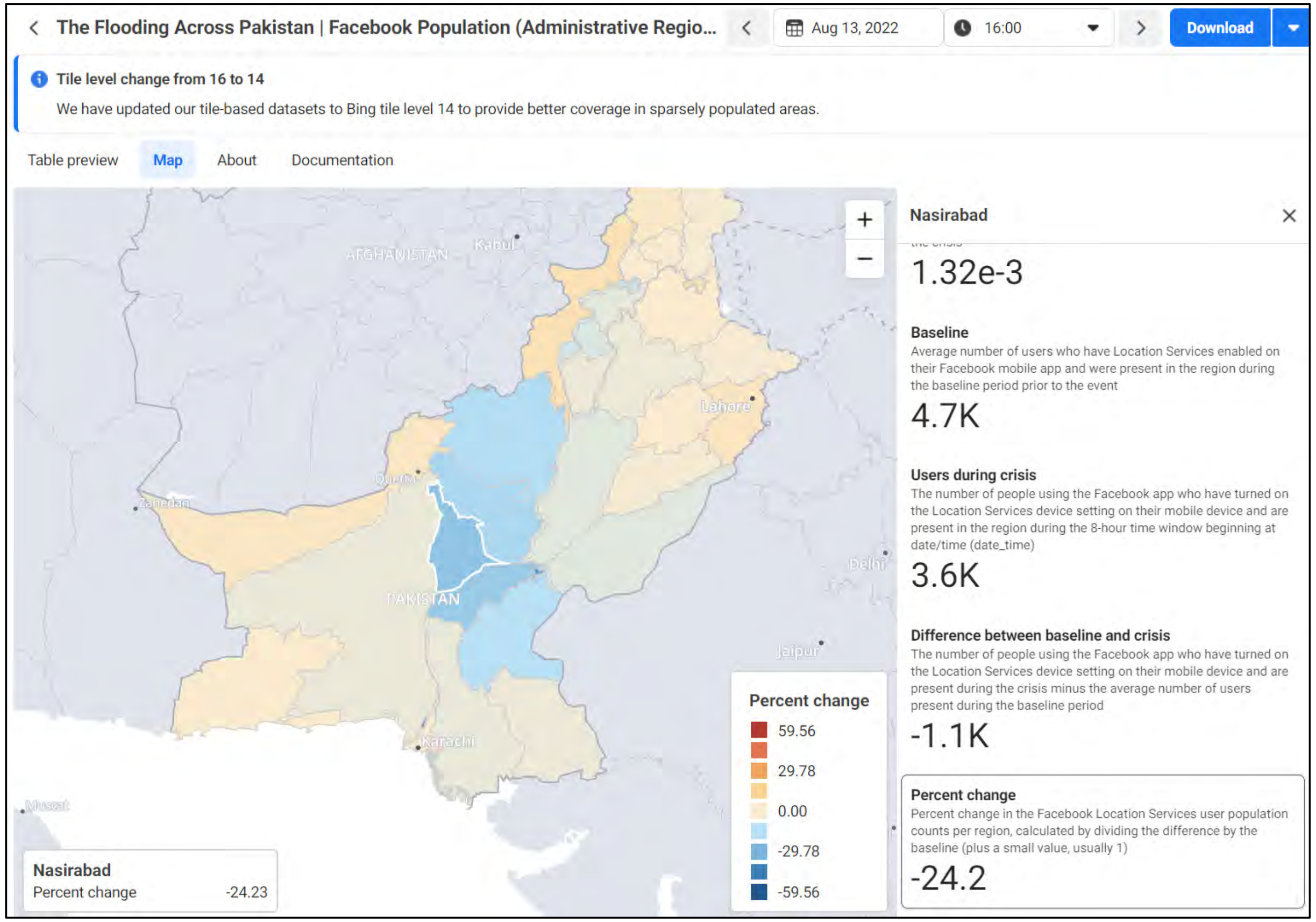
INTERNATIONAL ORGANIZATION FOR MIGRATION
IOM OIM THE UN MIGRATION AGENCY
Digicel
Funded by European Union Civil Protection and Humanitarian Aid

Jesper Dejby, Tracey Li, Maximilian Albert and Véronique Lefebvre

world pop
FLOWMINDER.ORG

Understanding mobility patterns in climate stressed regions





Lu X et al. Global Environmental Change 2016.

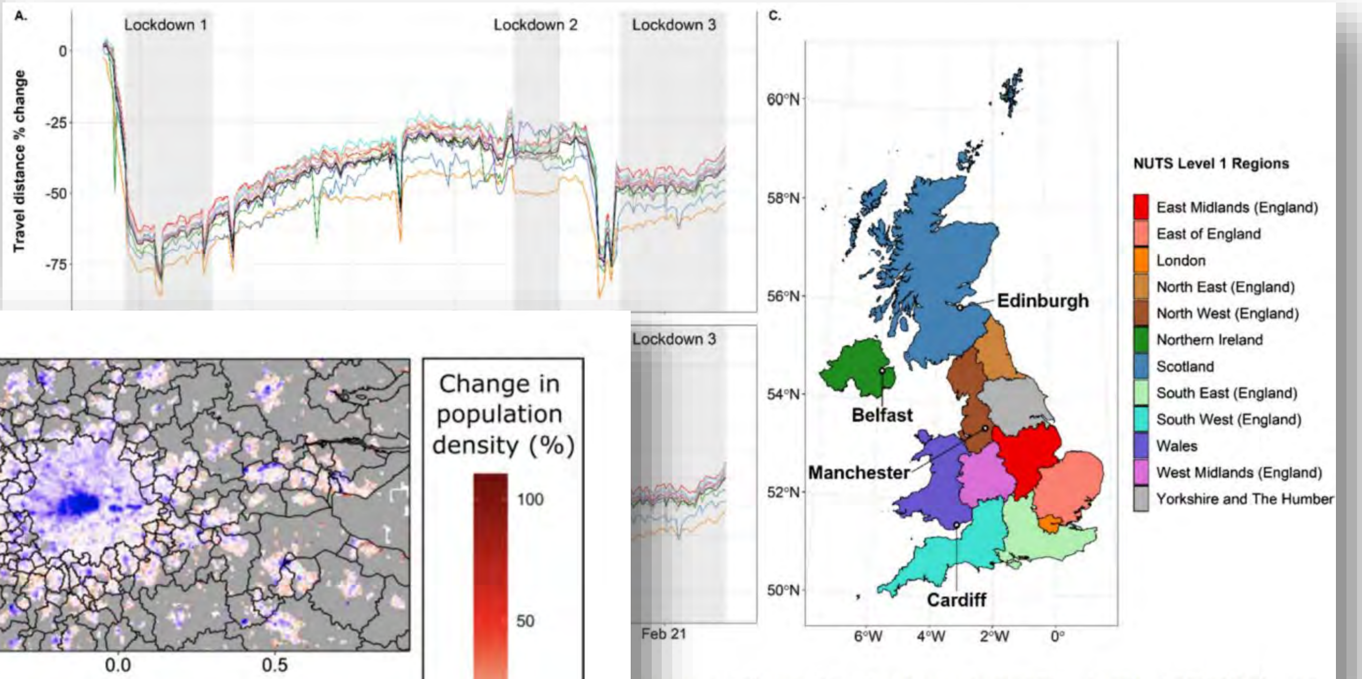
Shepherd *et al.*
International Journal of Health Geographics (2021) 20:46
https://doi.org/10.1186/s12942-021-00299-5

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*]



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

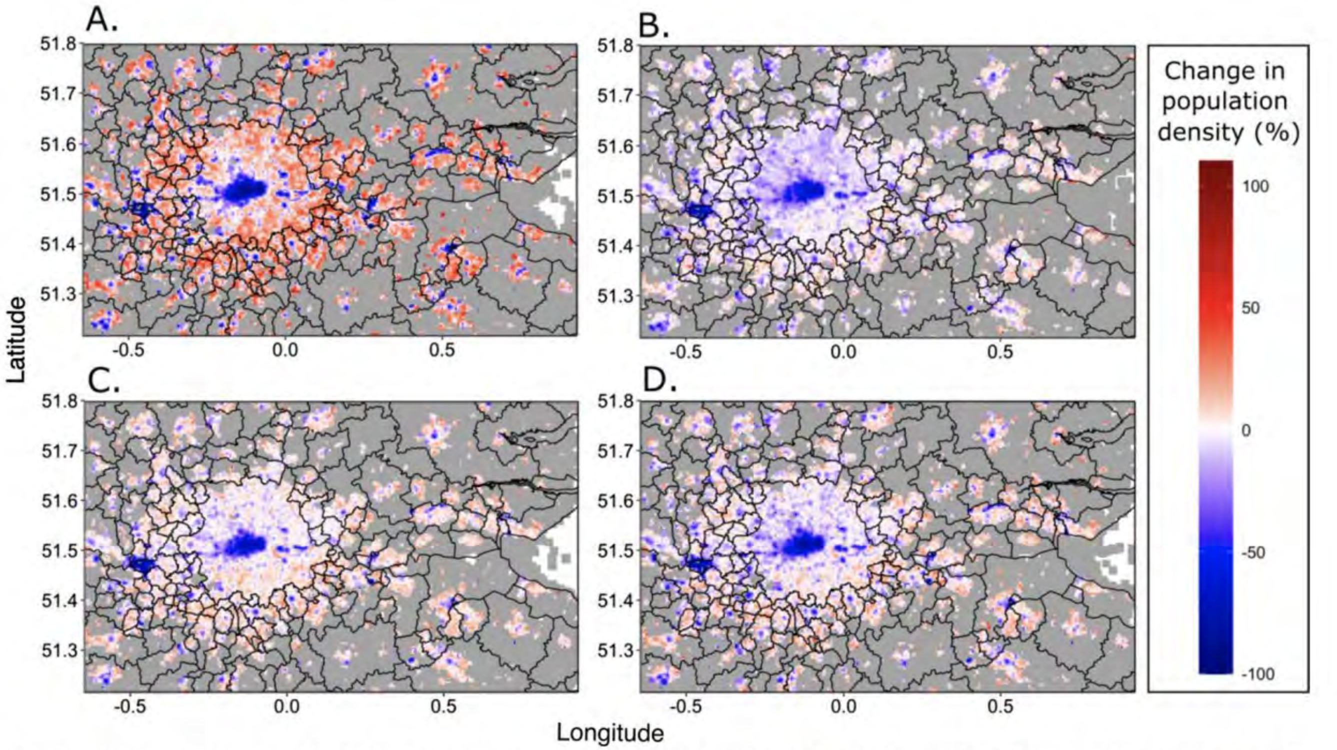
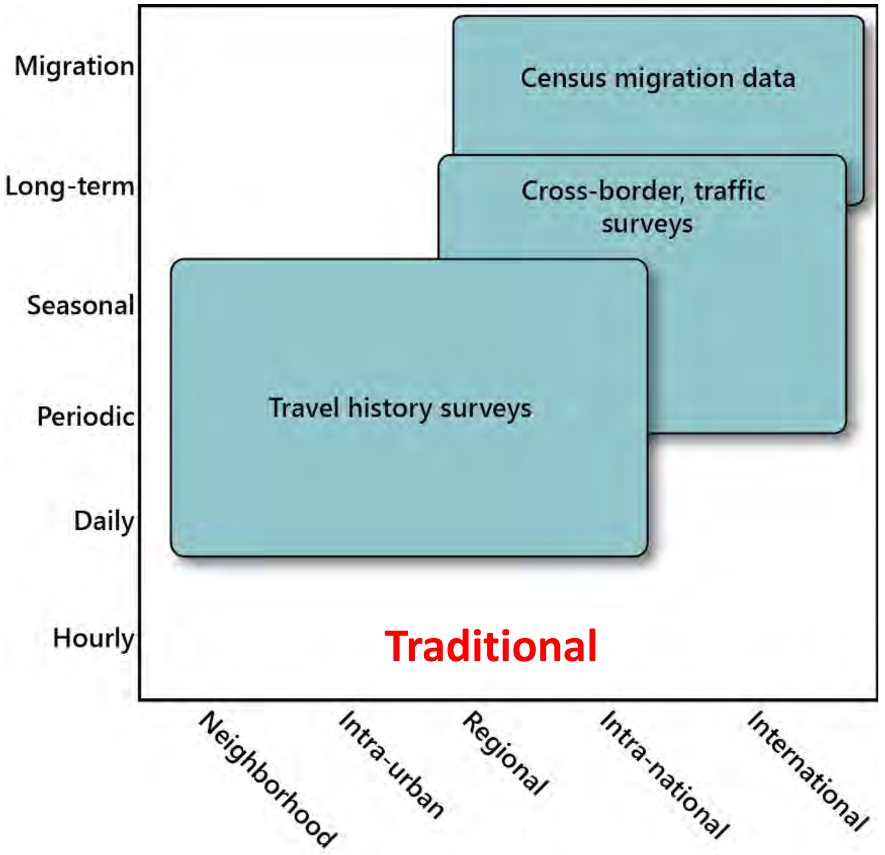


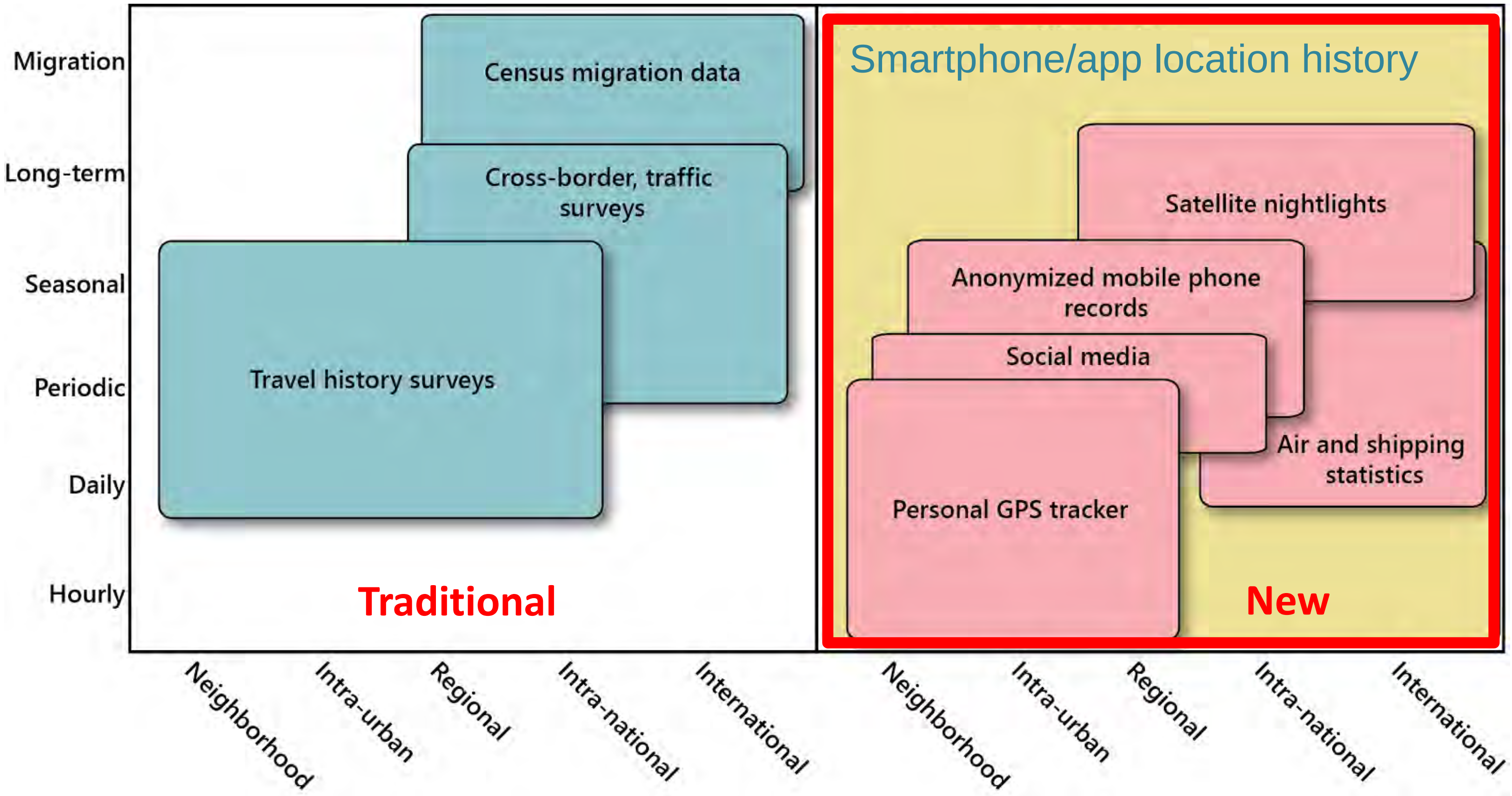
Fig. 4 Relative changes in the average population density of daytime Facebook users within London under different mobility restrictions. **A** Lockdown one (05/04/2020–12/05/2020). **B** Summer 2020 (05/07/2020–31/08/2020). **C** Lockdown two (05/11/2020—01/12/2020). **D** Lockdown three (05/01/2021–08/03/2021).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

Data sources for measuring human mobility



Lai et al (2019) JTM; Tatem (2015) International Health; Ruktanonchai et al (2018) Int J Health Geogr

Data sources for measuring human mobility



Lai et al (2019) JTM; Tatem (2015) International Health; Ruktanonchai et al (2018) Int J Health Geogr

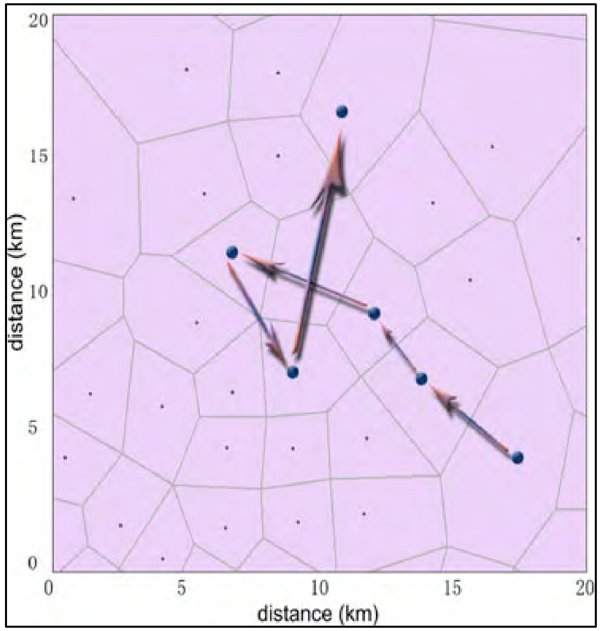
Mobile phone geo-locations

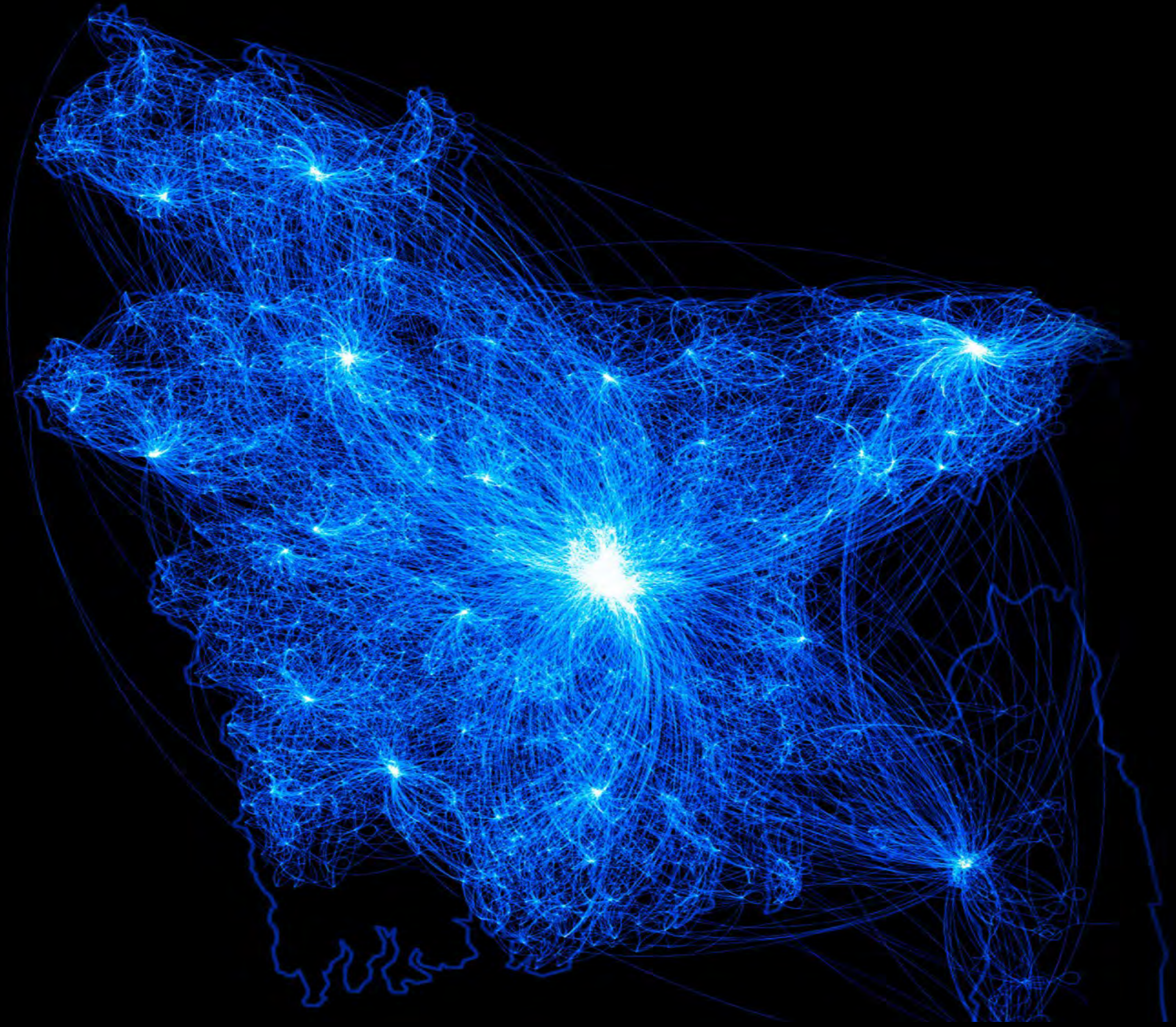
Time 1

Geolocated by nearest tower, Wi-Fi, IP address, or GPS

Time 2

Network operators record time and tower/location of call for billing, etc.





Case studies: measuring domestic migration and seasonal changes in human mobility

Mobile phone data for migration statistics

ARTICLE

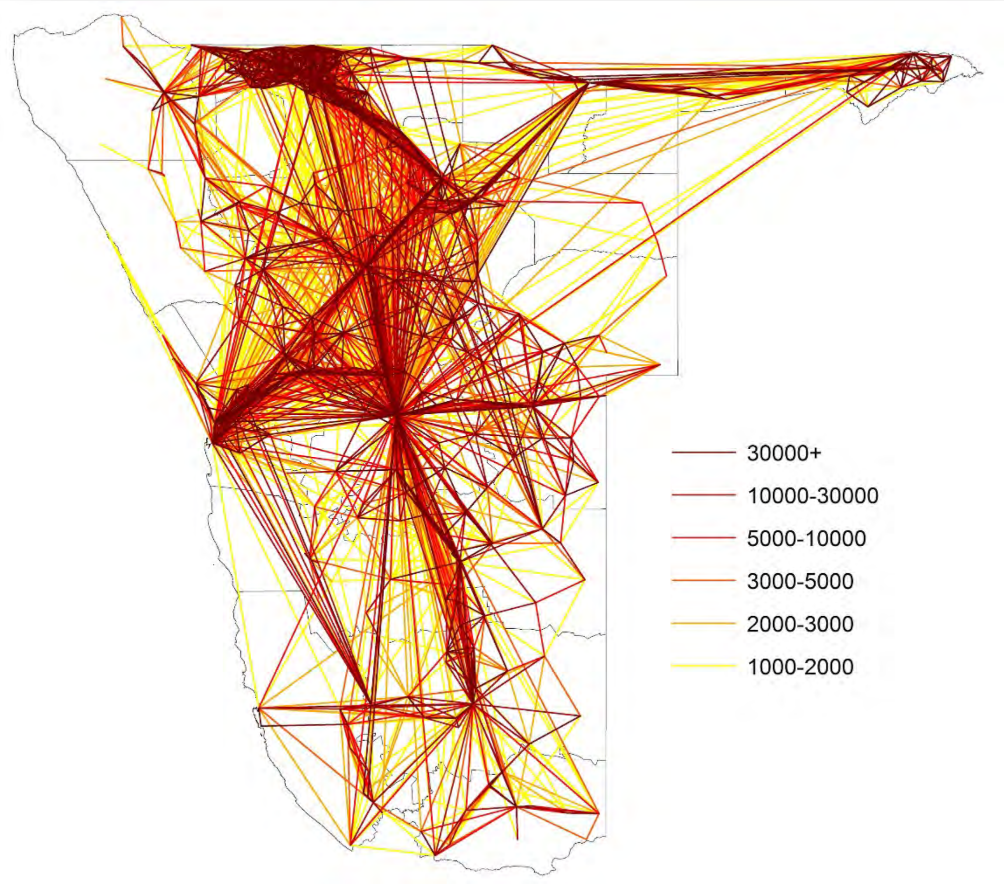
https://doi.org/10.1057/s41599-019-0242-9 OPEN

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

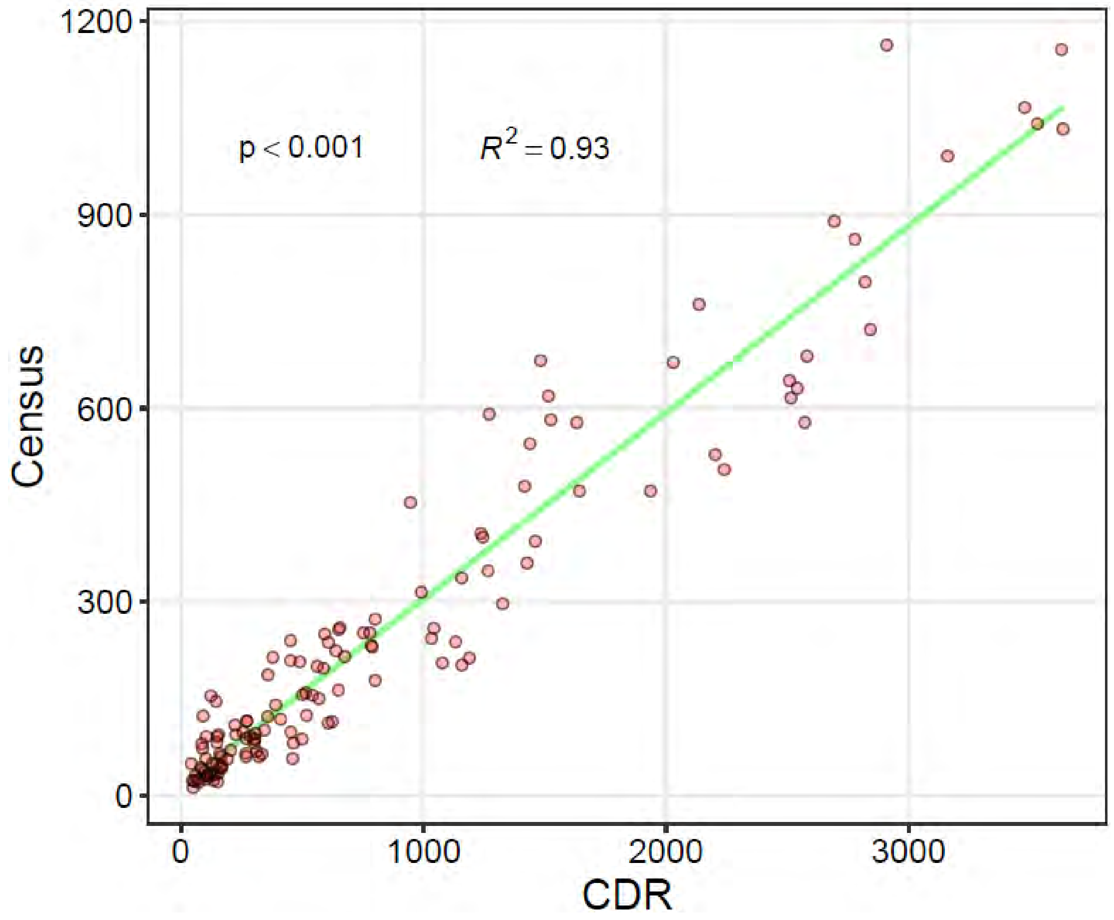


Lai S et al. *Nature Palgrave Communications 2019*

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
- **Migrant user**: A mobile phone user changed home locations between two years.

Highly correlation between CDR and census-derived migrations



Migration Prediction Models

- **CDR-based linear models (CDRLMs)**: simply using CDR-derived migrating user data alone or combined with covariates

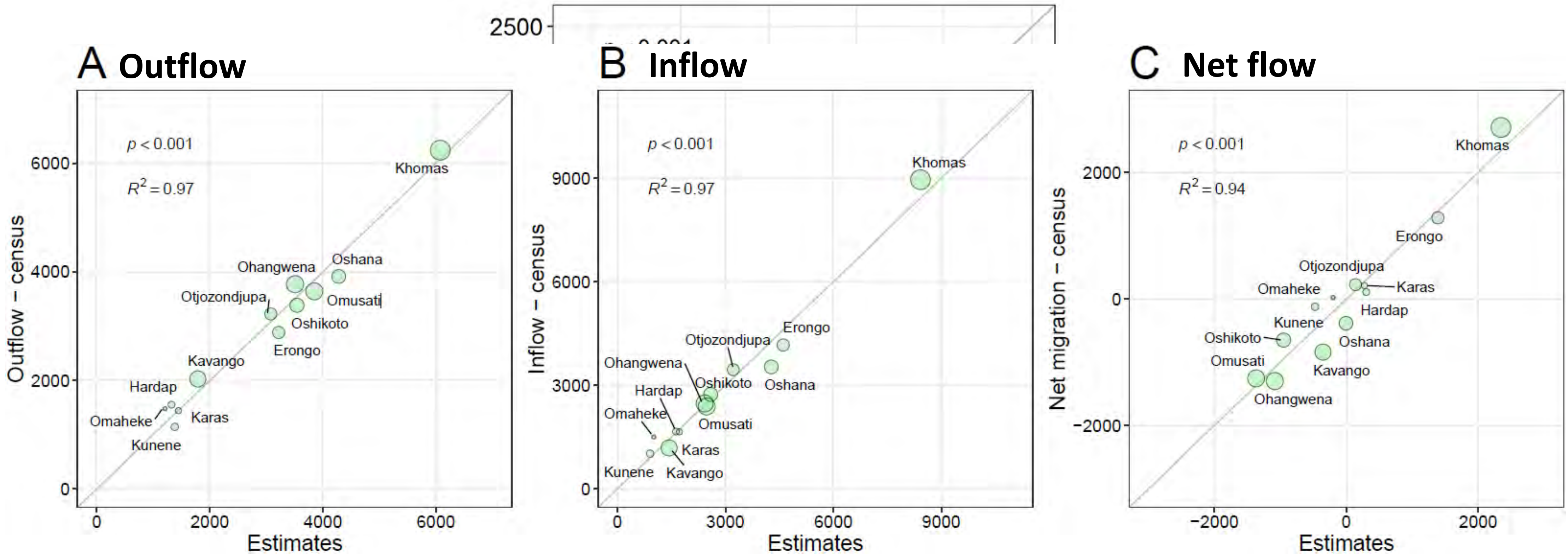
$$MIG_{i,j} = \beta_0 + \beta_1 CDR_{i,j} + \vec{\beta}[X]$$

- **Validation and goodness-of-fit indicators**: we used a leave-one-out-cross-validation (LOOCV) approach to calculate the root-mean-square error (RMSE). The model with the lowest RMSE was determined as the best model.

Type	Model	Independent variables	
		CDRs	Other variables
CDR-based linear model (CDRLM)	1	Yes	None
	2		$+ POP_i + POP_j + DIST_{i,j}$
	3[a]		$+ URBAN_i + URBAN_j + DIST_{i,j}$
	4		$+ RAIN_i + RAIN_j + DIST_{i,j}$

POP_i and POP_j : Population of origin i and destination j.
$URBAN_i$ and $URBAN_j$: Proportion of population living in urban areas.
$RAIN_i$ and $RAIN_j$: Annual average precipitation (mm).
$DIST_{i,j}$: Euclidean distance between centroids of origin i and destination j.
[a] Optimal model of each model family for regions except Zambezi, based on the lowest root-mean-square error (RMSE).

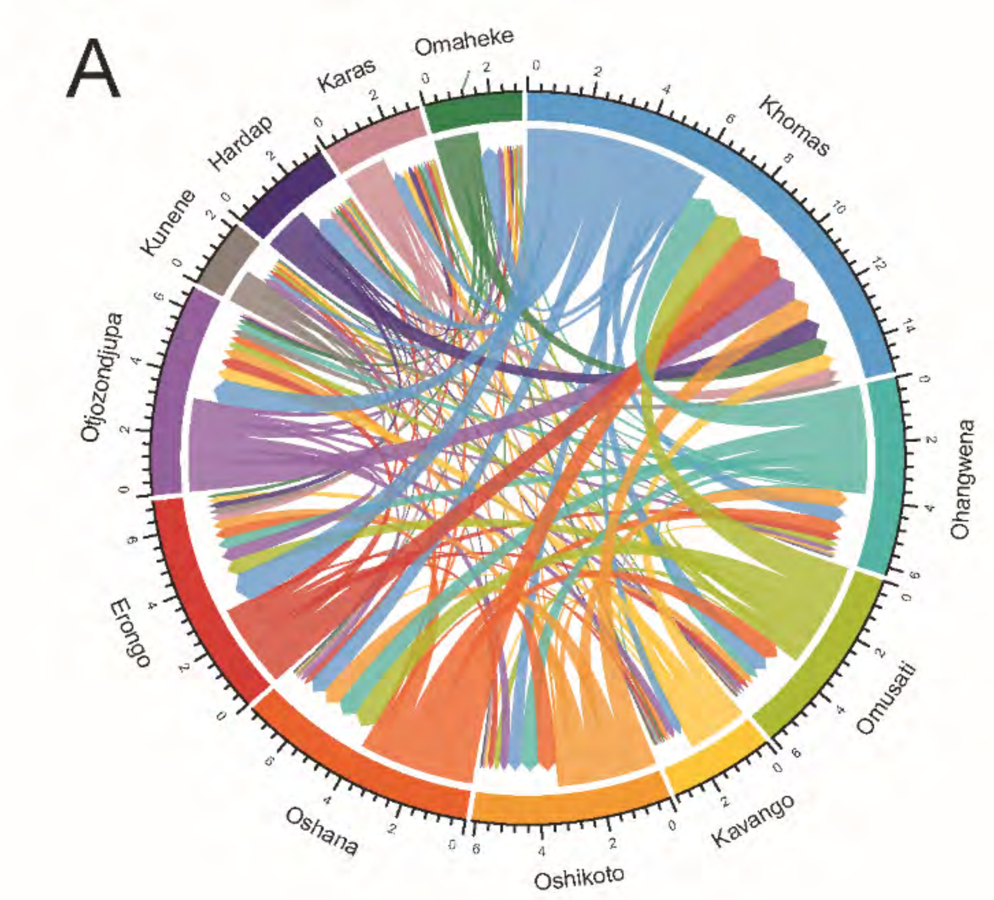
CDRLM vs Census-derived migration



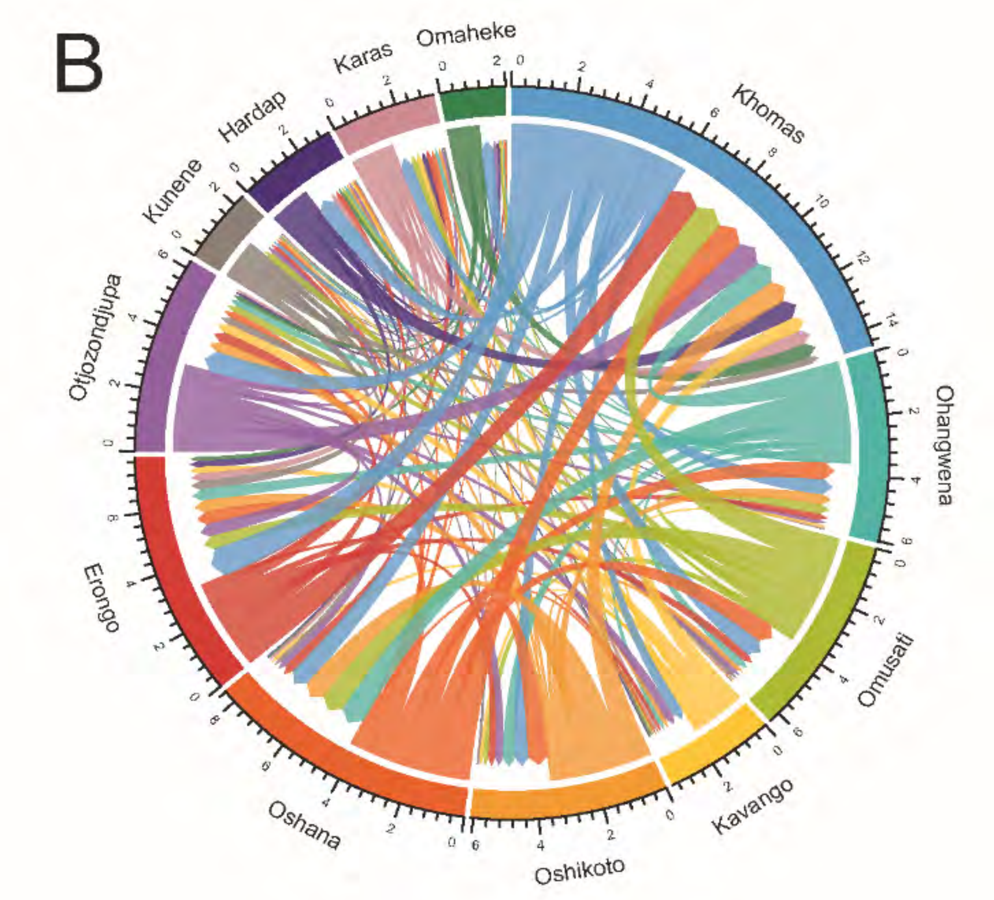
Based on the optimal model with the lowest RMSE

CDRs and census data show very similar migration patterns

Census

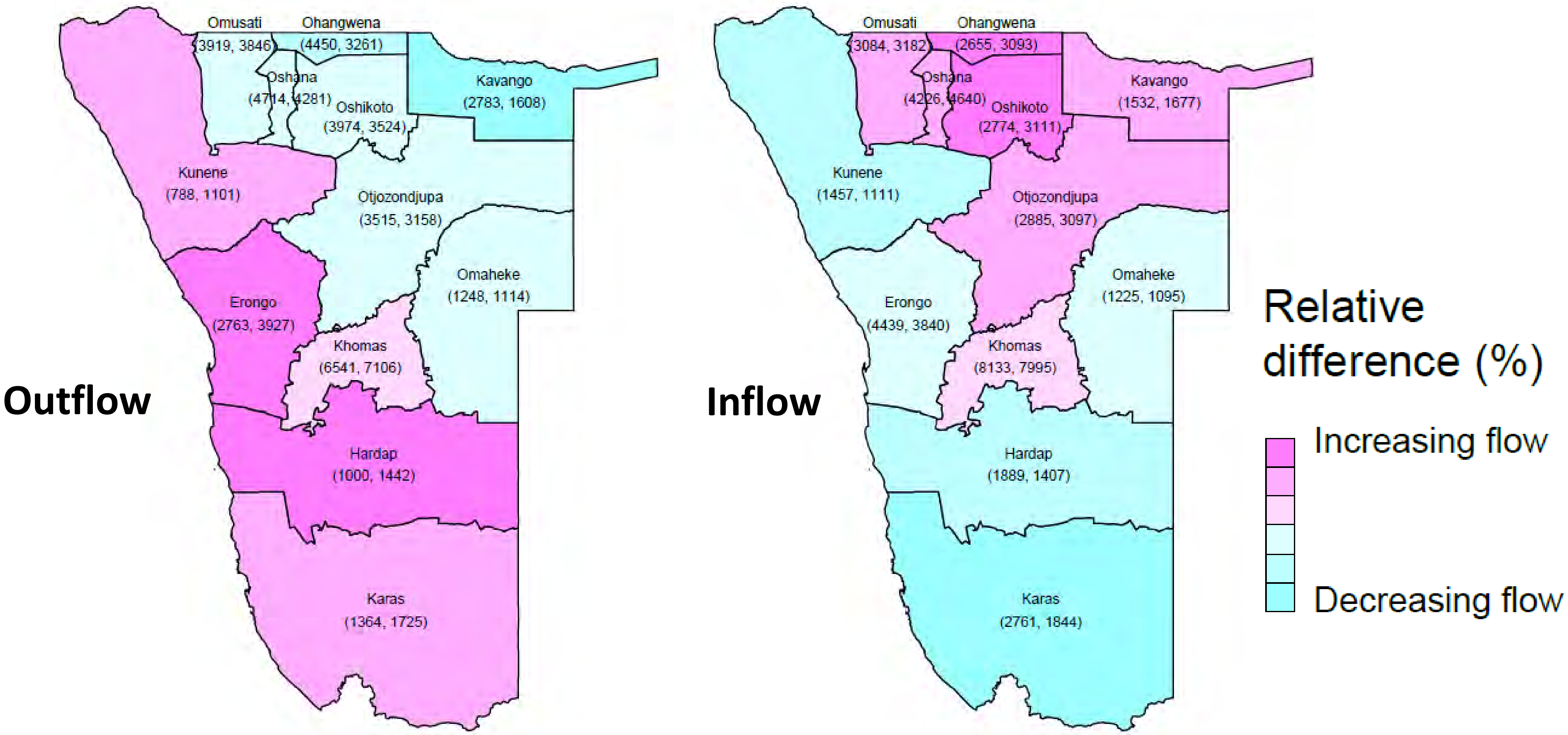


CDRLM



Note: The Zambezi region as an outliner is excluded.

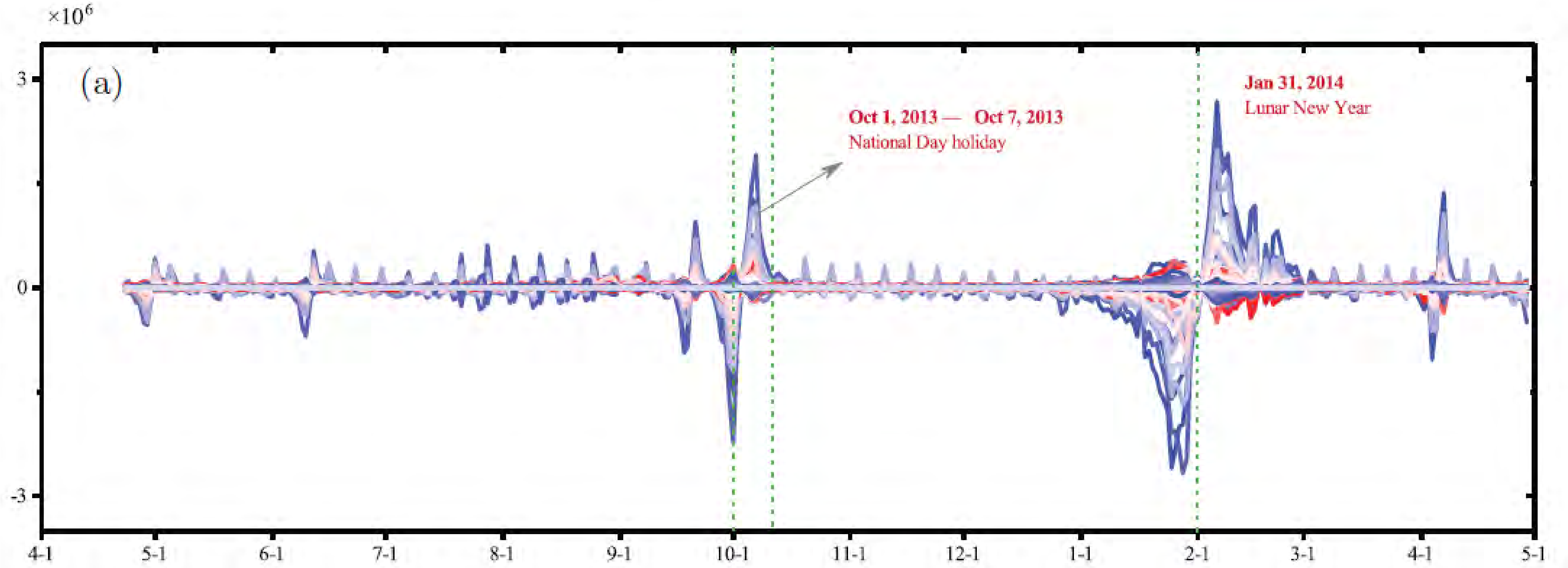
Updating migration statistics across years



Migrants departing and arriving in 2012 compared to 2011

The Zambezi region as an outliner is excluded.

Seasonal movements

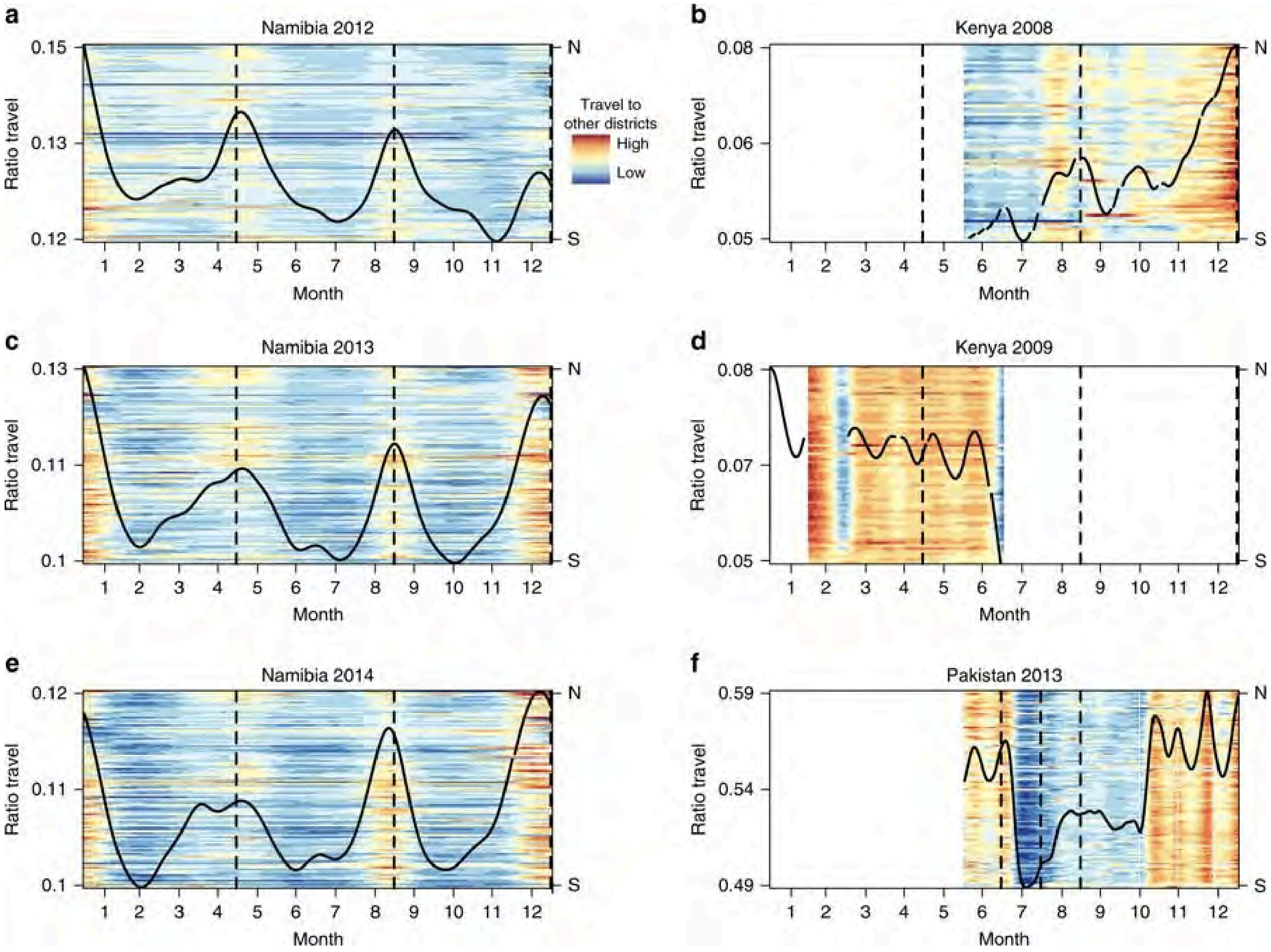


Temporal patterns of population flows in China in from April 23, 2013 to April 30, 2014.

Each curve represents the change of the net population flow in a prefecture (~340 prefectures in China).

Song et al. International Journal of Modern Physics C 2021.

Mobility change over time in other countries



nature COMMUNICATIONS

ARTICLE

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

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

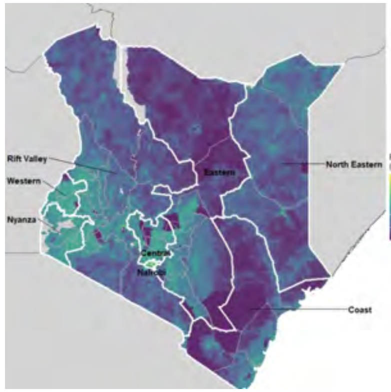
Amy Wesolowski[1], Elisabeth zu Erbach-Schoenberg[2,3], Andrew J. Tatem[2,3], Christopher Lourenço[2,4], Cecile Viboud[5], Vivek Charu[5], Nathan Eagle[6], Kenth Engø-Monsen[7], Taimur Qureshi[7], Caroline O. Buckee[6,8] & C.J.E. Metcalf[9,10]

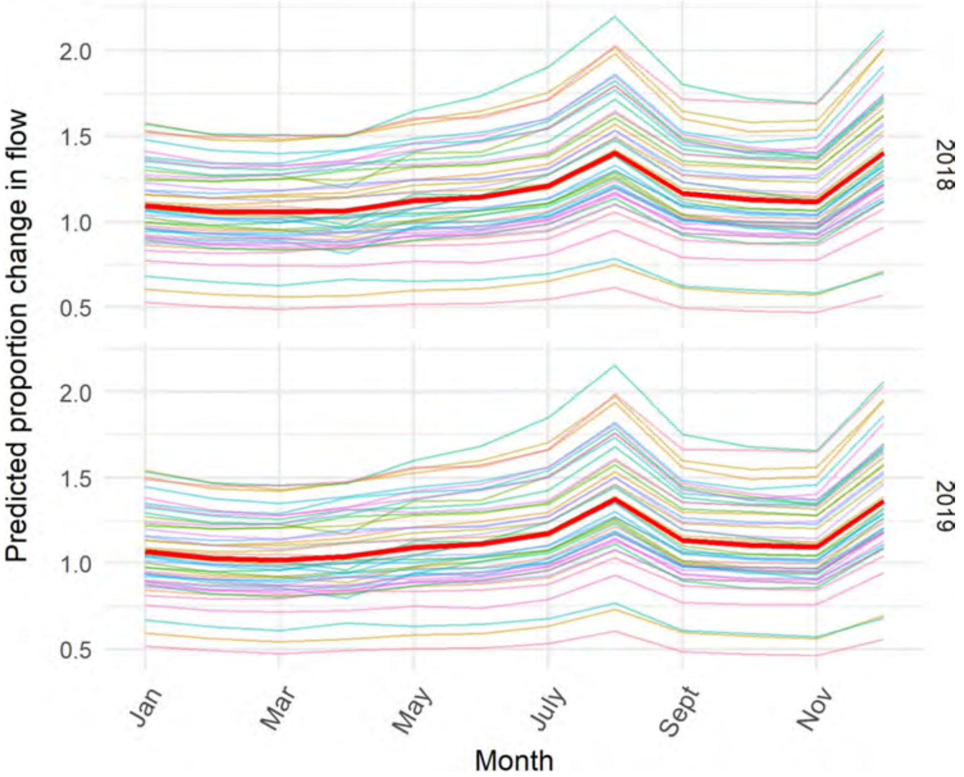
Article | Open Access | Published: 28 July 2021

Practical geospatial and sociodemographic predictors of human mobility

Corrine W. Ruktanonchai, Shengjie Lai, Chigozie E. Utazi, Alex D. Cunningham, Patrycja Koper, Grant E. Rogers, Nick W. Ruktanonchai, Adam Sadilek, Dorothea Woods, Andrew J. Tatem, Jessica E. Steele & Alessandro Sorichetta

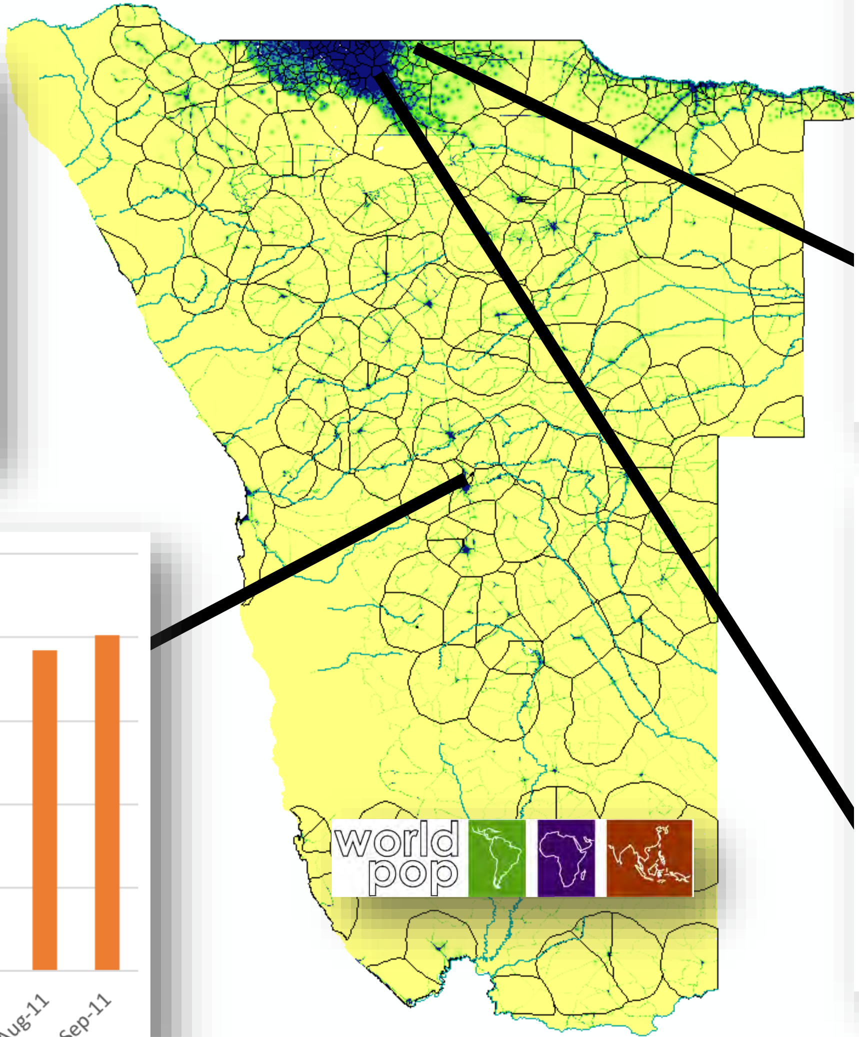
$$\log(y_{it}) = \beta_0 + A_i + B_t + C_{it} + X'_{it}\beta + \epsilon_{it}$$

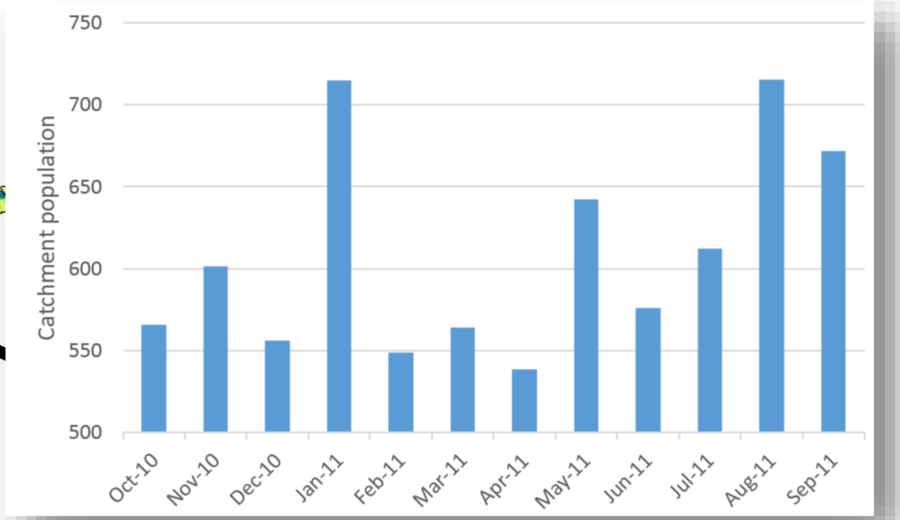


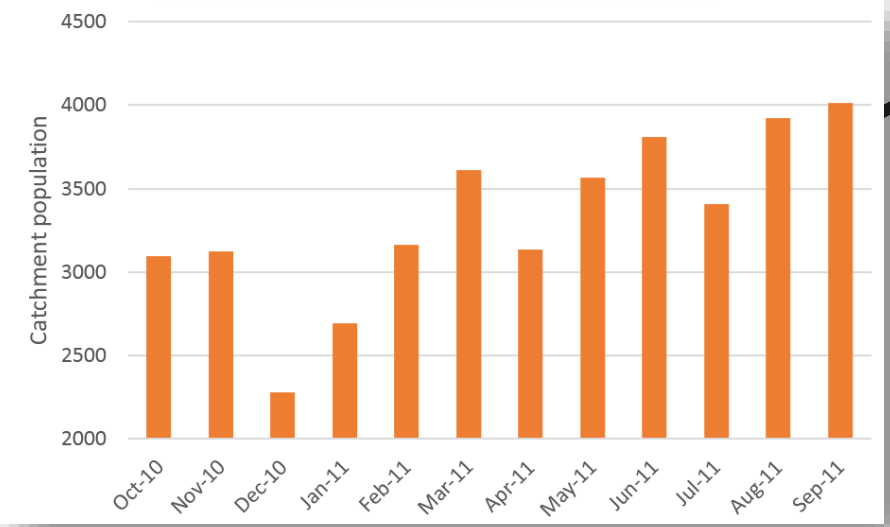


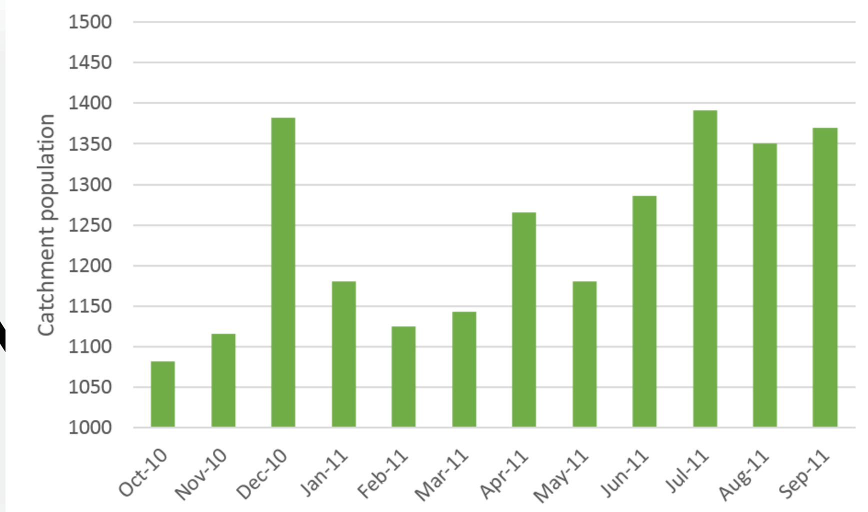
Covariate
% population living in urban extent
% people living in povertyy[1]
% women with no primary education
Travel time (minutes) to the nearest urban centre[2]
school holidays (days)
Aridity index
Enhanced Vegetation Index (EVI)
Precipitation (mm)[3]
Temperature (°C)[3]
VIIRS Night-time lights

Mobility impacts: Intervention/Healthcare demands









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

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]

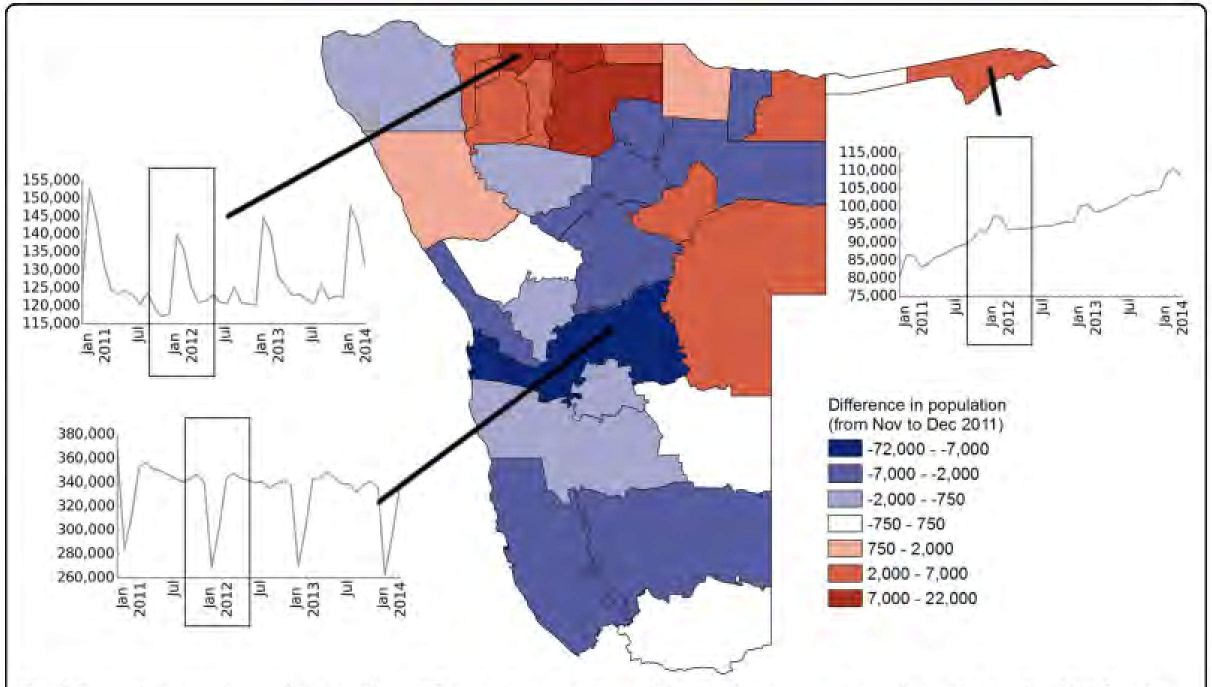
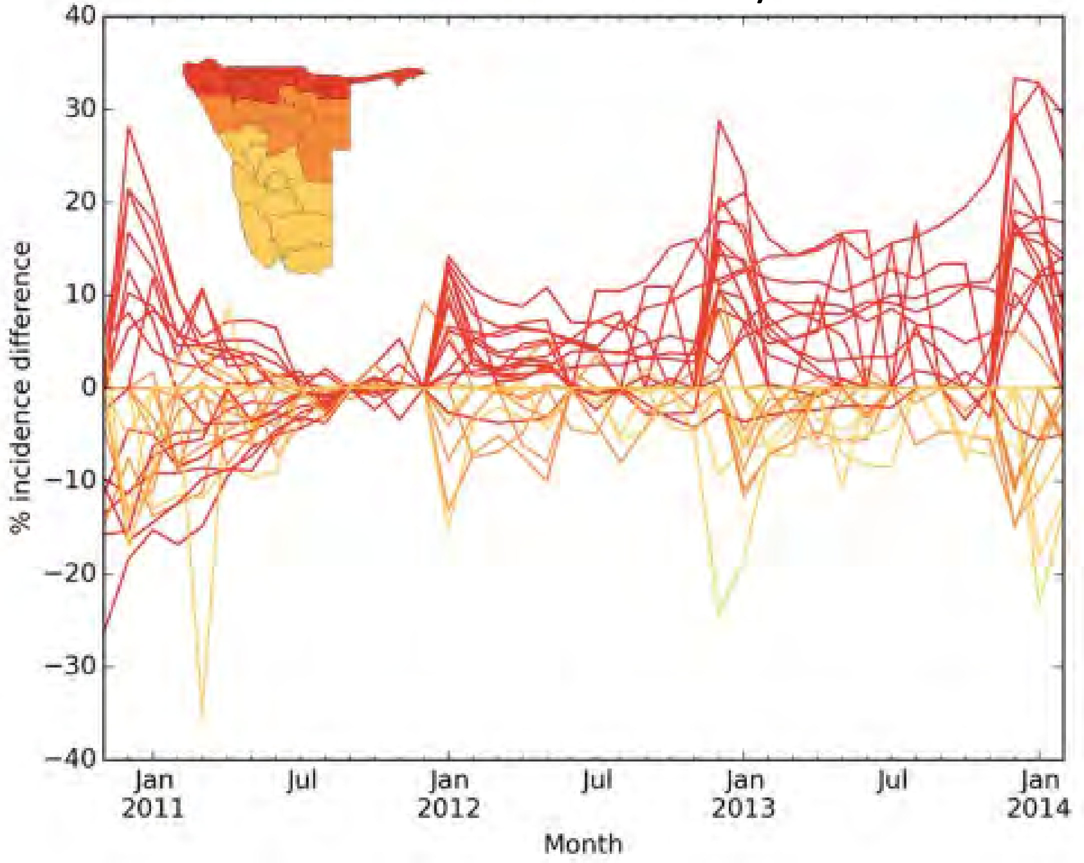


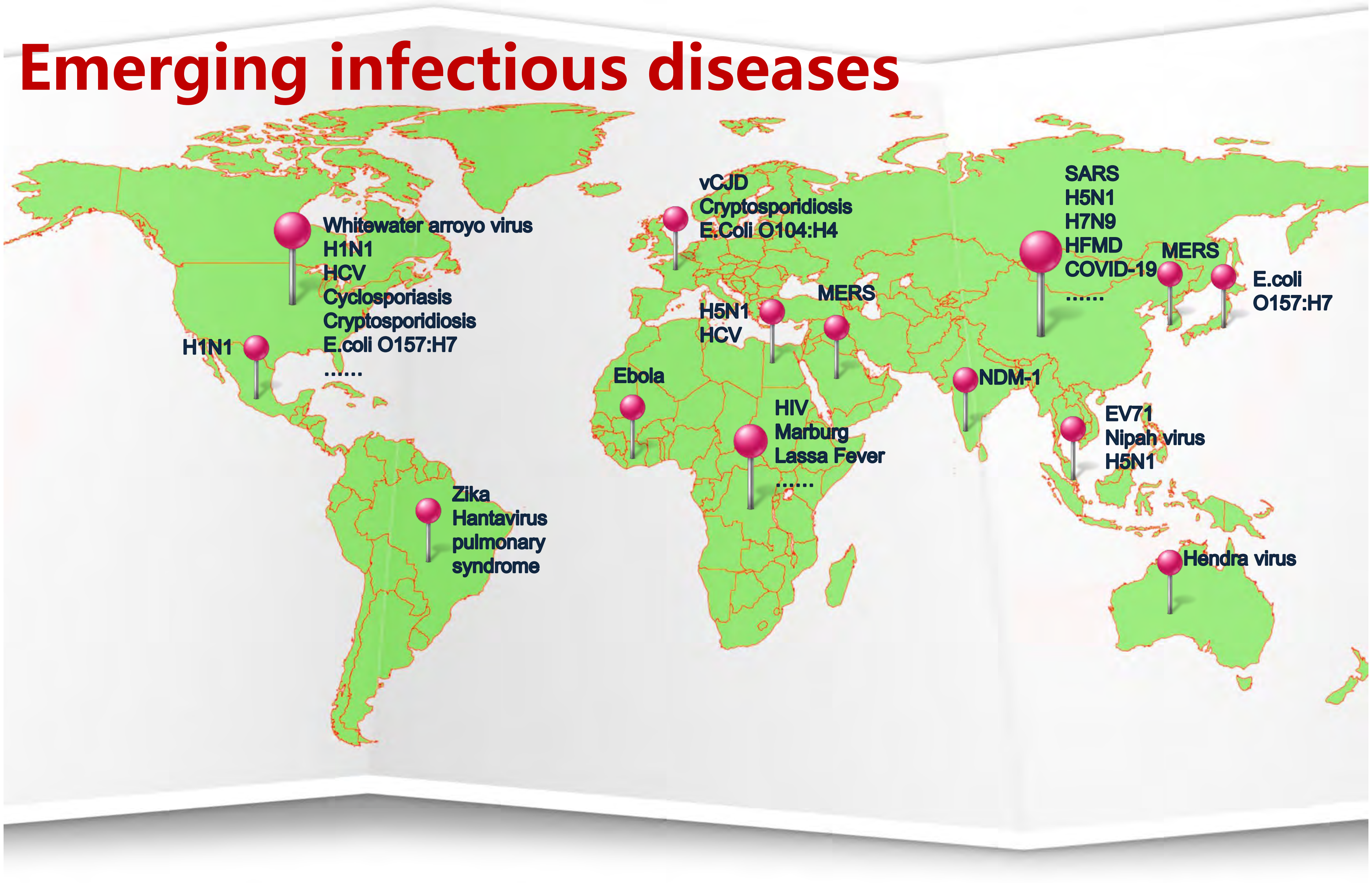
Fig. 4 Seasonal changes in population numbers: Difference in predicted population number between November and December 2011 for each health district. Insets show predicted population number for selected health districts over the whole study period

Mobility impacts: Health metrics

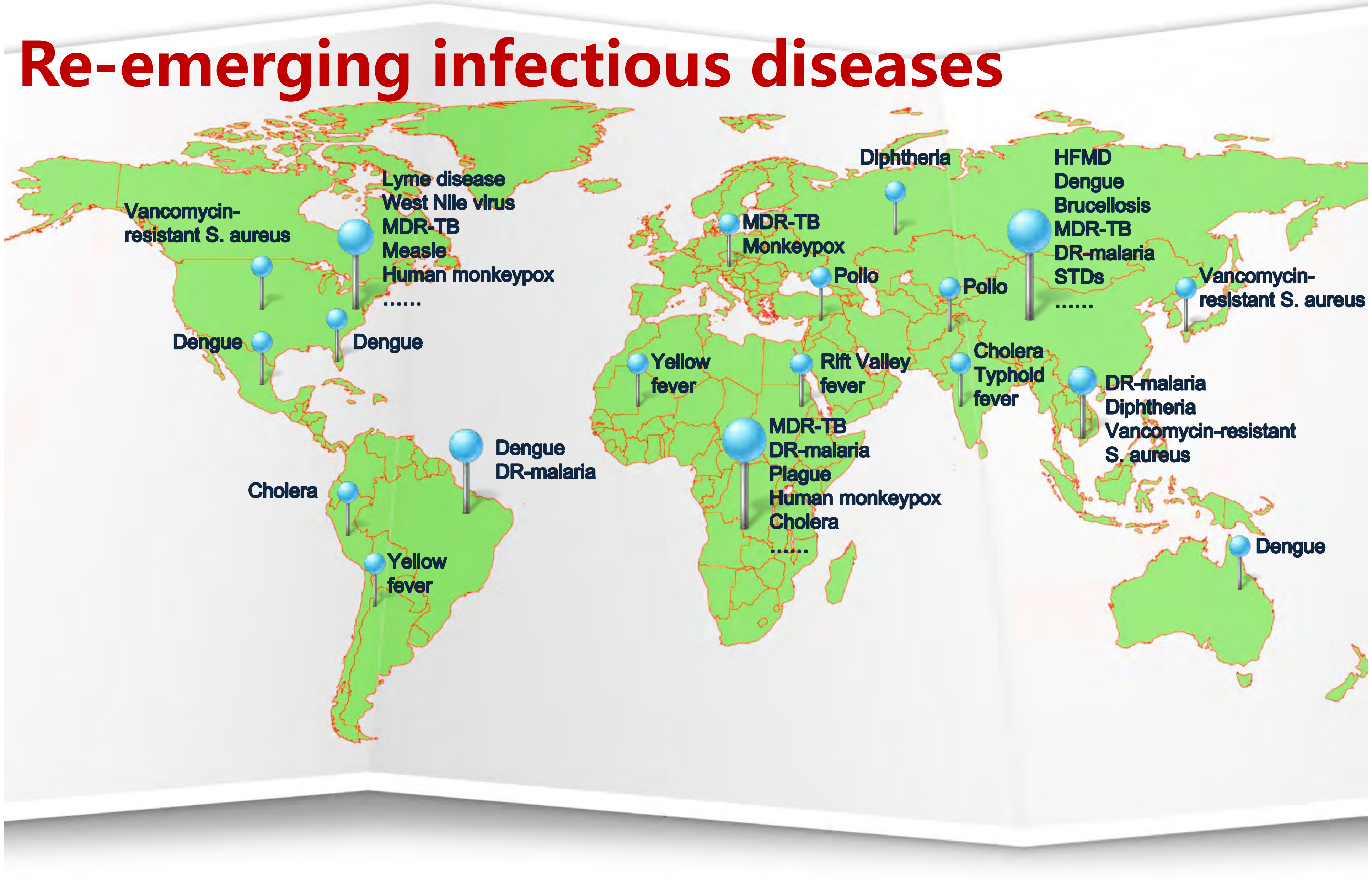
% incidence difference by district



Mobility impacts: Transmission dynamics

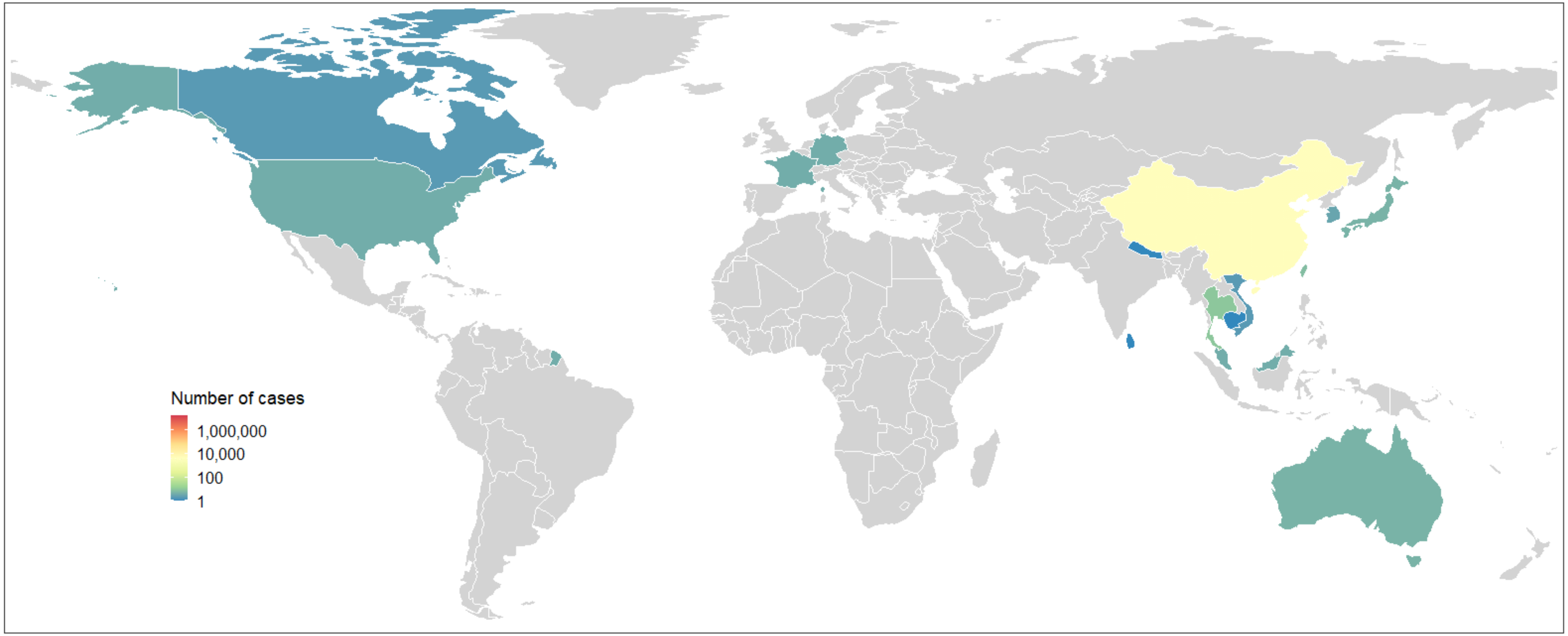


Mobility impacts: Transmission dynamics



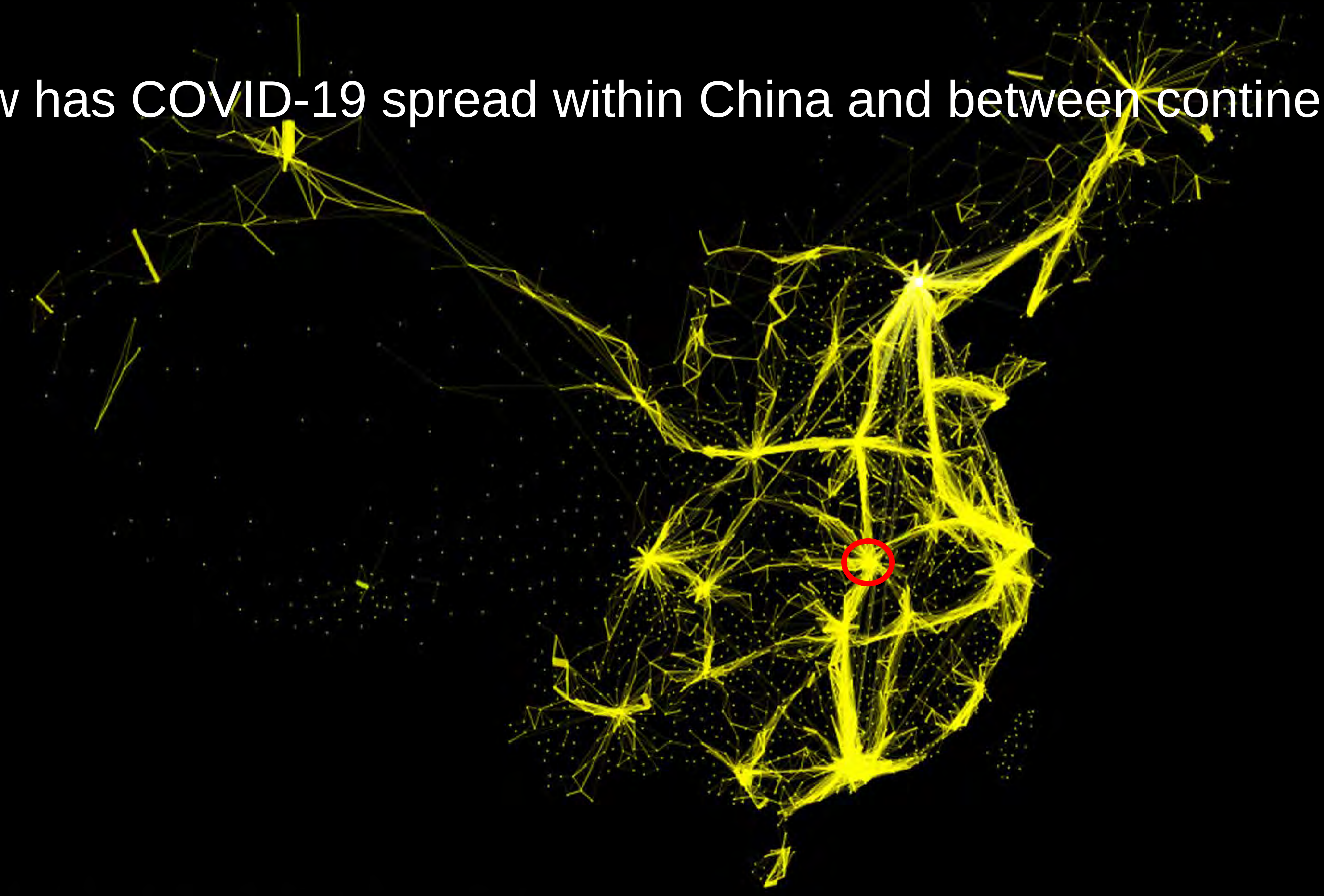
Human mobility and COVID-19 spread

Week 4 in 2020; Cumulative COVID-19 cases: 5014



Case studies: Evaluating spread risk of SARS-CoV-2 and variants through human movements

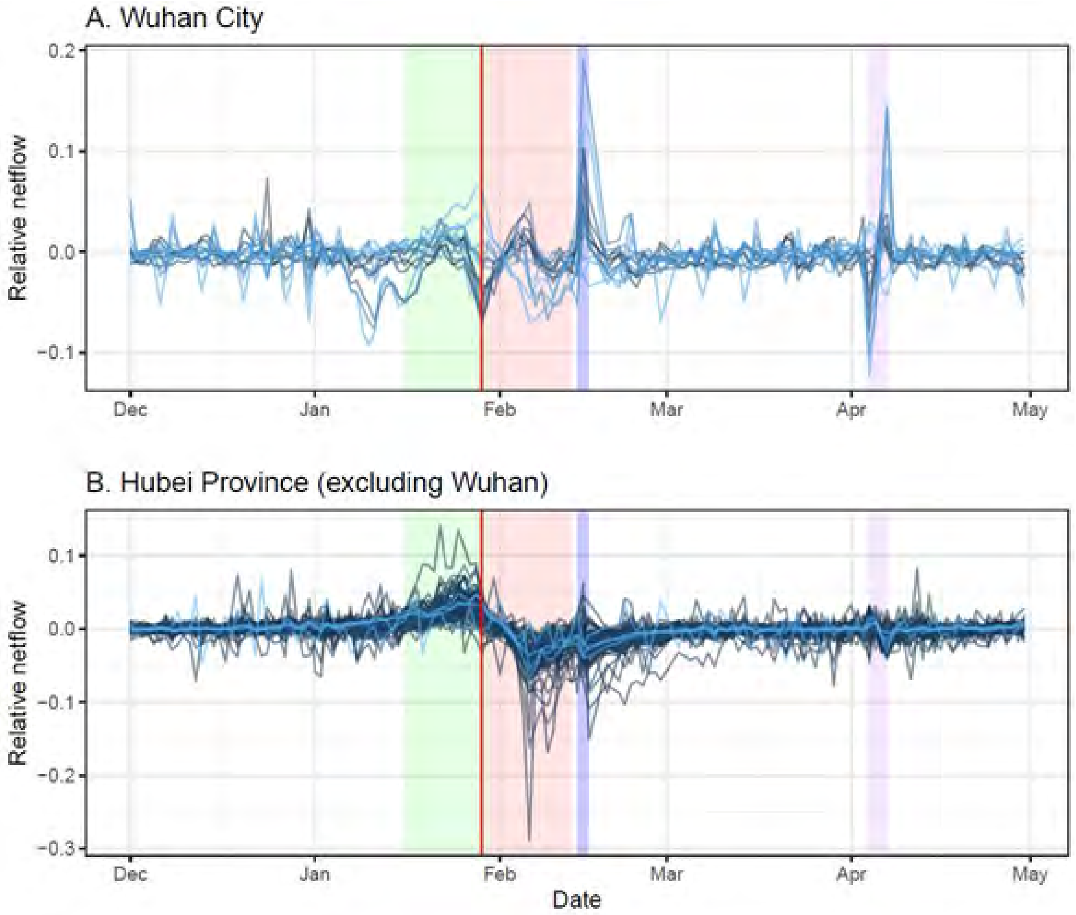
How has COVID-19 spread within China and between continents?



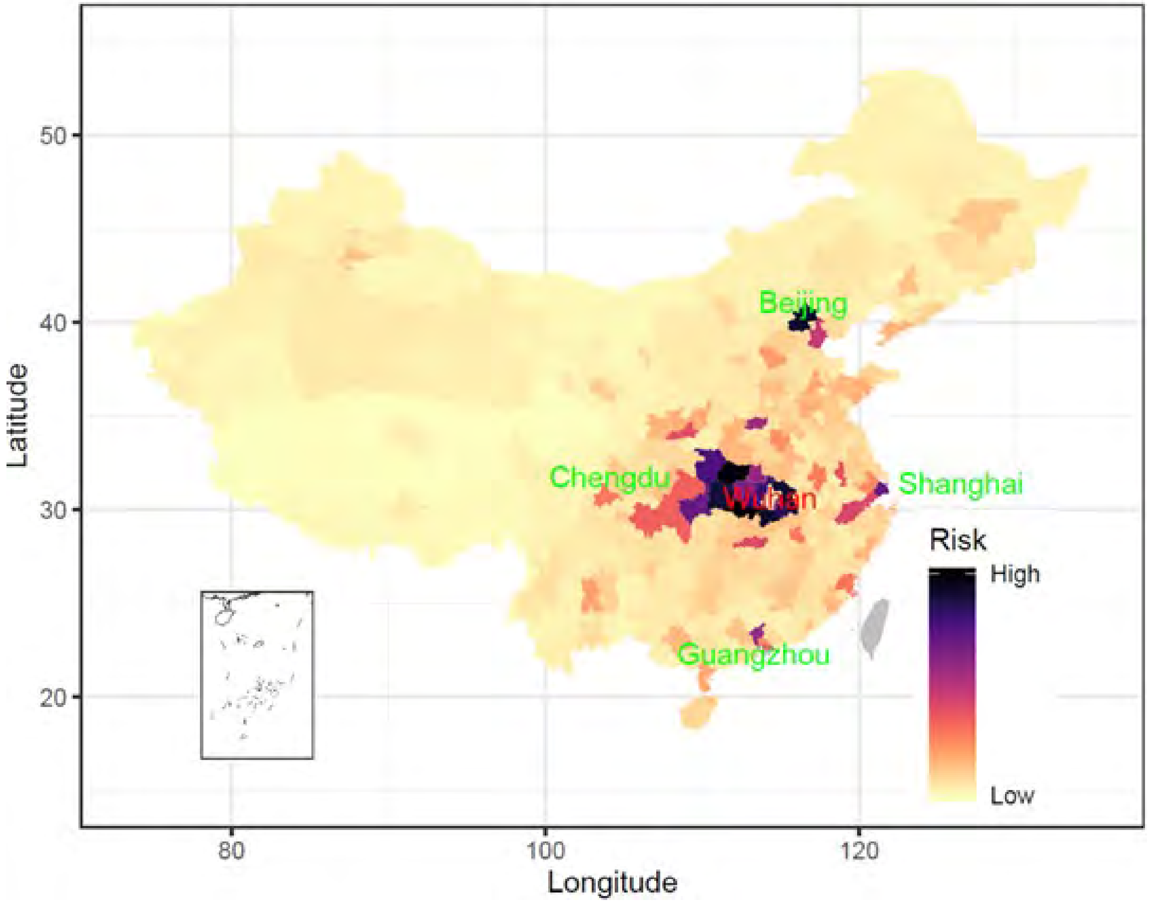
Based on Baidu LBS data, 2013.7-2014.3

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

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
[4]Bluedot, Toronto, Canada
[*]Email: Shengjie.Lai@soton.ac.uk; A.J.Tatem@soton.ac.uk

Updated version on MedArxiv
Updated on February 5th, 2020

Download a PDF version in English

Download a PDF version in Chinese

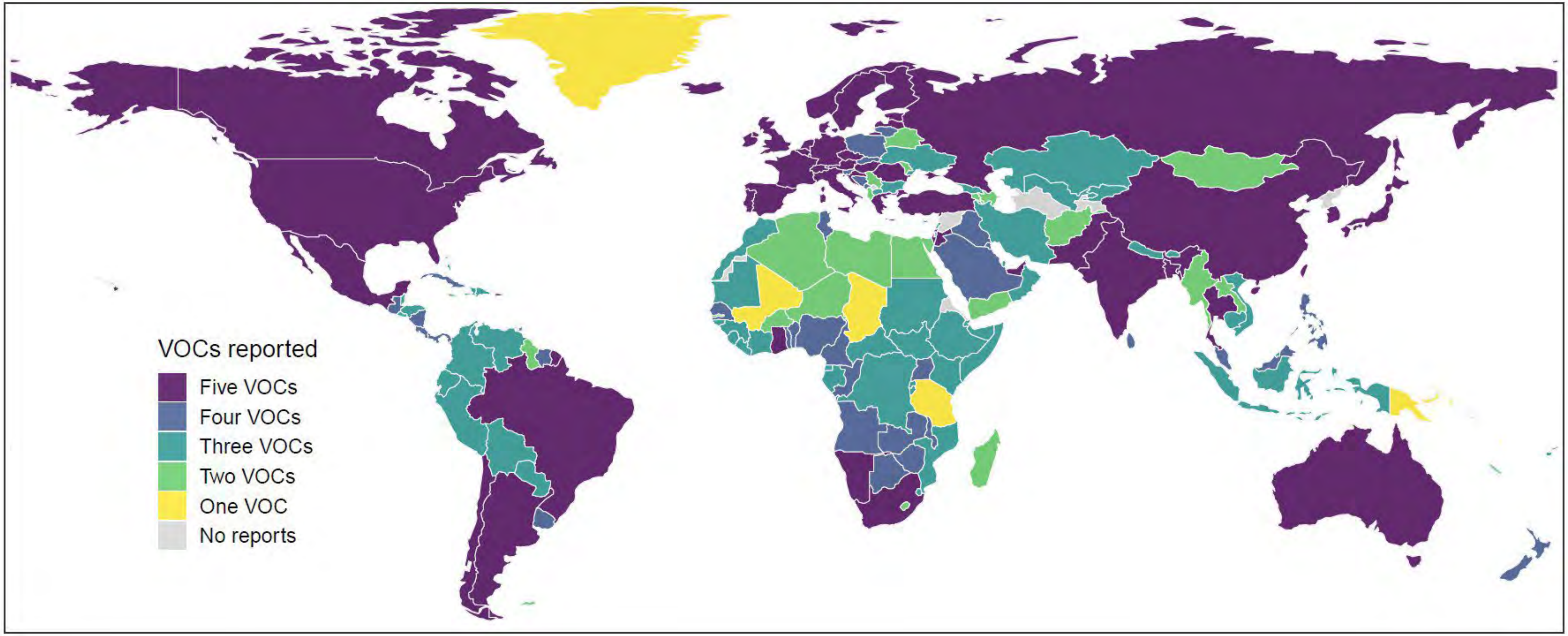
Destinations of airline travellers from 18 high-risk cities in mainland China by continent or region

OXFORD ACADEMIC

JOURNAL of TRAVEL MEDICINE

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

Variants of concern (VOCs)



Data sources: WHO, as of 14 Dec 2021

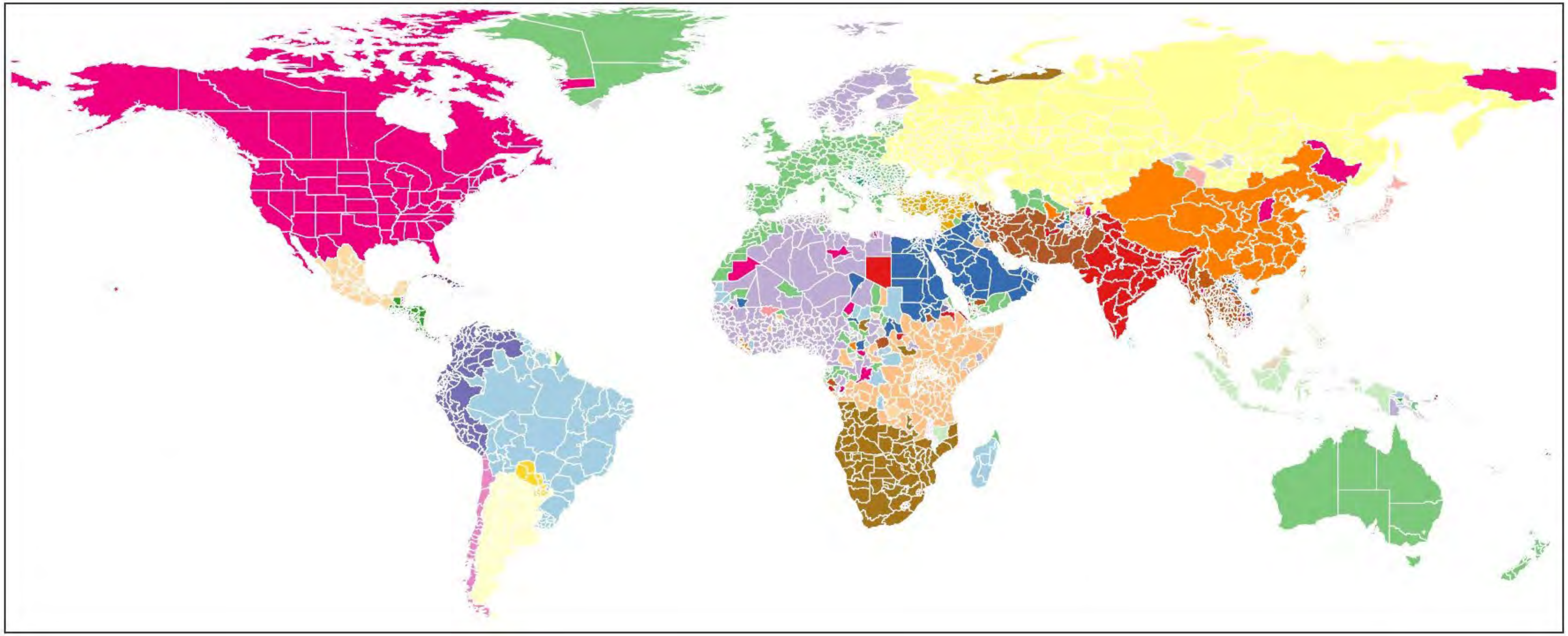
Li & Lai , et al. Nature 2021

December 17th, 2021

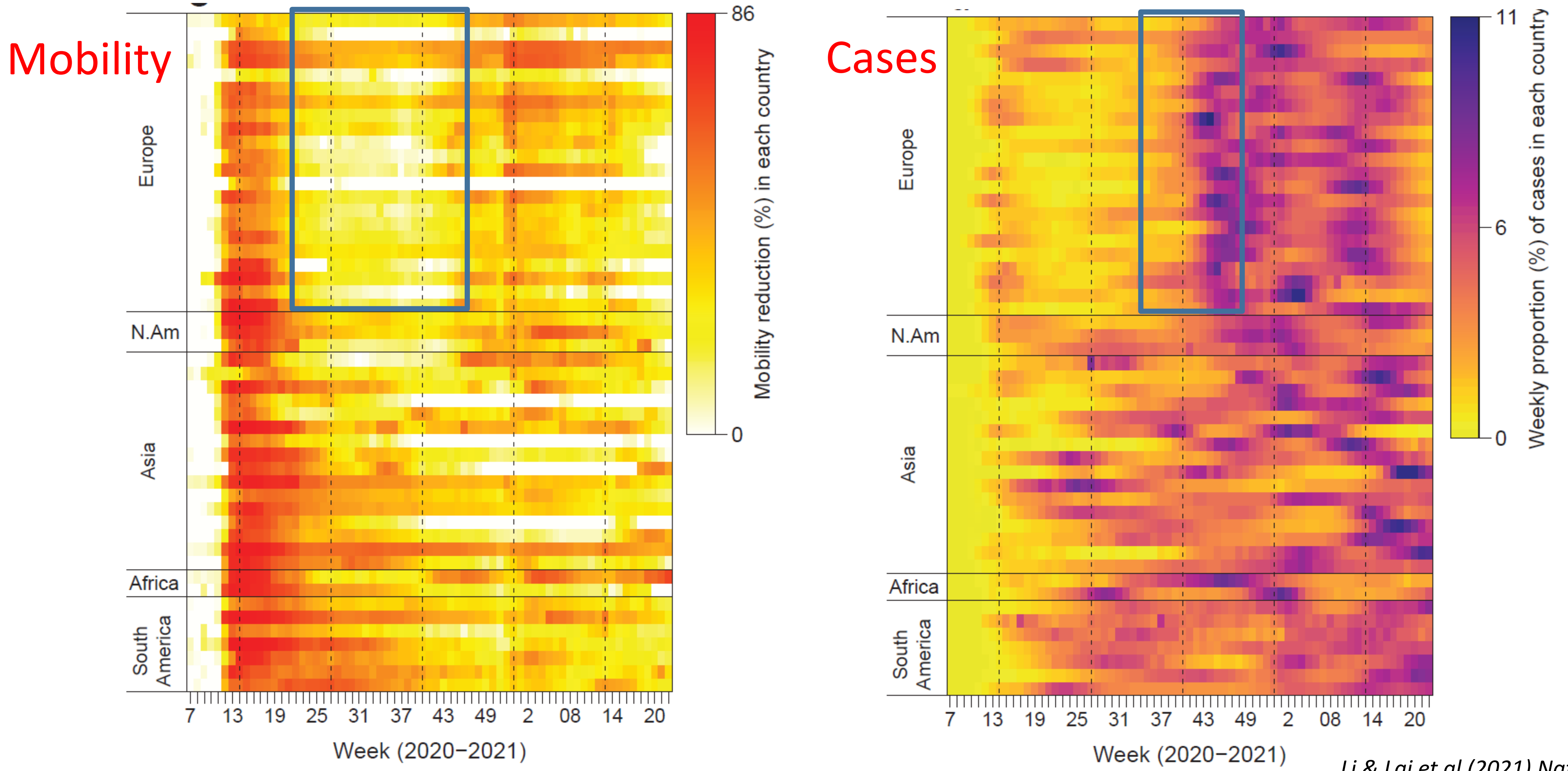
Exploring international travel patterns and connected communities for understanding the spreading risk of VOC Omicron

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

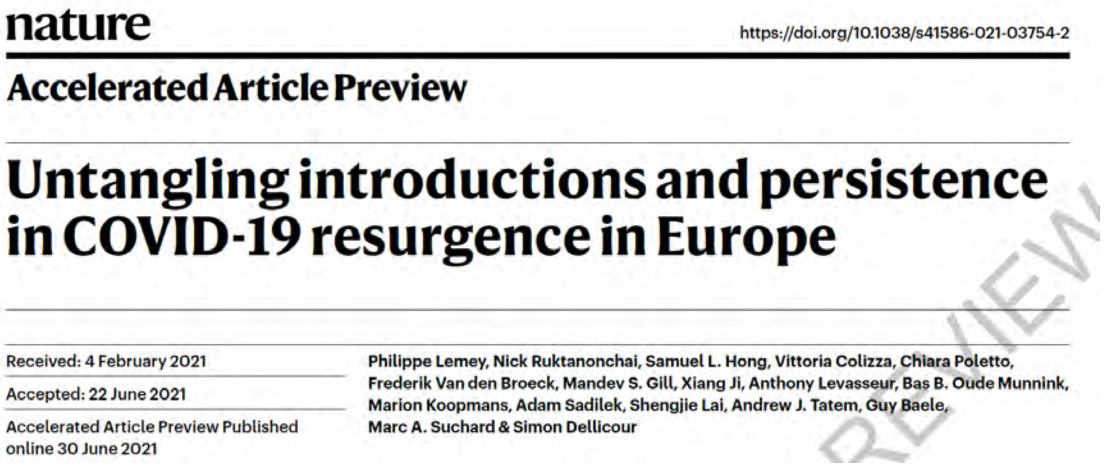
Download a PDF version



Resurgence after relaxing travel restrictions



Li & Lai et al (2021) Nature



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

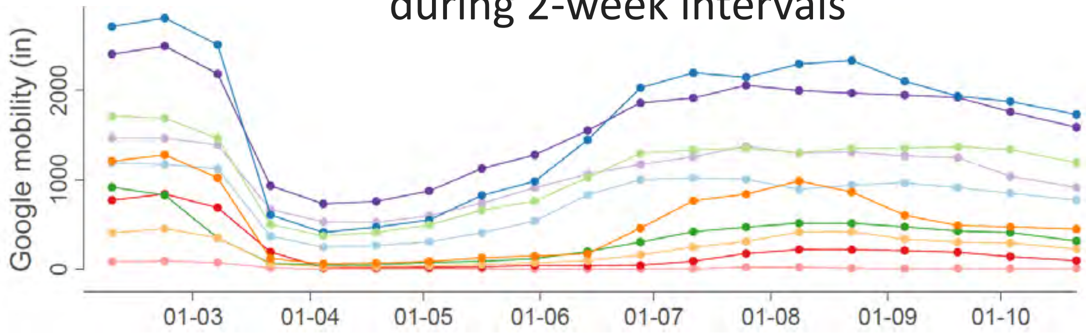
Philippe Lemey, Nick Ruktanonchai, Samuel L. Hong, Vittoria Colizza, Chiara Poletto, Frederik Van den Broeck, Mandev S. Gill, Xiang Ji, Anthony Levasseur, Bas B. Oude Munnink, Marion Koopmans, Adam Sadilek, Shengjie Lai, Andrew J. Tatem, Guy Baele, Marc A. Suchard & Simon Dellicour

REVIEW

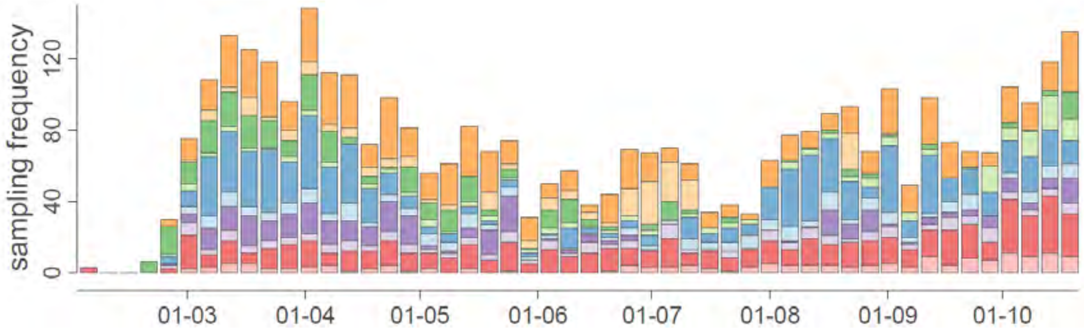
10 European countries

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

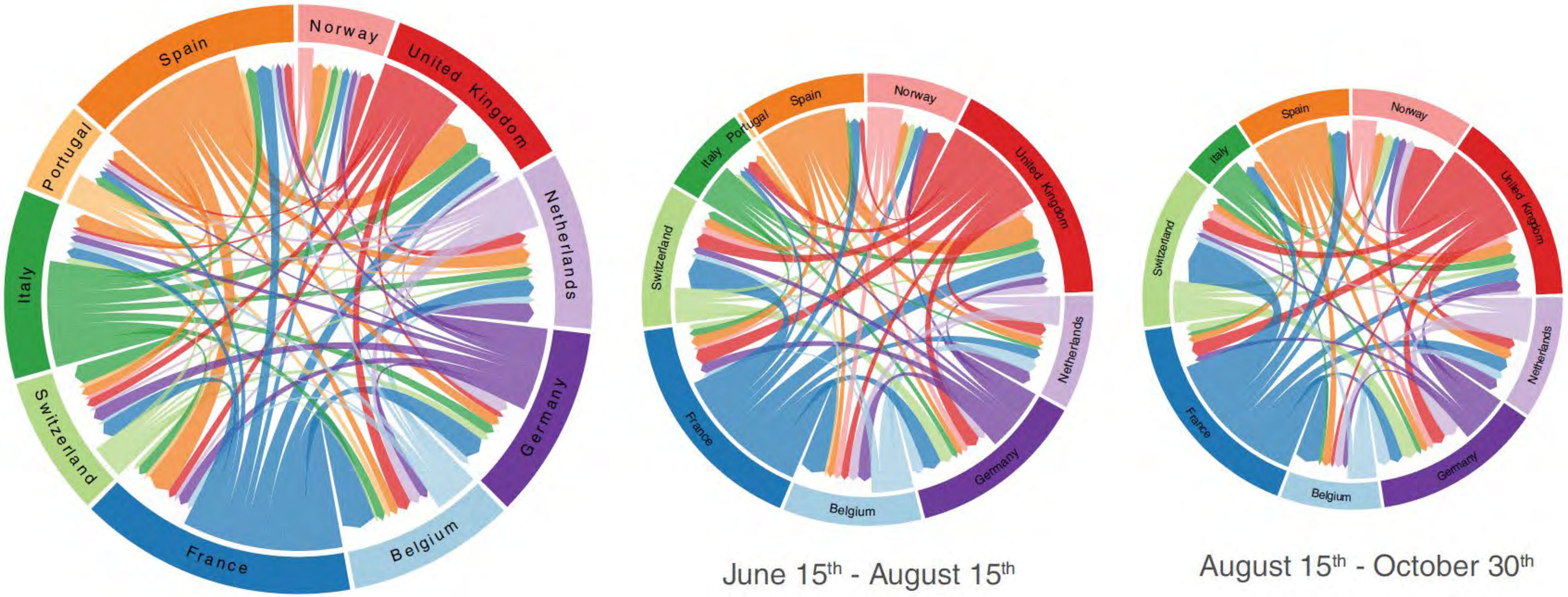
Google mobility in the 10 countries during 2-week intervals



weekly genome sampling by country



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



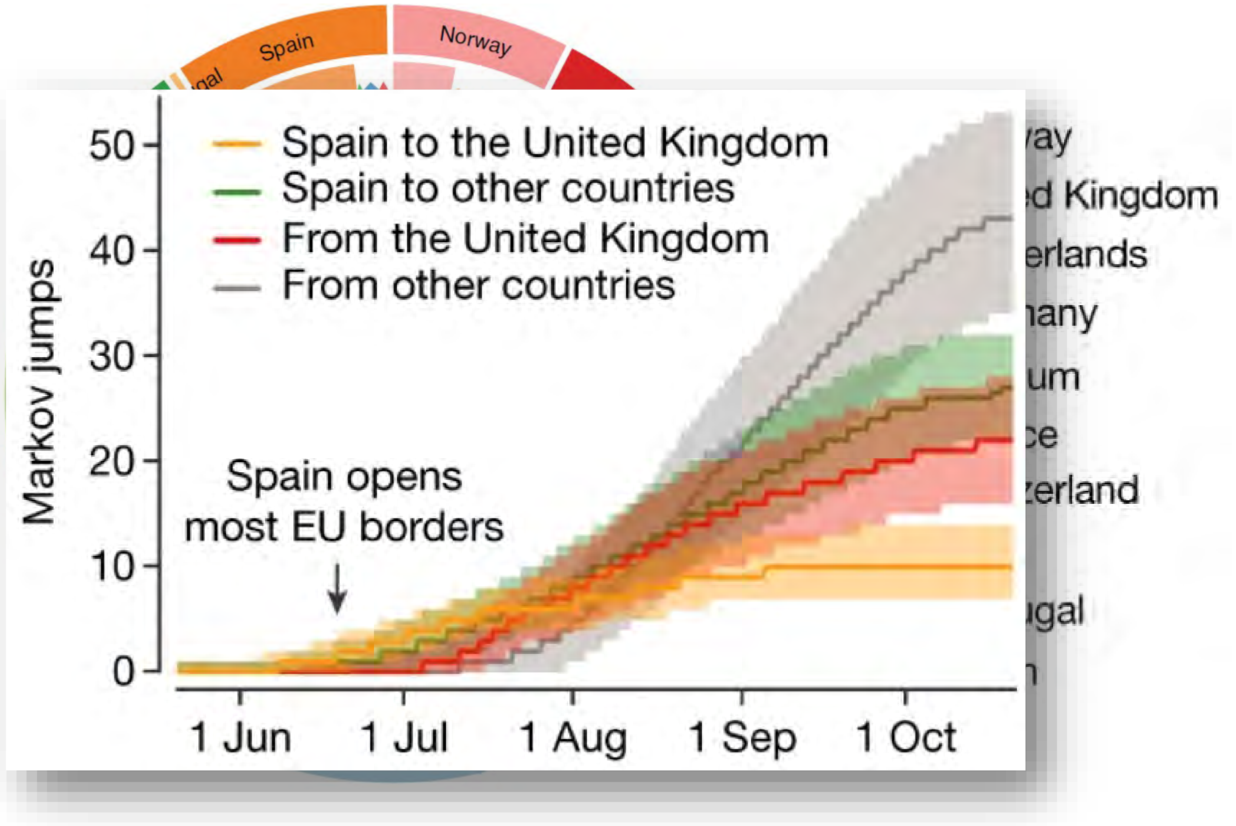
February 1st - June 15th

June 15th - August 15th

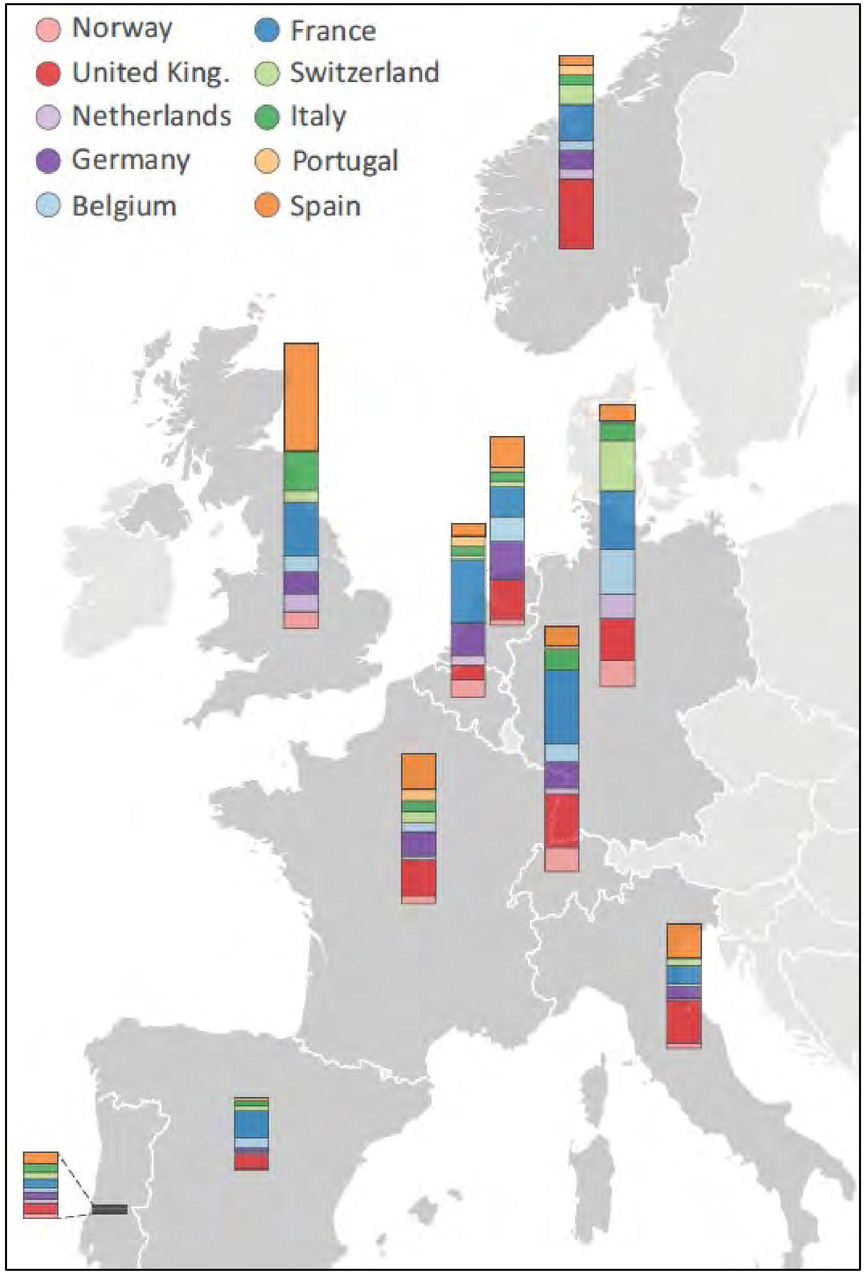
August 15th - October 30th

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

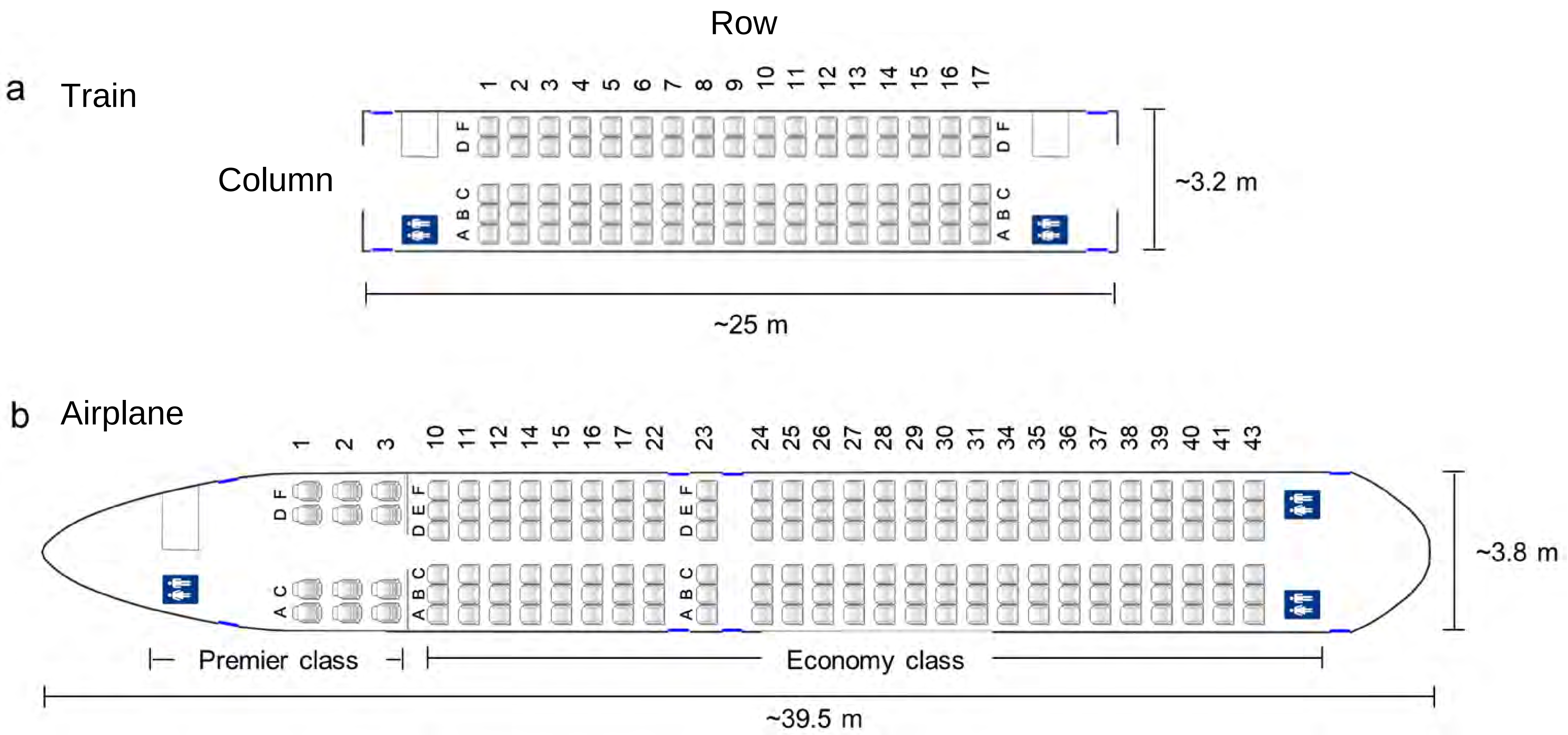
Estimated geographical origin of viral influx of lineage B.1.177 over the summer in Europe



15 June–15 August 2020

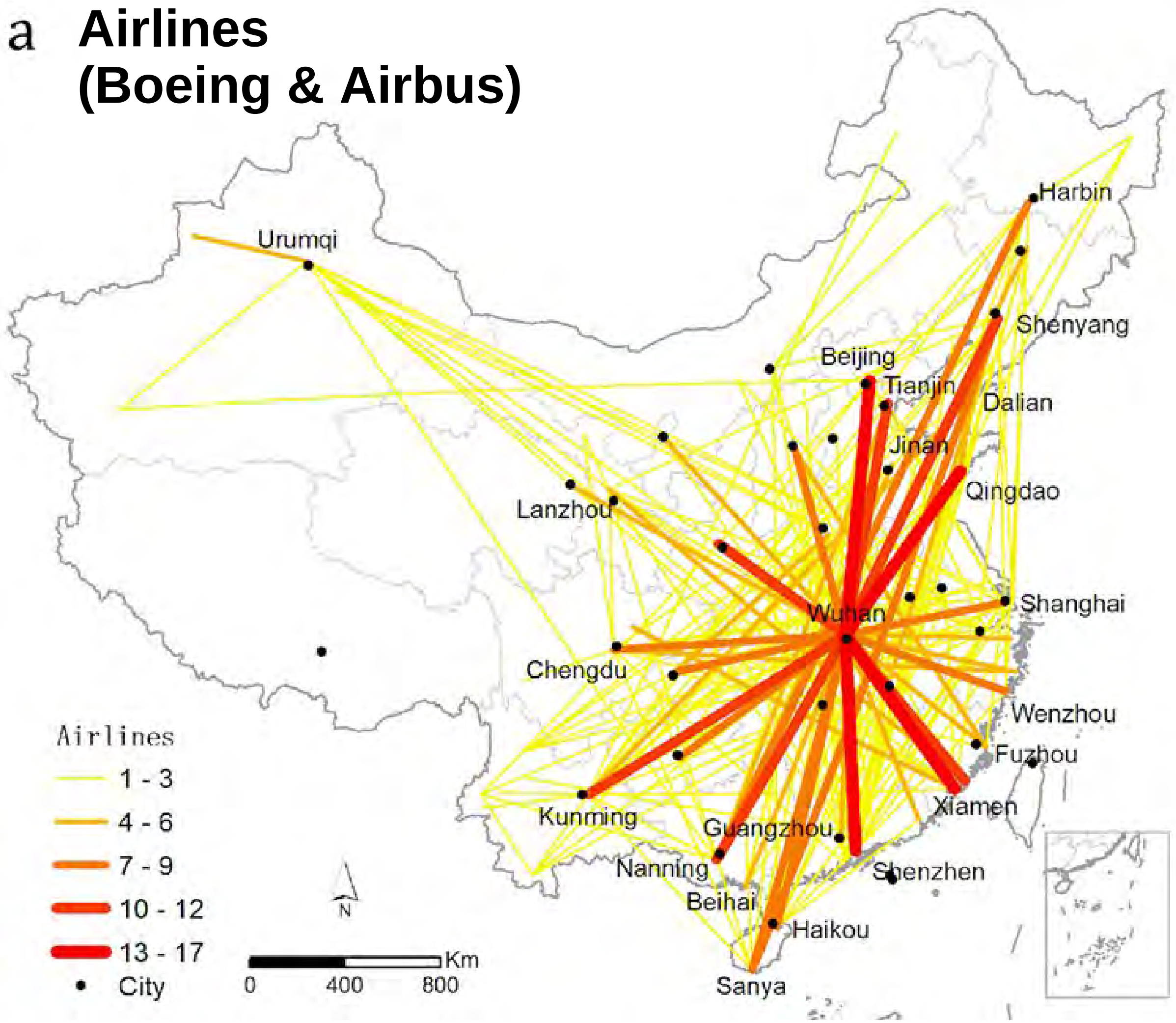


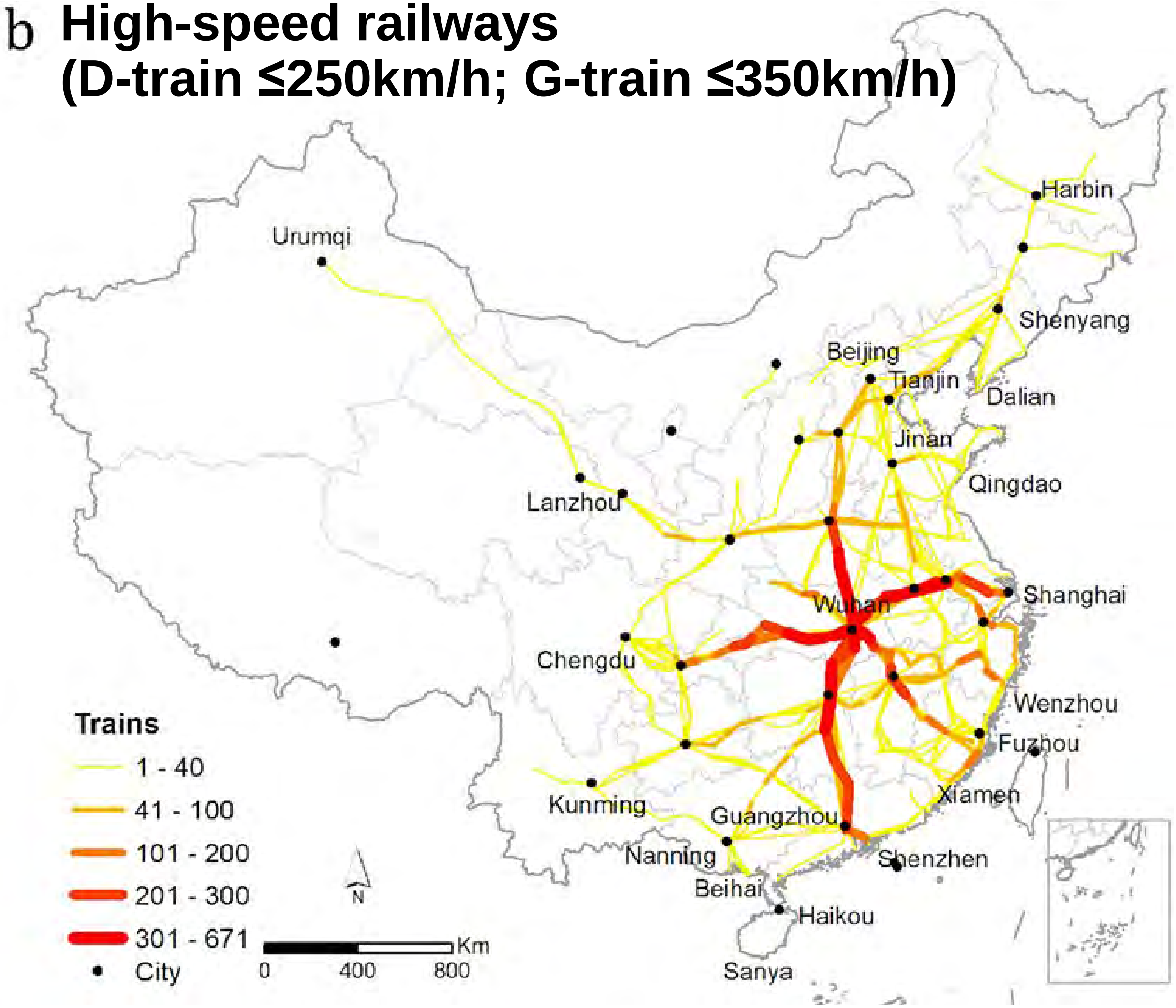
How high is the risk of COVID-19 transmission on train and plane?



Hu et al, CID 2020; 2021

Domestic airlines and high-speed trains from Wuhan
20 Dec 2019 – 23 Jan 2020





Hu et al, CID 2020; https://www.medrxiv.org/content/10.1101/2020.12.21.20248383v1

Attack rate of COVID-19 among passengers departing from Wuhan

Scenario 1: estimating the **upper bound of risk**, assuming that there was no family or friend relationship between travellers, nor any contacts before and after the journey.

Scenario 2: estimating the **lower bound of risk**, assuming passengers seating immediately adjacent to the index patient with same destinations were family or friends, as the transmission of SARS-CoV-2 between them were more likely to happen at home or working place.

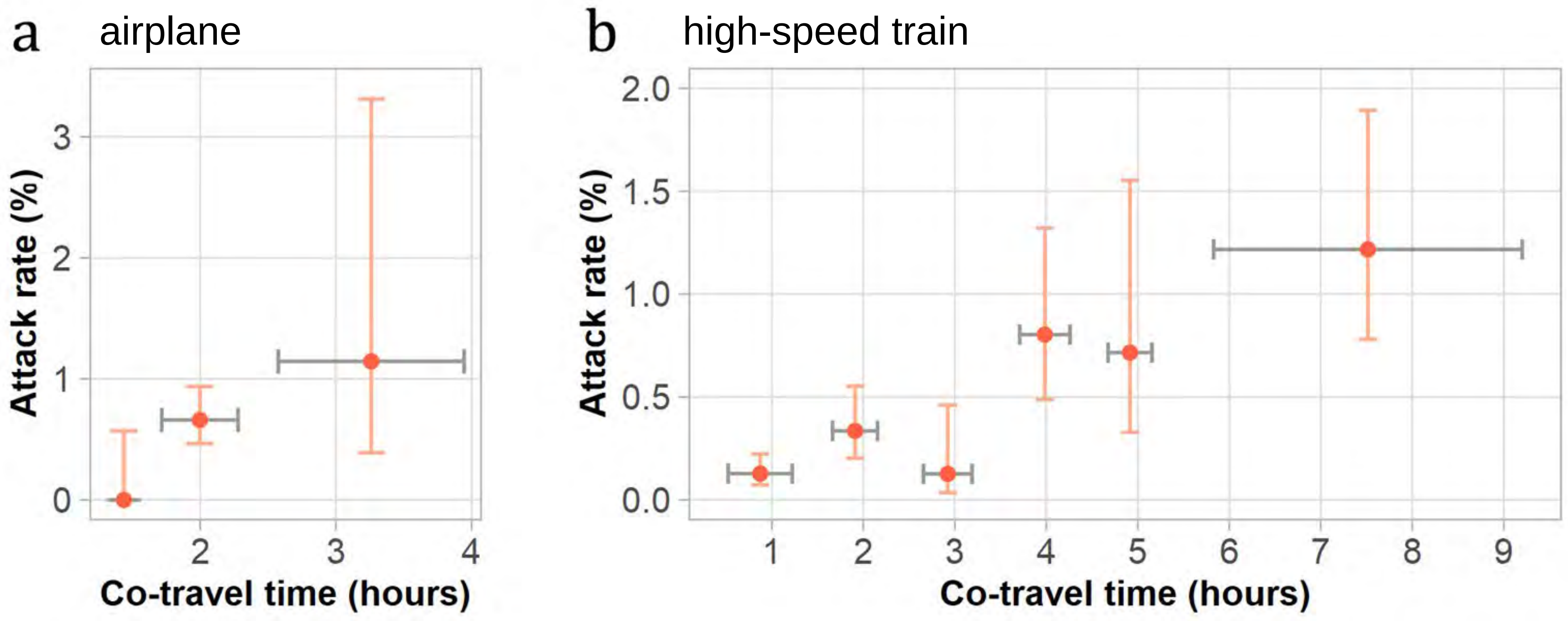
The risk varied by seat location

~ 2 secondary cases /10 index patients on airplanes
~ 1 secondary cases /10 index patients on trains and trains

COVID-19 attack rate and travel time

Travel time of airplane passengers: 1.1 - 4.3 hours (mean 2.0, SD 0.5)

Travel time of train passengers: 0.2 - 12.6 hours (mean 2.2, SD 2.0)



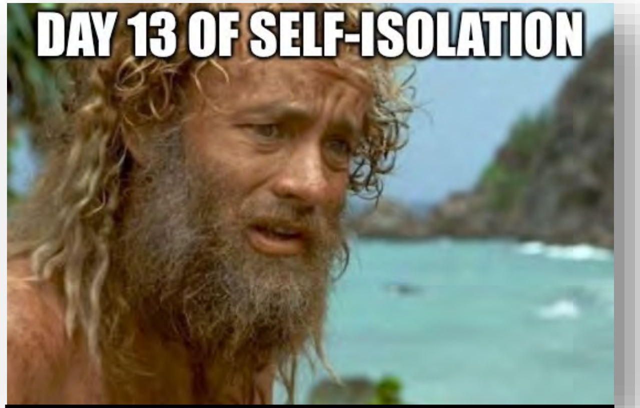
The risk was not significantly different between the types of aircraft (Boeing and Airbus) and trains (D-train ≤250km/h; G-train ≤350km/h)

Hu et al, CID 2020; https://www.medrxiv.org/content/10.1101/2020.12.21.20248383v1

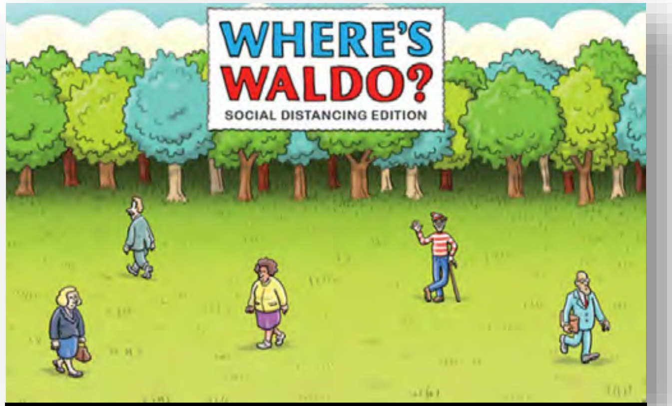
Case studies: Assessing impacts of interventions on COVID-19 transmission

Which non-pharmaceutical interventions (NPIs) had the biggest effects in containing COVID-19 at the early stage?

Travel restrictions



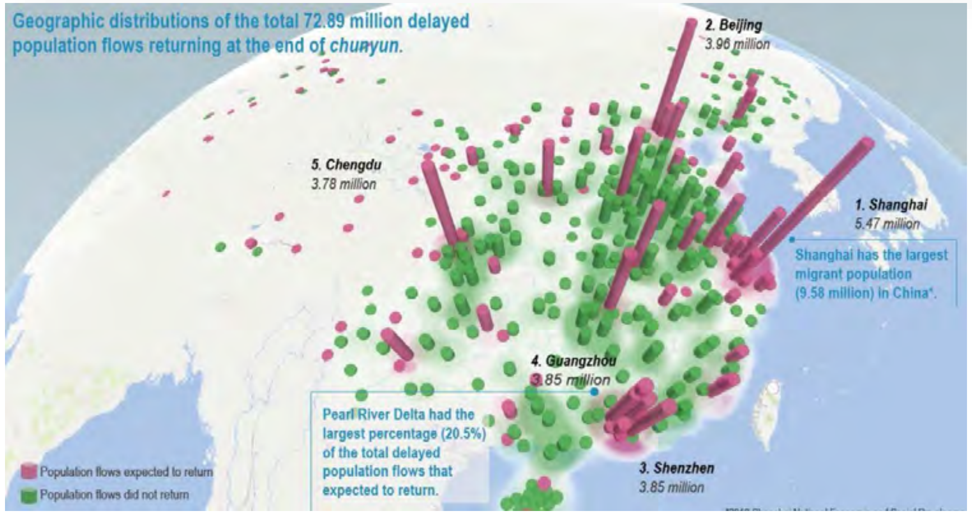
Early detection and isolation of cases

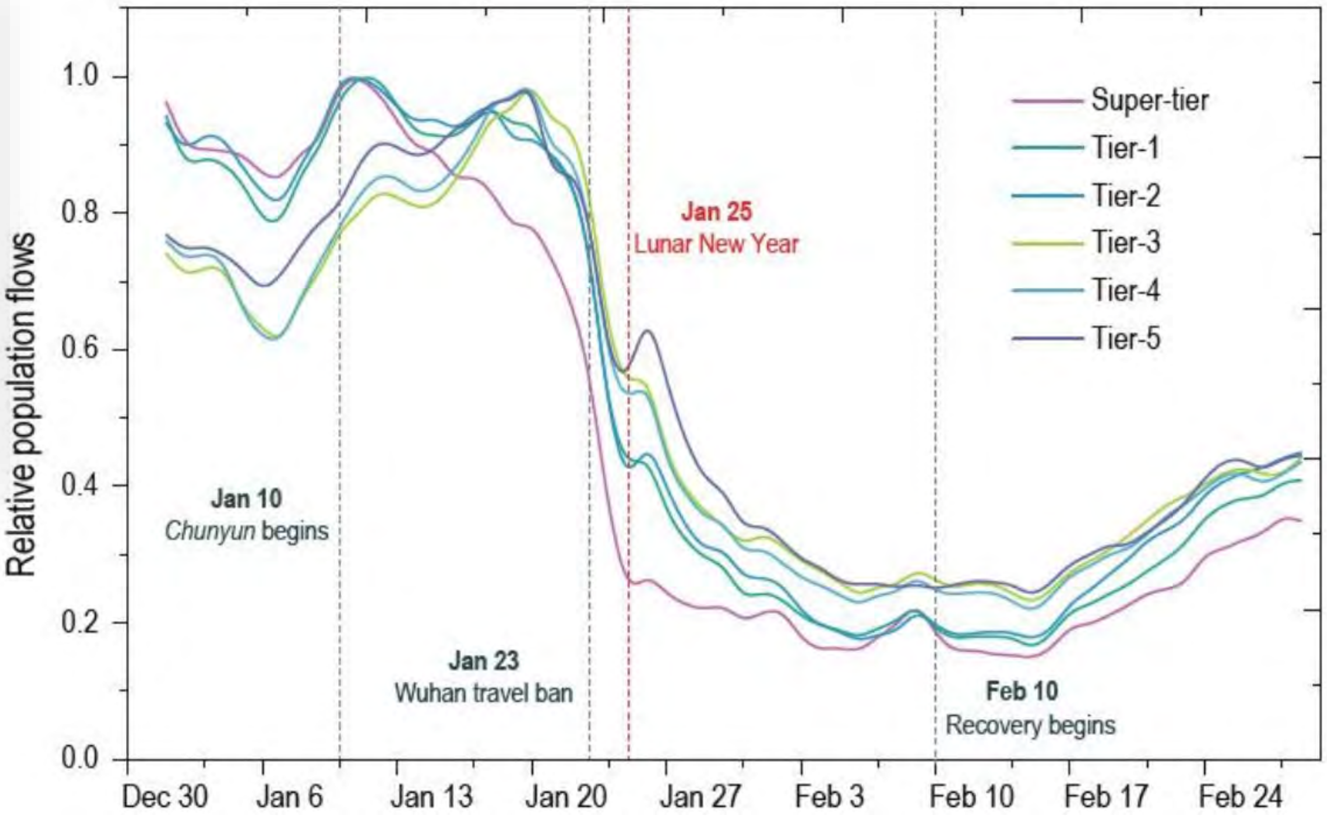


Social distancing

Mobility changes in China, 2020


OXFORD
ACADEMIC
NSR National Science Review
Issues More Content ▾ Publish ▾ Alerts About ▾
Article Contents
Abstract
Author notes
Supplementary data
ACCEPTED MANUSCRIPT
Mobility in China, 2020: a tale of four phases
Suo-yi Tan, Shengjie Lai, Fan Fang, Ziqiang Cao, Bin Sai, Bing Song, Bitao Dai, Shuhui Guo, Chuchu Liu, Mengsi Cai, Tong Wang, Mengning Wang, Jiaxu Li, Saran Chen, Shuo Qin, Jessica R Floyd, Zhidong Cao, Jing Tan, Xin Sun, Tao Zhou, Wei Zhang, Andrew J Tatem,





Tian S et al. National Science Review 2021 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

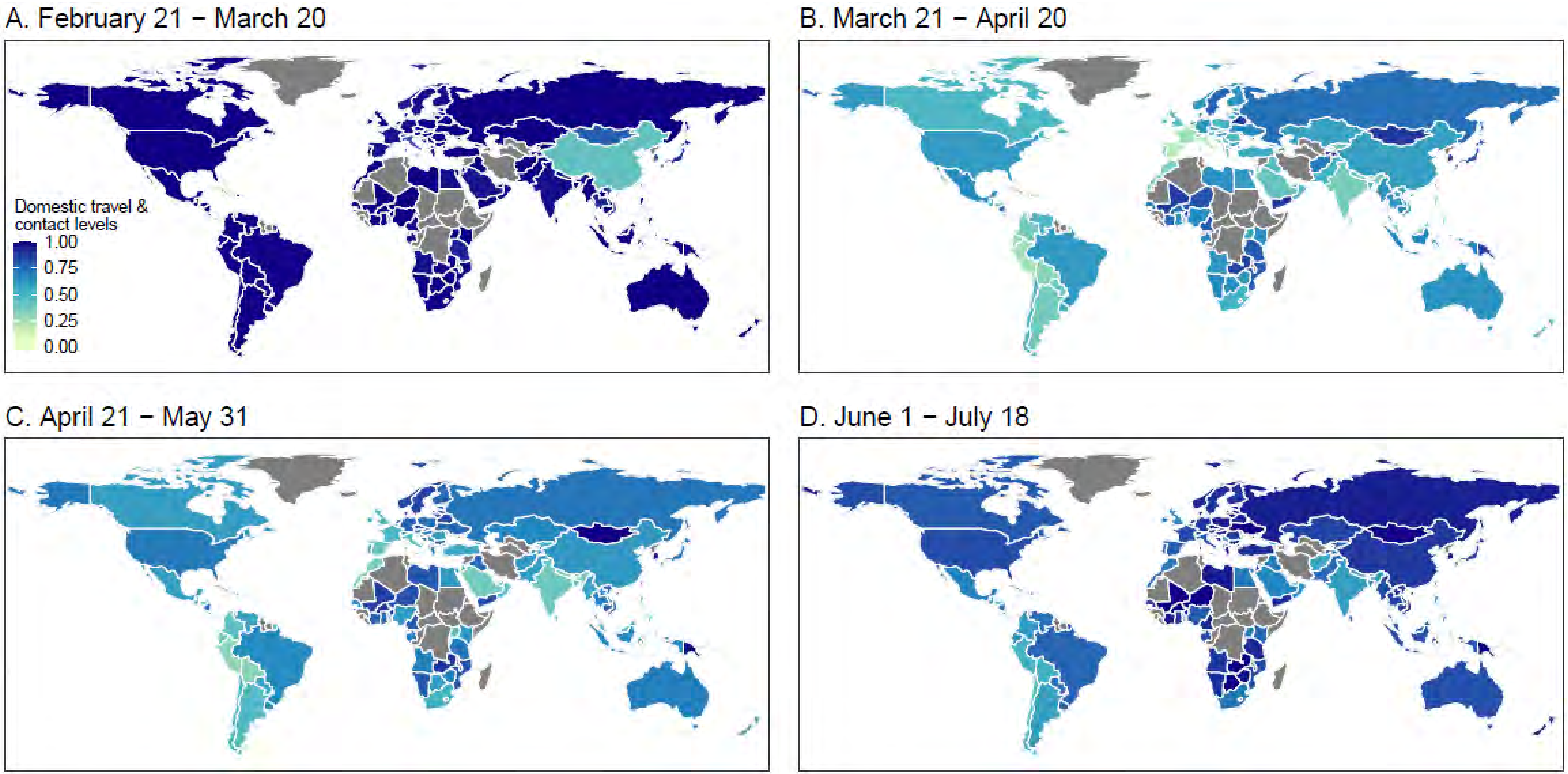
We use data to address some of the world's greatest humanitarian issues.

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.

Watch Full Video

https://dataforgood.fb.com/

Global domestic mobility changes during the first wave of pandemic

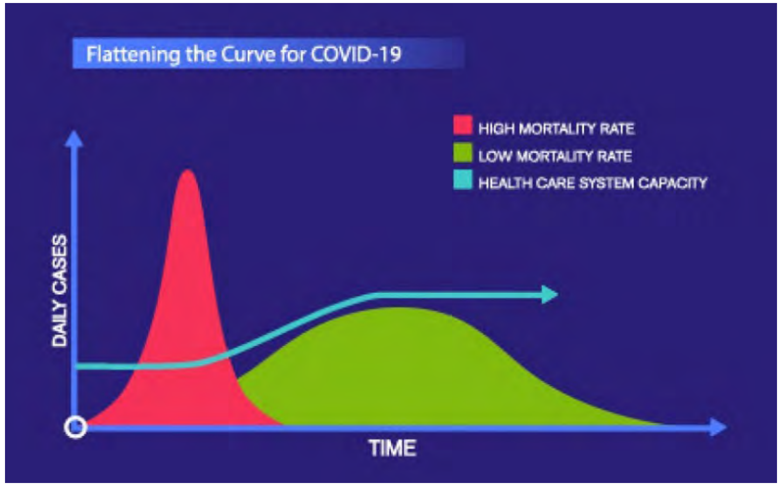


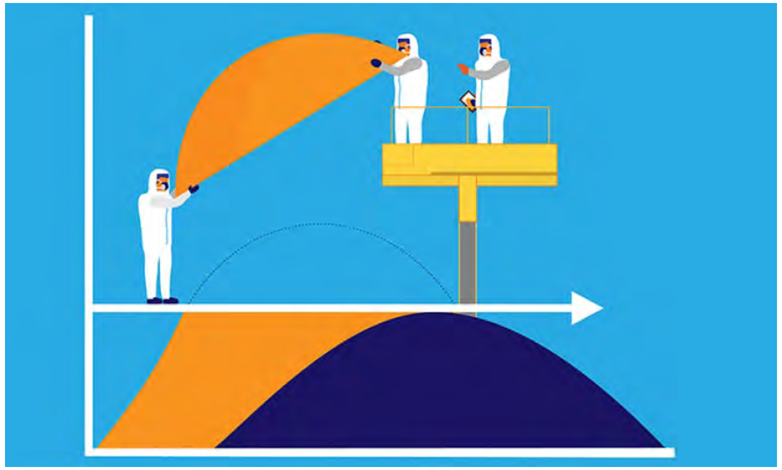
Mainland China used Baidu data, taking Jan 5 – 22, 2020 as a baseline.
All other 134 countries/territories/areas used Google data, taking Jan 5 – Feb 15, 2020 as a baseline

Lai S et al. Engineering 2021.

COVID-19 Models for Decision-Making

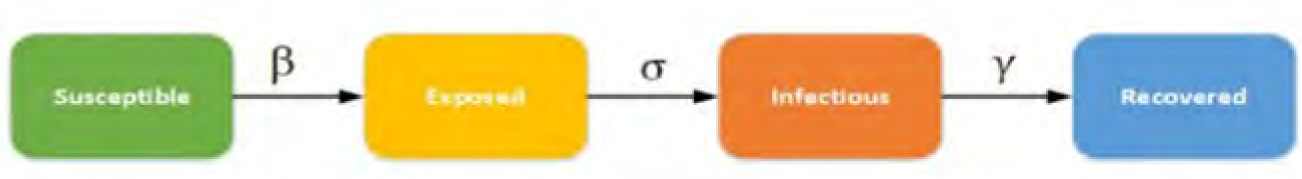
- Mathematical epidemic models
  - Compartmental model
  - Agent-based model
  - …
- Statistical models
  - Generalised linear model
  - Generalised additive model
  - …
- Geospatial/spatiotemporal model
- Age/gender-stratified model
- Travel network-based model
- Bayesian model
- Machine learning
-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



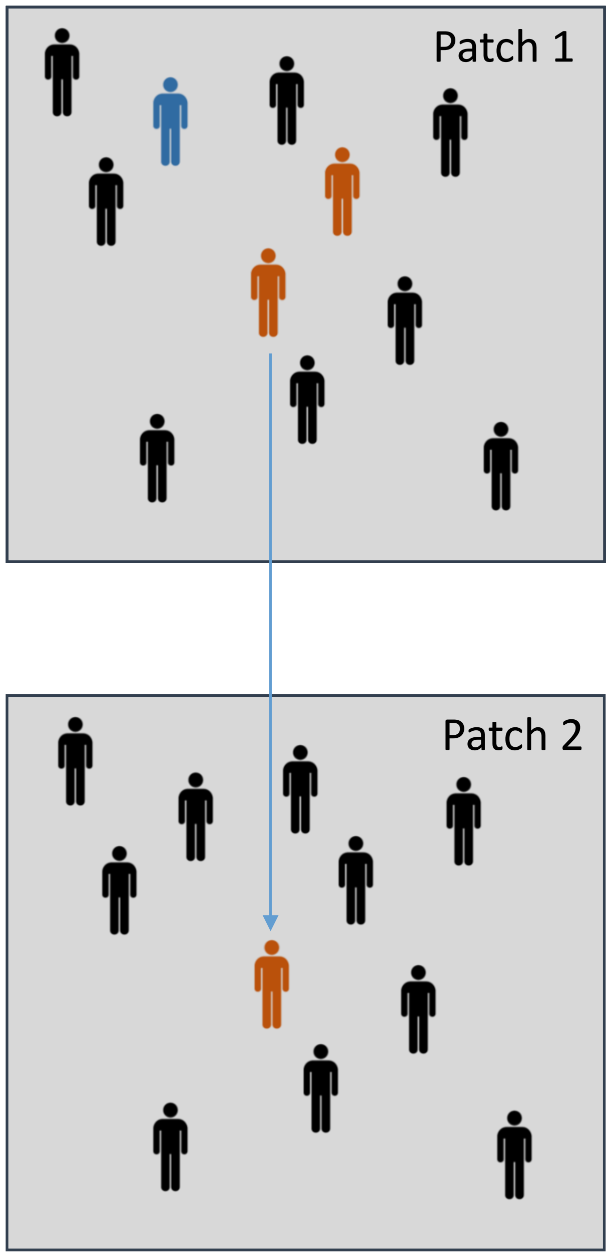


Multi-patch epidemiological model

- Subpopulation: Susceptible, Exposed, Infectious, Recovered



- If each city/country is a patch, we can:
  - Model spread between areas
  - Simulate disease control measures (e.g. lockdowns) in certain areas but not others
  - Account for differences between areas (e.g. disease prevalence, demographics, movement/contact rate reductions)
- <u>Our mobility data helps define rates of movement within and between patches</u>



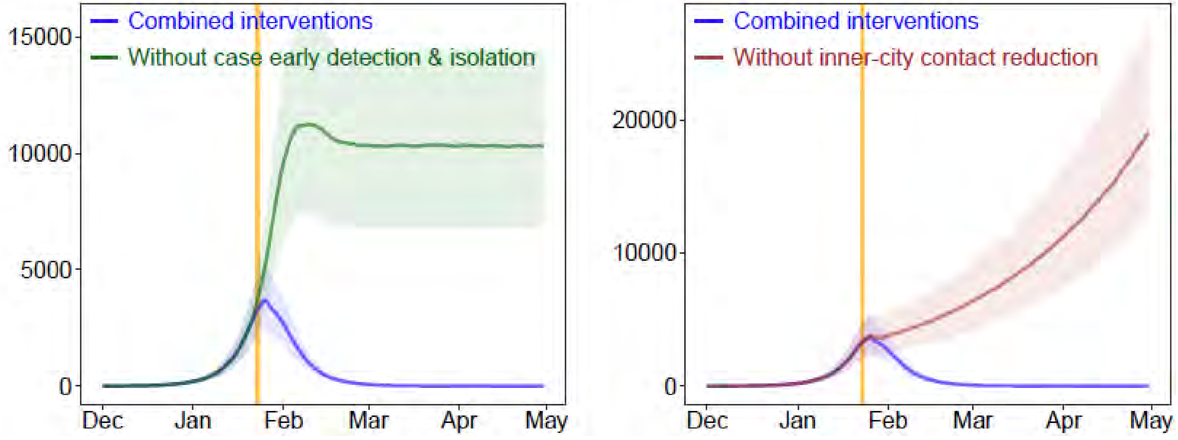
NPI effectiveness + Coordinated strategies?

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



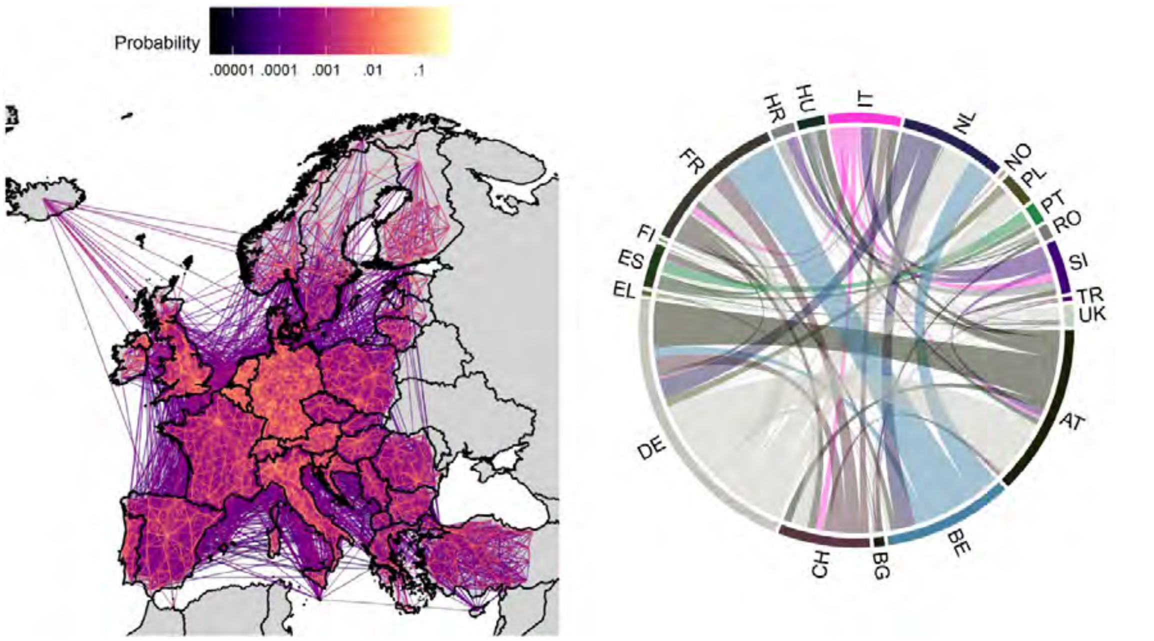
Science

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]



How to effectively combine NPIs and vaccination to prevent COVID-19 resurgences?

nature human behaviour

ARTICLES

https://doi.org/10.1038/s41562-021-01063-2

Check for updates

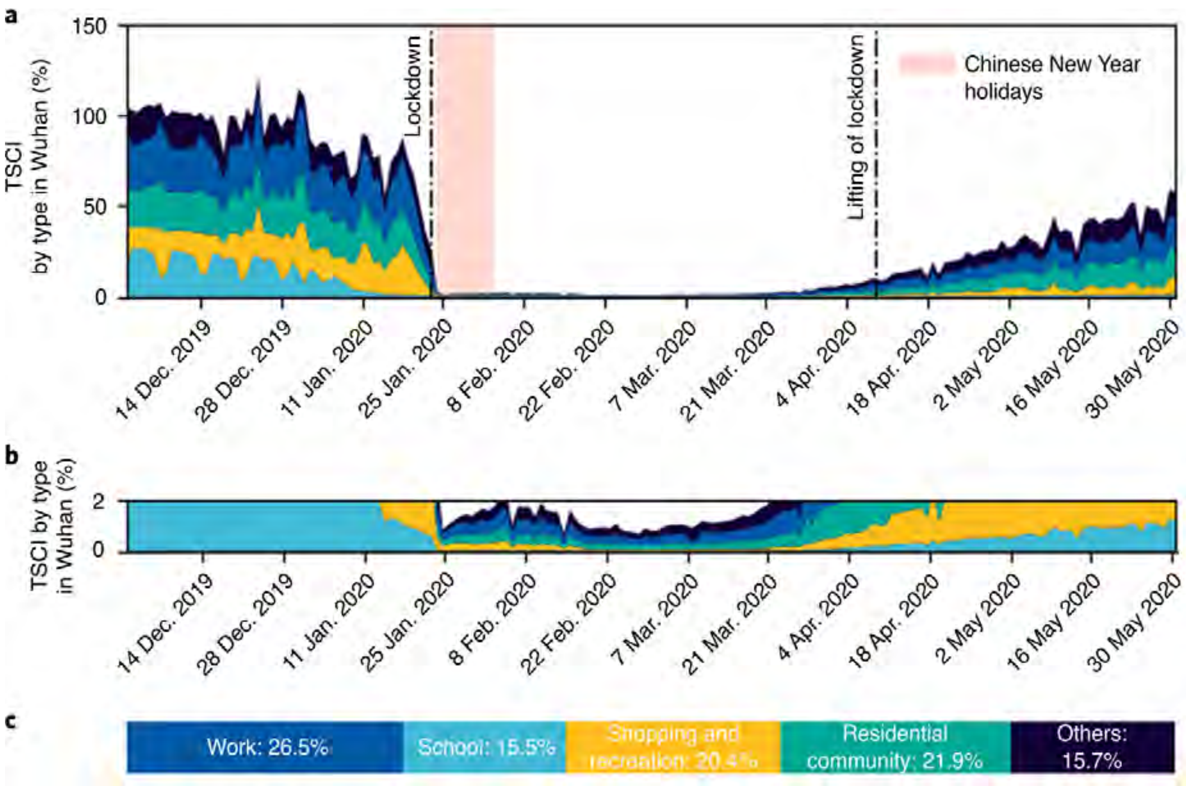
Integrated vaccination and physical distancing interventions to prevent future COVID-19 waves in Chinese cities

Bo Huang[1,2,3,13] ✉, Jionghua Wang[1,13], Jixuan Cai[4,13], Shiqi Yao[1], Paul Kay Sheung Chan[5,6] ✉, Tony Hong-wing Tam[3], Ying-Yi Hong[7], Corrine W. Ruktanonchai[8,9], Alessandra Carioli[8], Jessica R. Floyd[8], Nick W. Ruktanonchai[8,9], Weizhong Yang[10], Zhongjie Li[11], Andrew J. Tatem[8] ✉ and Shengjie Lai[8,10,12,13]

香港中文大學
The Chinese University of Hong Kong

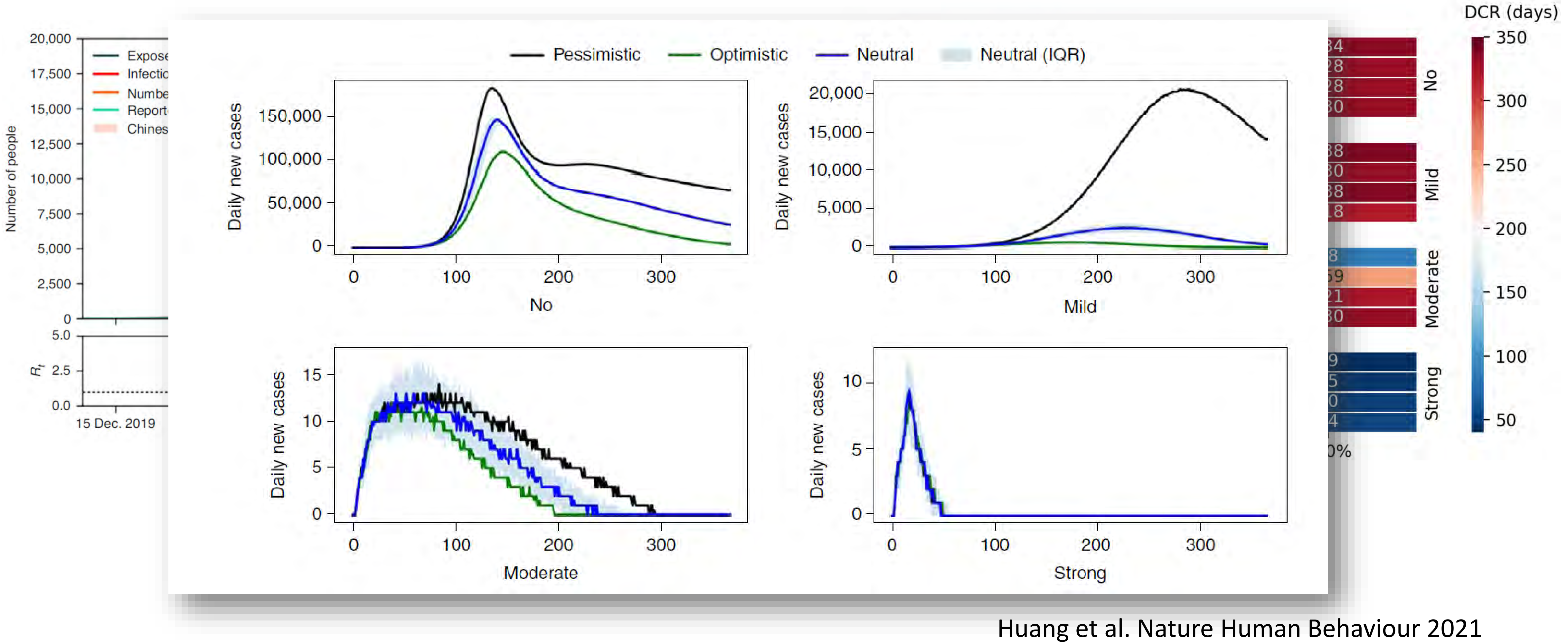
Tencent

Change in total social contact index (TSCI) in Wuhan



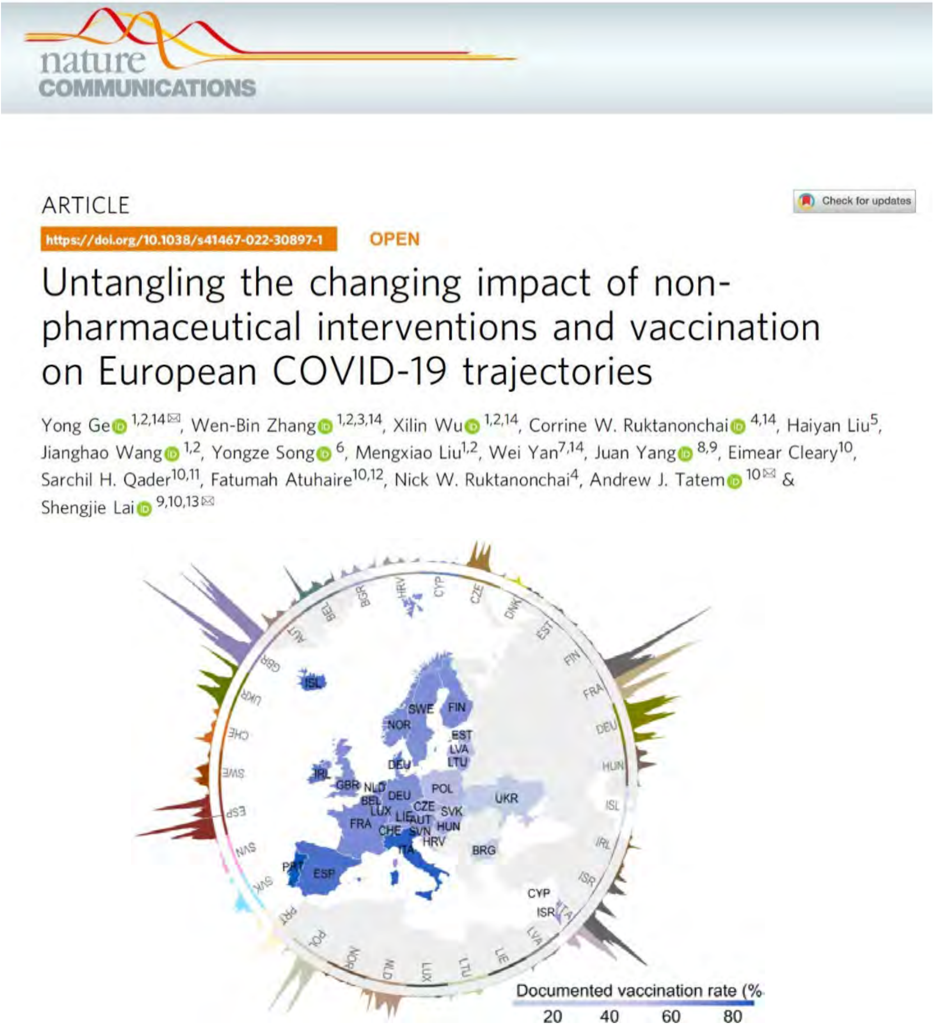
Changes in human contacts in Wuhan with different levels of population density, mobility and physical distancing measures

Estimated effects of control measures on containing a resurgence under different scenarios



Huang et al. Nature Human Behaviour 2021

Changing real-world effects of NPIs and vaccination on COVID-19?


nature COMMUNICATIONS

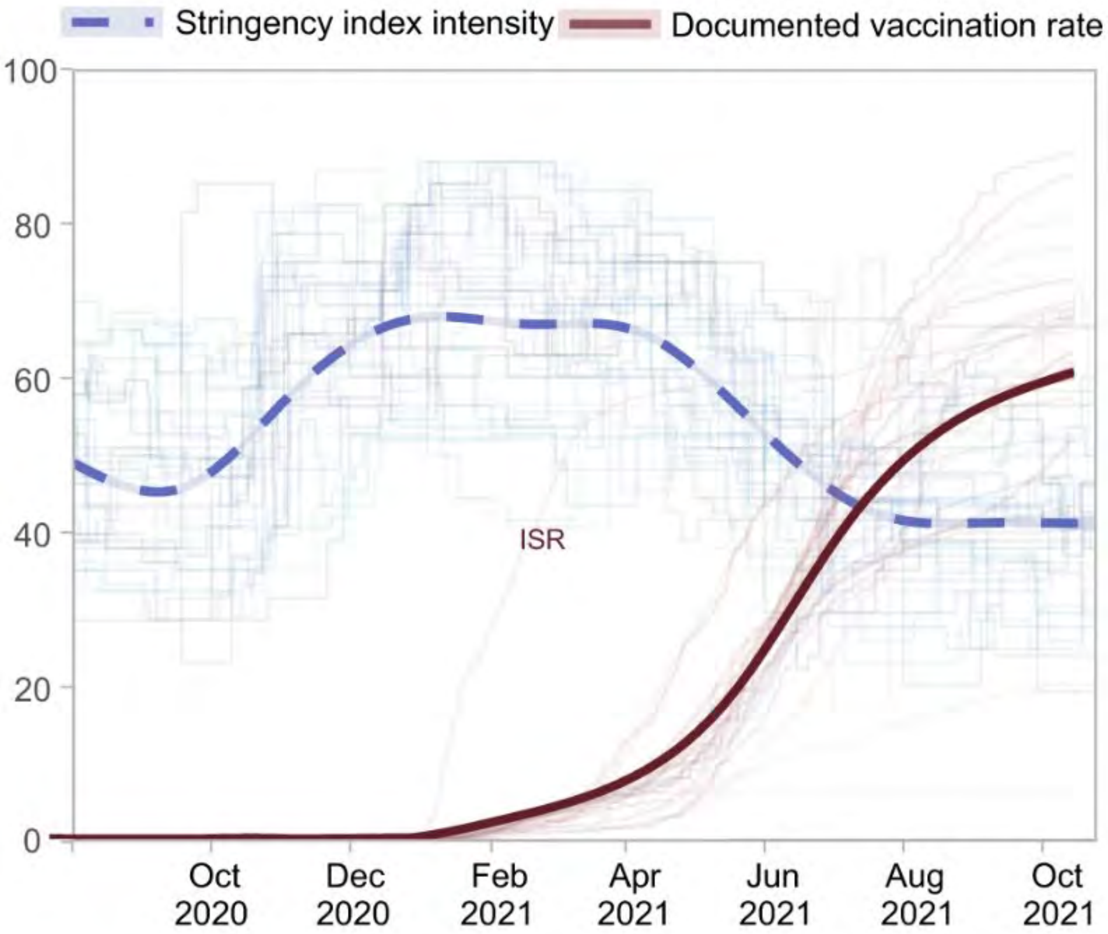
ARTICLE

Check for updates

https://doi.org/10.1038/s41467-022-30897-1 OPEN

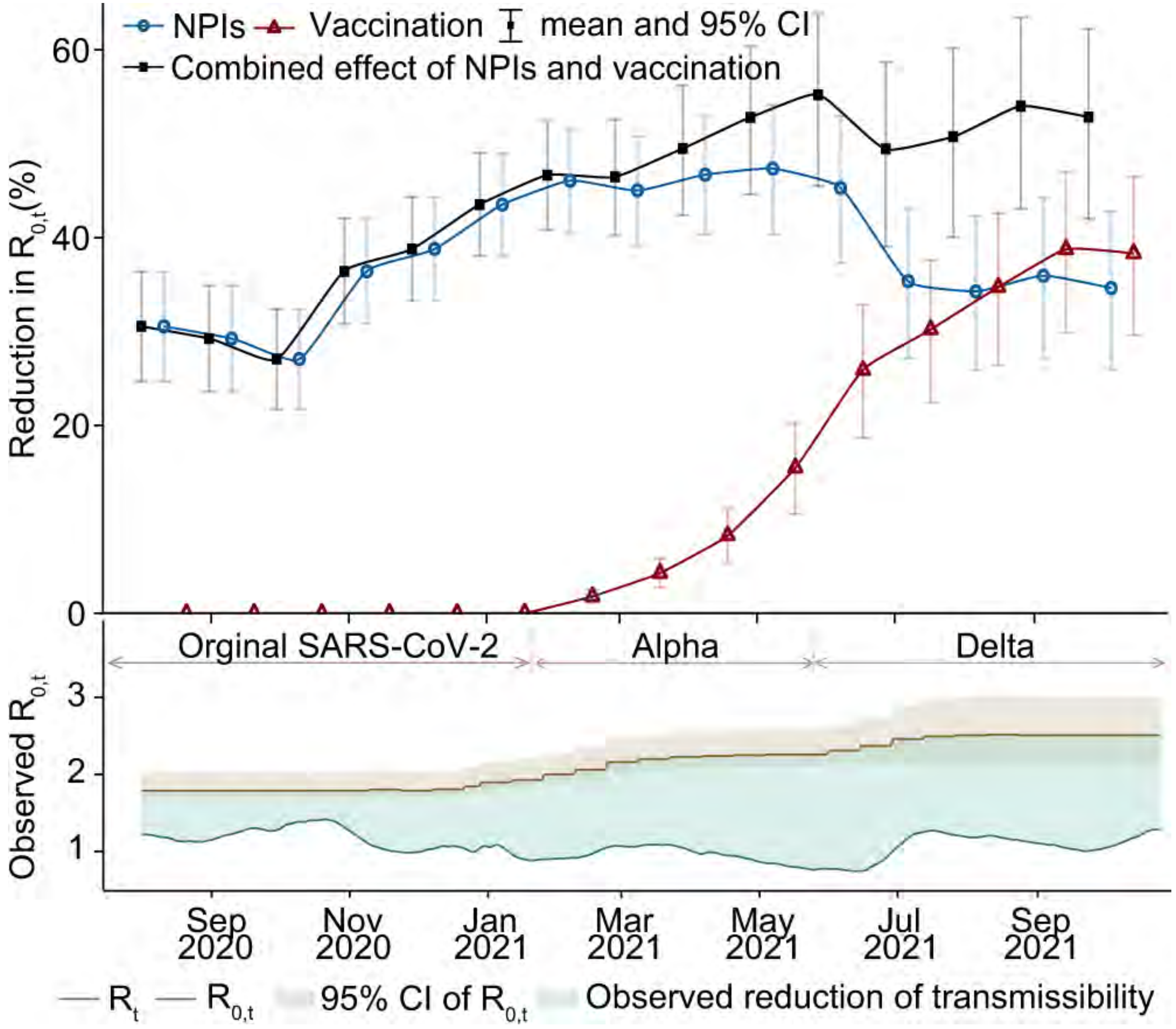
Untangling the changing impact of non-pharmaceutical interventions and vaccination on European COVID-19 trajectories

Yong Ge[1,2,14✉], Wen-Bin Zhang[1,2,3,14], Xilin Wu[1,2,14], Corrine W. Ruktanonchai[4,14], Haiyan Liu[5], Jianghao Wang[1,2], Yongze Song[6], Mengxiao Liu[1,2], Wei Yan[7,14], Juan Yang[8,9], Eimear Cleary[10], Sarchil H. Qader[10,11], Fatumah Atuhaire[10,12], Nick W. Ruktanonchai[4], Andrew J. Tatem[10✉] & Shengjie Lai[9,10,13✉]

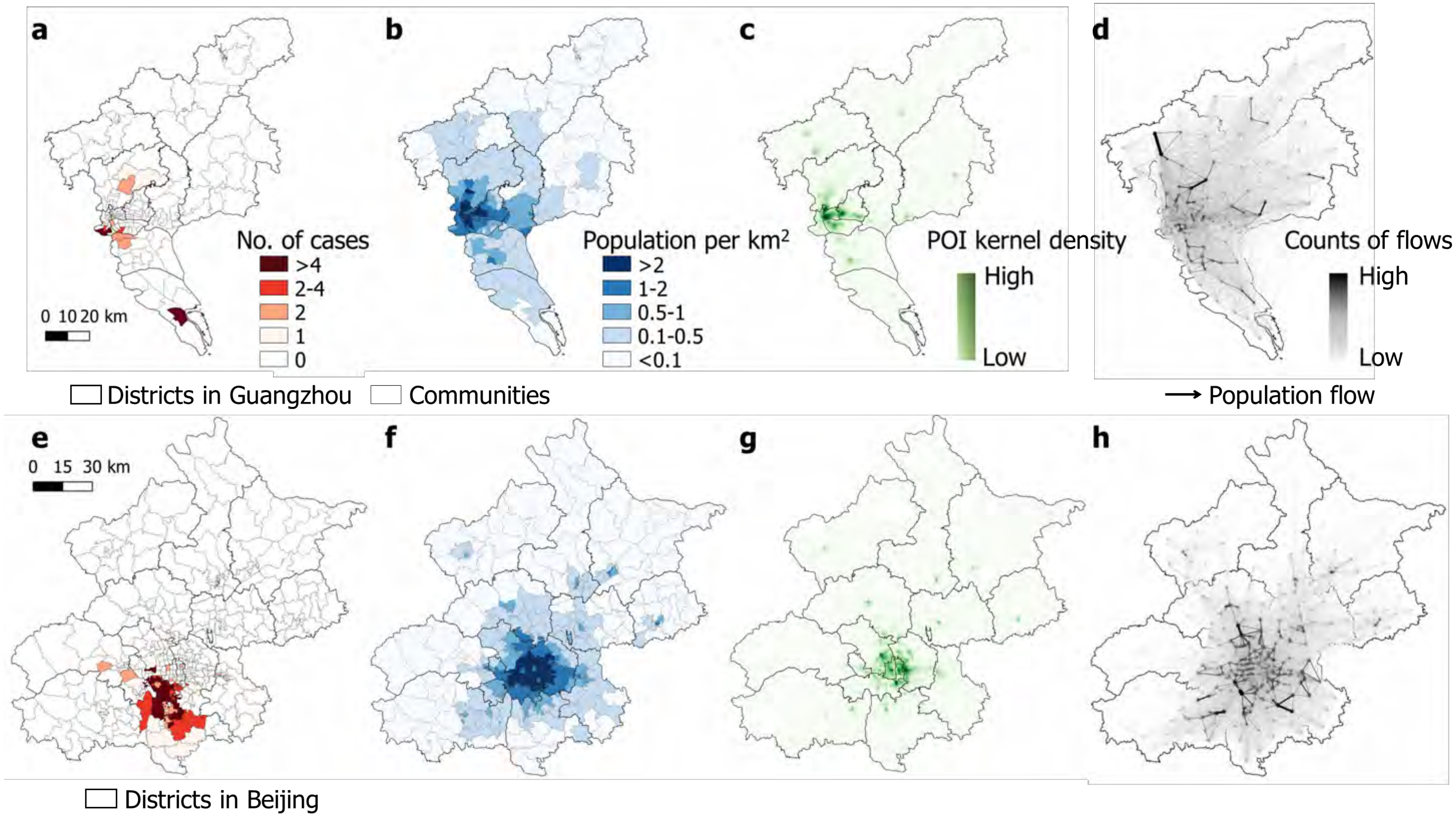


Overall monthly effects

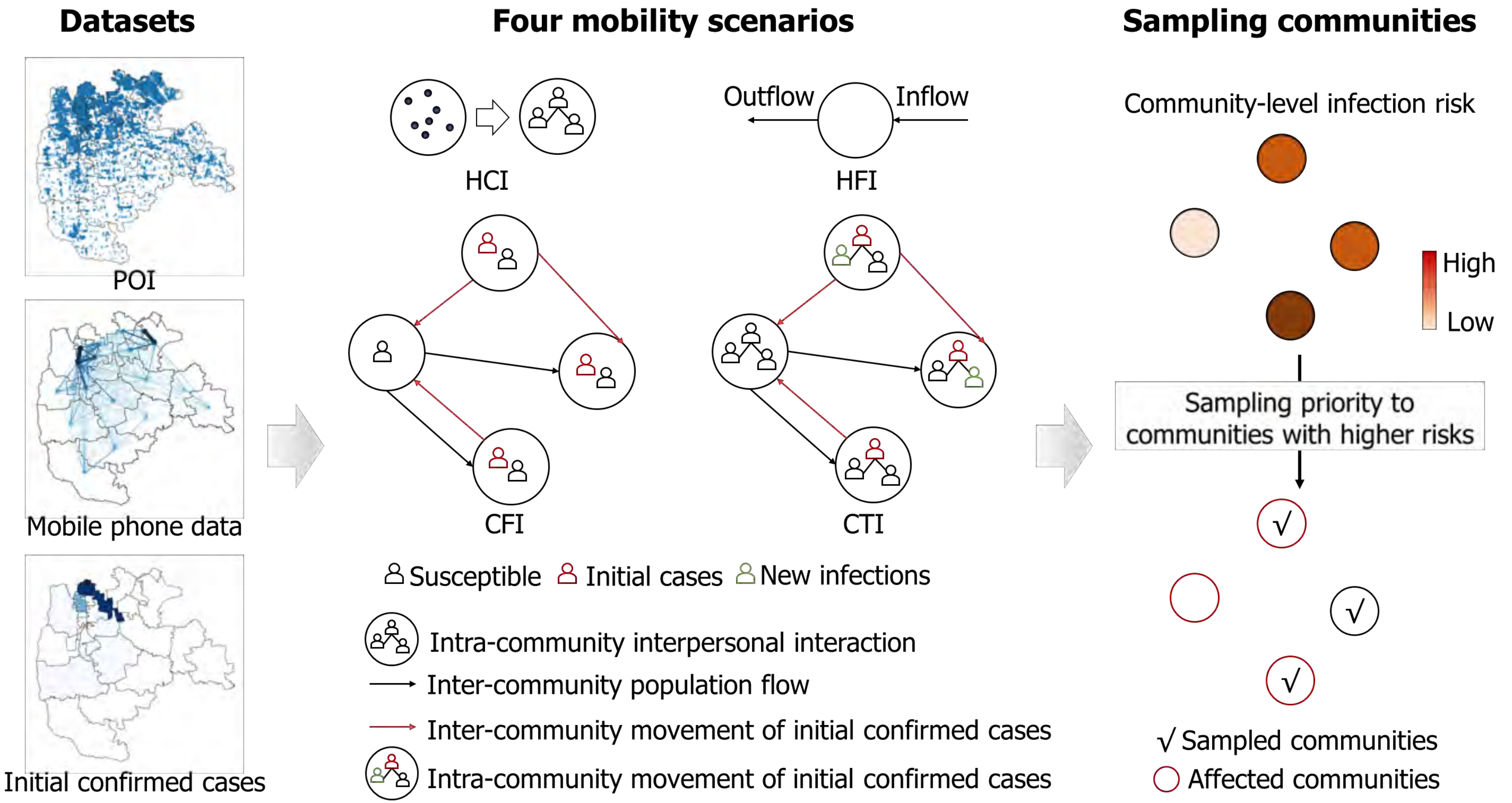
- Combined effect of NPIs and vaccination resulted in a 53% (95% CI: 42–62%) reduction in R0 by October 2021
- NPIs and vaccination reduced the transmission by 35% and 38%, respectively
- Compared with vaccination, the change of NPI effect was less sensitive to emerging variants



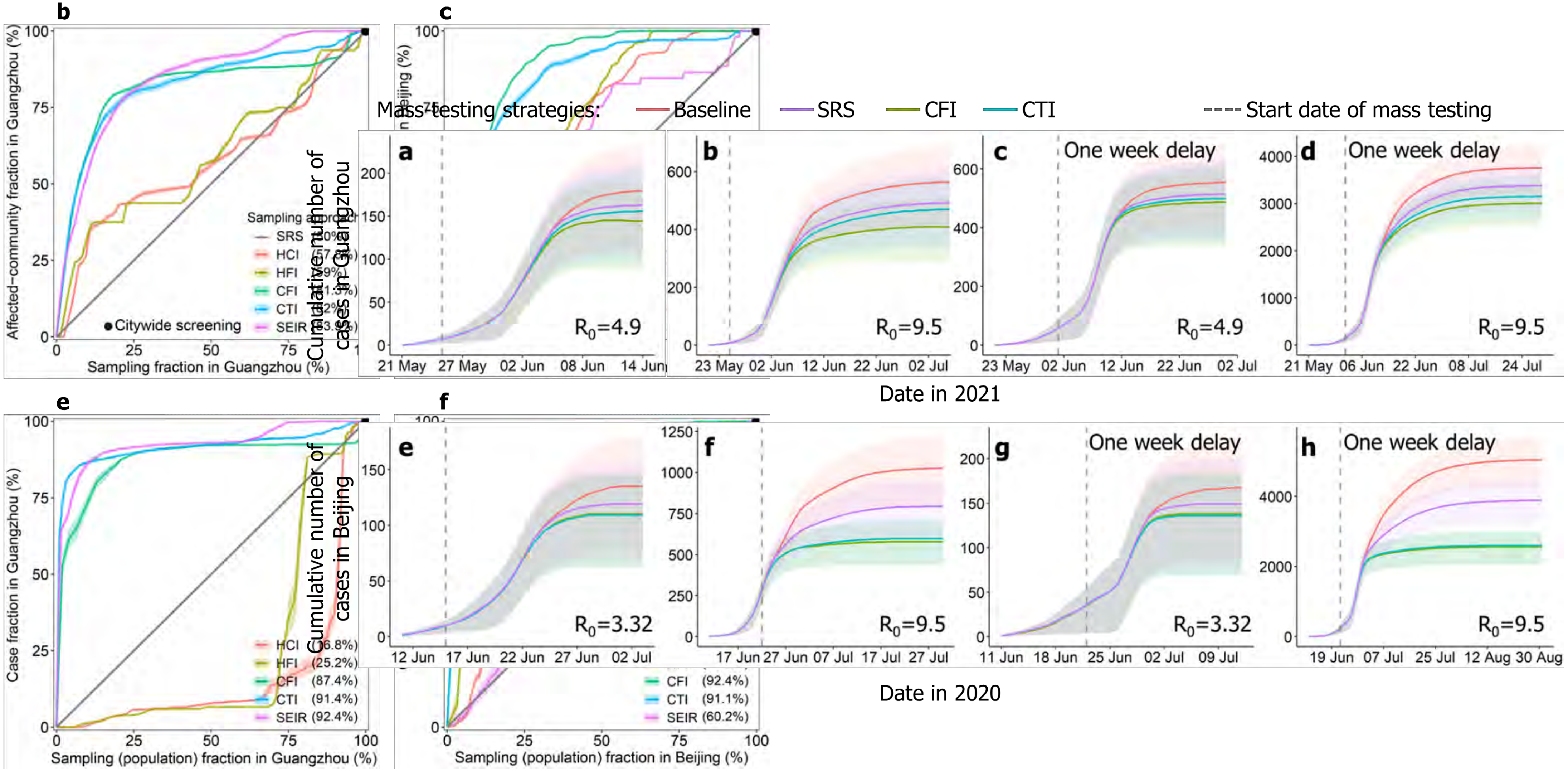
Mobility-based spatial sampling improves detection of emerging infections in mass testing



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

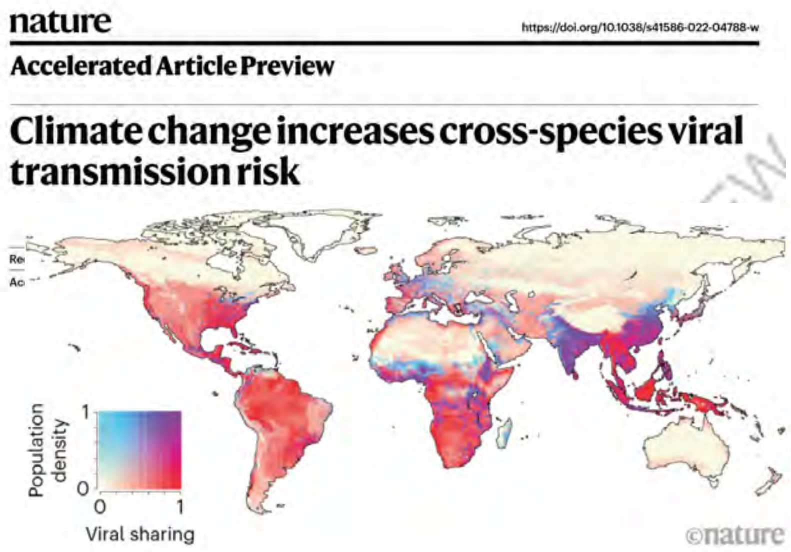


Mobility-based spatial sampling improves detection of emerging infections in mass testing

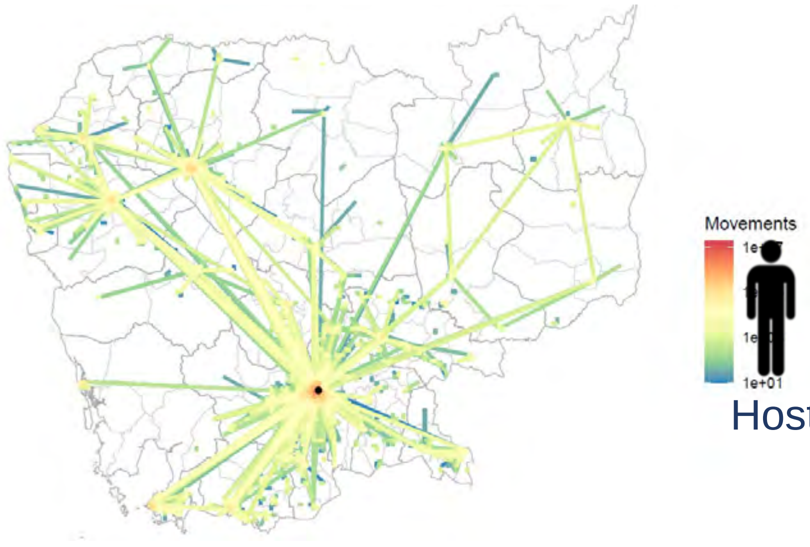


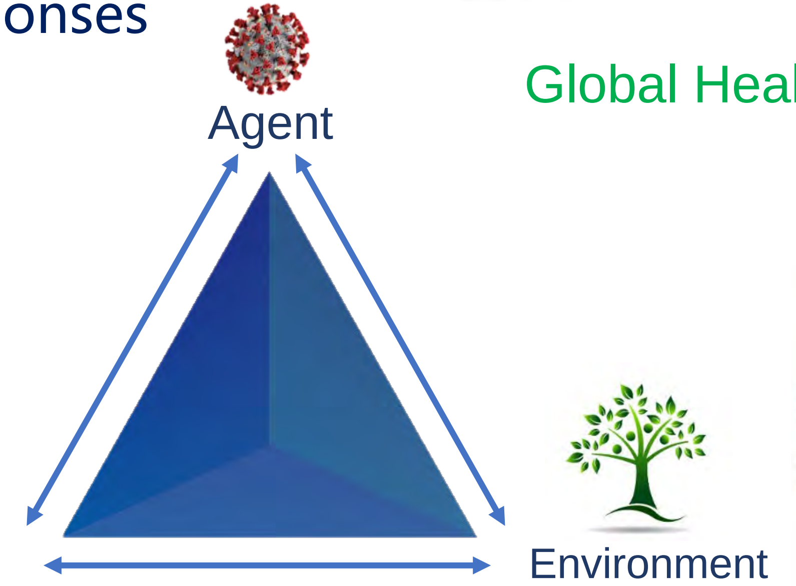
Wrap-up

- The growing reach and volume of human mobility play a key role in socioeconomic development and epidemics
- New forms of mobility data are aiding our abilities to model, assess and respond to outbreaks/other events
- Integration of data, methods, tech & evidence can improve disease responses across sectors



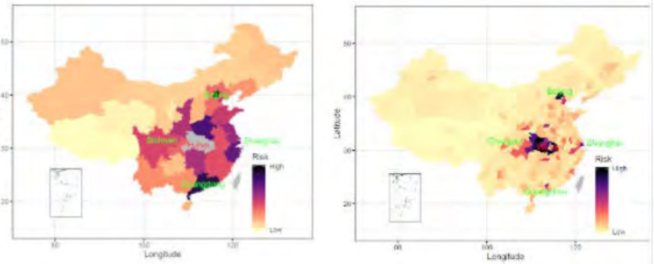
Global Health - One Health





WorldPop COVID-19 research and data

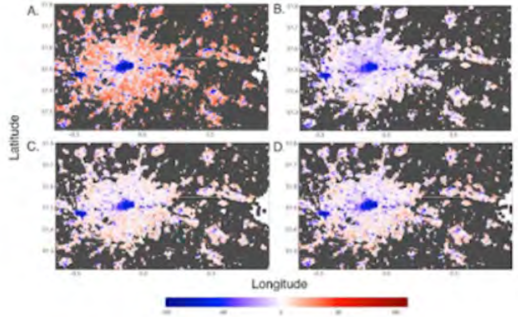
https://www.worldpop.org/covid19



Research

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

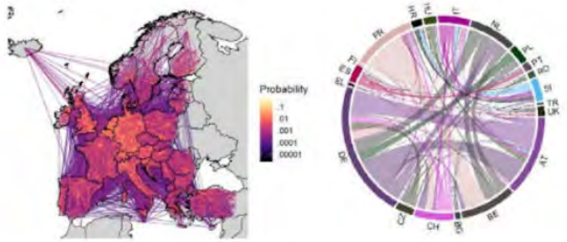
LEARN MORE »



Research

Domestic and international mobility trends in the United Kingdom during the COVID-19 pandemic: An analysis of Facebook data.

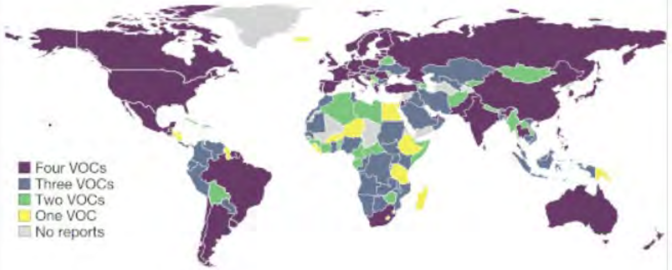
LEARN MORE »



Research

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

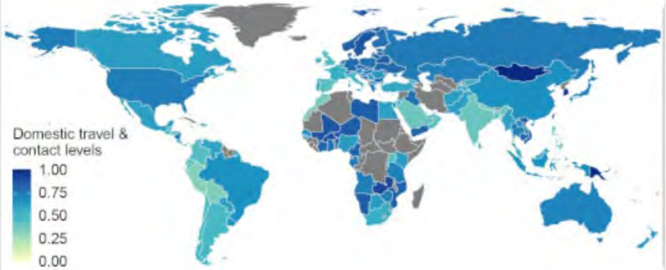
LEARN MORE »



Research

The emergence, genomic diversity and global spread of SARS-CoV-2.

LEARN MORE »



Research

Assessing the effect of global travel and contact restrictions on mitigating the COVID-19 Pandemic.

LEARN MORE »

Research

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

LEARN MORE »

worldpop

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

COVID-19 work:
www.worldpop.org/covid19