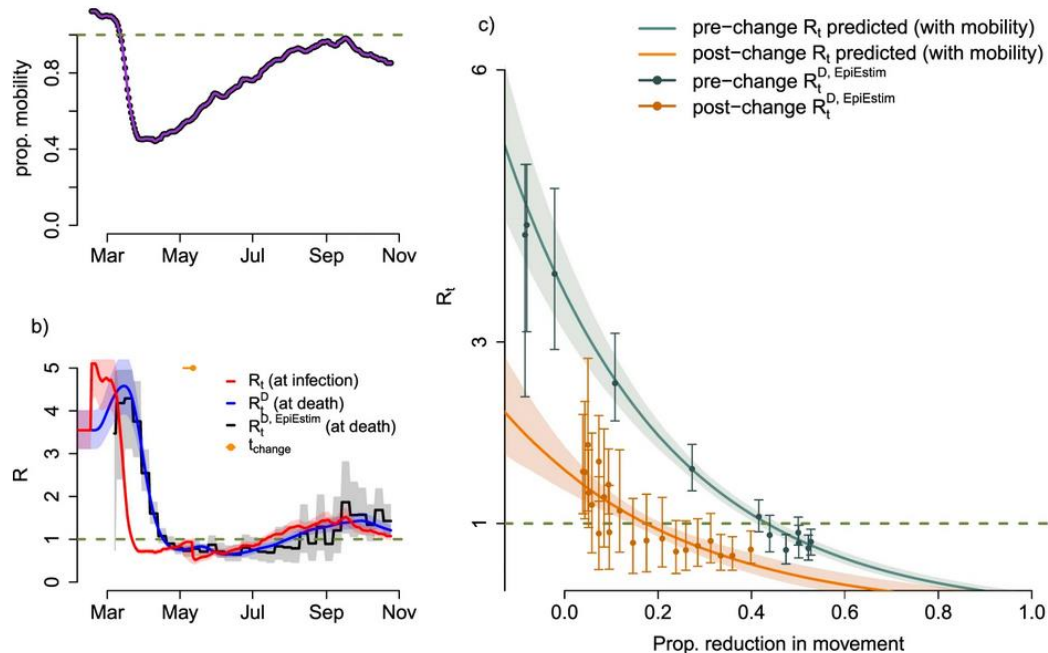


# General human mobility models



# Mobility is a major driver of disease dynamics and spread in people...

## Lockdown restrictions and COVID-19 in the UK



ARTICLE

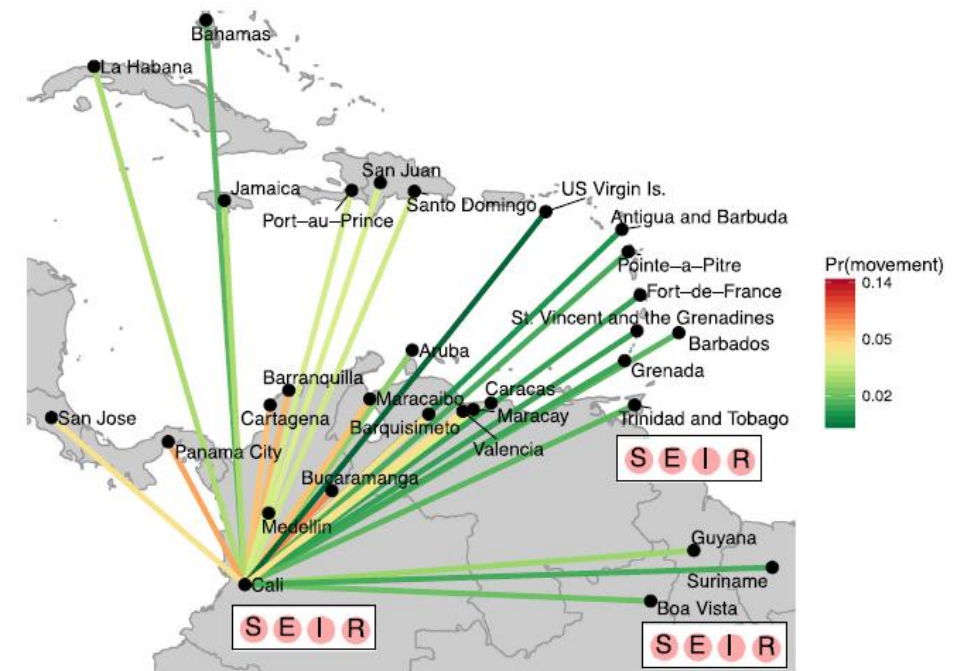
<https://doi.org/10.1038/s41467-021-21358-2>

OPEN

## Reduction in mobility and COVID-19 transmission

Pierre Nouvellet<sup>1,2</sup>, Sangeeta Bhatia<sup>1</sup>, Anne Cori<sup>1</sup>, Kylie E. C. Ainslie<sup>1</sup>, Marc Baguelin<sup>1</sup>, Samir Bhatt<sup>1</sup>

## Spatial spread of Zika in the Americas



RESEARCH ARTICLE

Open Access

## Projecting the end of the Zika virus epidemic in Latin America: a modelling analysis

Kathleen M. O'Reilly<sup>1,2\*</sup>, Rachel Lowe<sup>2,3,4</sup>, W. John Edmunds<sup>2,3</sup>, Philippe Mayaud<sup>5</sup>, Adam Kucharski<sup>2,3</sup>, Rosalind M. Eggo<sup>2,3</sup>, Sebastian Funk<sup>2,3</sup>, Deepit Bhatia<sup>6,7</sup>, Kamran Khan<sup>6,7</sup>, Moritz U. G. Kraemer<sup>8,9,10</sup>

# ... and in wildlife

## ECOLOGY LETTERS

Ecology Letters, (2018) 21: 588–604

doi: 10.1111/ele.12917

### REVIEW AND SYNTHESIS

#### Going through the motions: incorporating movement analyses into disease research

Eric R. Dougherty<sup>1\*,†</sup>   
Dana P. Seidel<sup>1,†</sup> Colin J. Carlson<sup>†</sup>  
Orr Spiegel<sup>2</sup>  and  
Wayne M. Getz<sup>1, 3</sup> 

##### Abstract

Though epidemiology dates back to the 1700s, most mathematical representations of epidemics still use transmission rates averaged at the population scale, especially for wildlife diseases. In simplifying the contact process, we ignore the heterogeneities in host movements that complicate the real world, and overlook their impact on spatiotemporal patterns of disease burden. Movement ecology offers a set of tools that help unpack the transmission process, letting researchers more

### ARTICLE

Received 18 Feb 2013 | Accepted 15 Oct 2013 | Published 19 Nov 2013

DOI: 10.1038/ncomms3770

## Continent-wide panmixia of an African fruit bat facilitates transmission of potentially zoonotic viruses

Alison J. Peel<sup>1,2</sup>, David R. Sargan<sup>1</sup>, Kate S. Baker<sup>1,2,3</sup>, David T. S. Hayman<sup>1,2,4,5,6</sup>, Jennifer A. Barr<sup>7</sup>, Gary Crameri<sup>7</sup>, Richard Suu-Ire<sup>8,9</sup>, Christopher C. Broder<sup>10</sup>, Tiziana Lembo<sup>11</sup>, Lin-Fa Wang<sup>7,12</sup>, Anthony R. Fooks<sup>5,13</sup>, Stephen J. Rossiter<sup>14</sup>, James L. N. Wood<sup>1</sup> & Andrew A. Cunningham<sup>2</sup>

DOI: 10.1111/1365-2664.14031

### RESEARCH ARTICLE

Journal of Applied Ecology 

## Journal of Animal Ecology

BRITISH  
ECOLOGICAL  
SOCIETY

Review

### Unifying spatial and social network analysis in disease ecology




Gregory F. Albery  Lucinda Kirkpatrick, Josh A. Firth, Shweta Bansal 

## Migrating Birds as Dispersal Vehicles for West Nile Virus

Jennifer Owen, Frank Moore, Nicholas Panella, Eric Edwards, Rachel Bru, Megan Hughes, and Nicholas Komar

Department of Biological Sciences, University of Southern Mississippi, Hattiesburg, MS 39406, USA

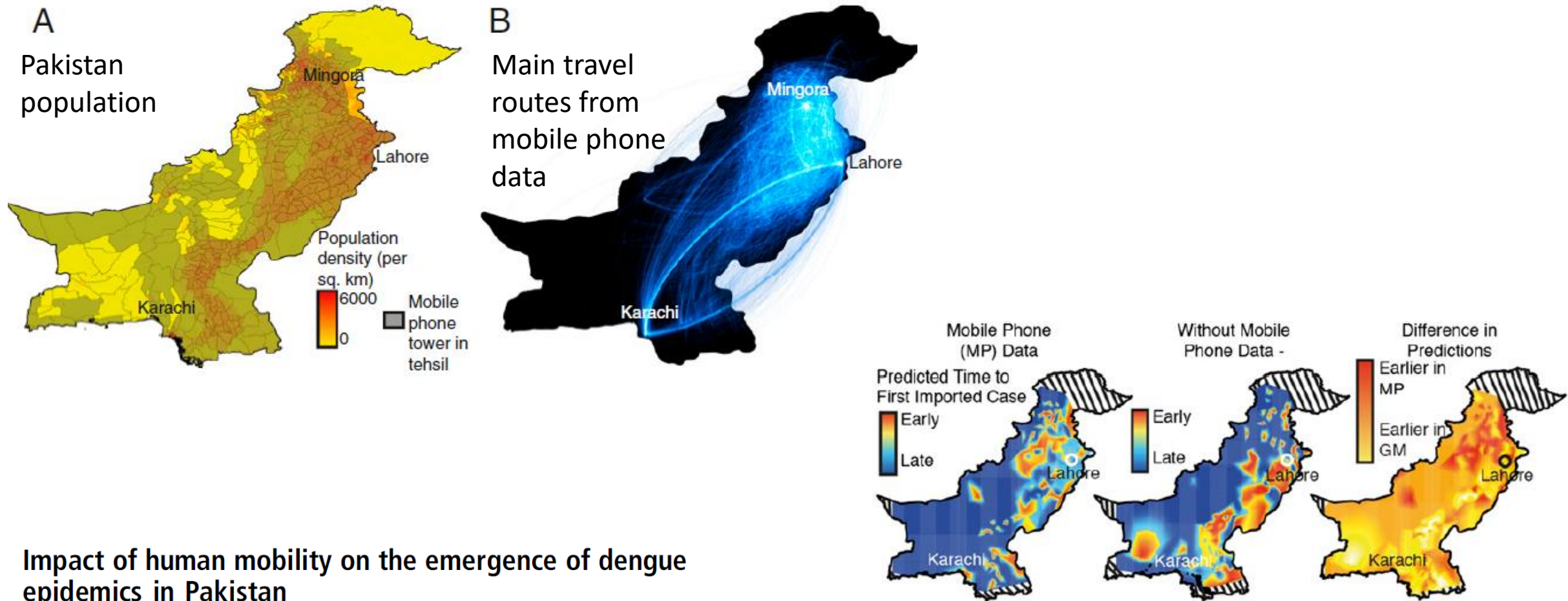
## Roads and forest edges facilitate yellow fever virus dispersion

Paula Ribeiro Prist<sup>1</sup>  | Leandro Reverberi Tambosi<sup>1,2</sup>  | Luís Filipe Mucci<sup>3</sup> | Adriano Pinter<sup>3</sup> | Renato Pereira de Souza<sup>4</sup> | Renata de Lara Muylaert<sup>5</sup>  |

# The problem

It is very challenging to measure (human) movement at the temporal and spatial scales required to incorporate into statistical or dynamical models of disease spread

# One emerging solution: mobile data



## Impact of human mobility on the emergence of dengue epidemics in Pakistan

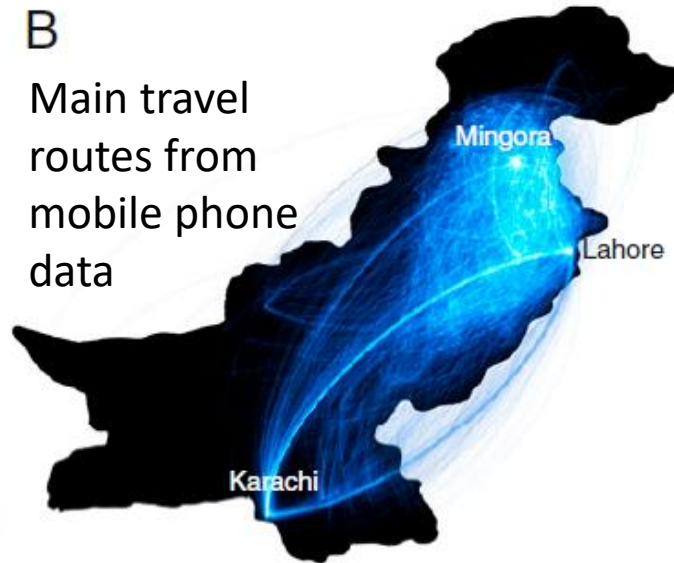
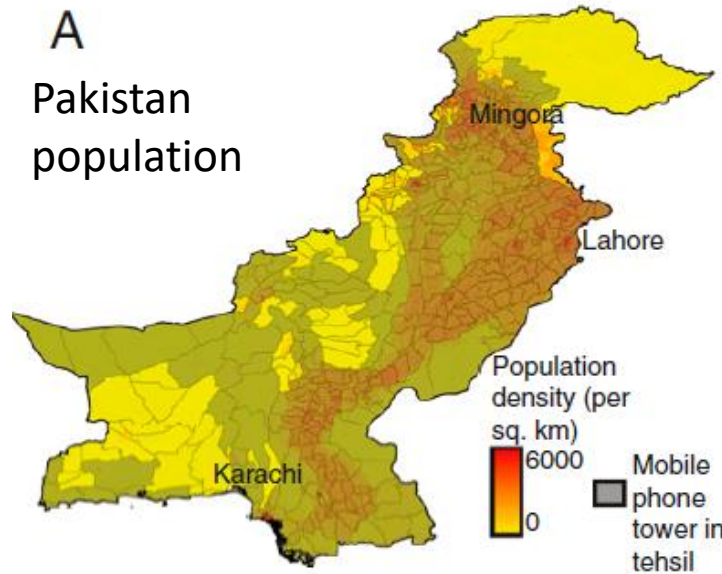
Amy Wesolowski<sup>a,b</sup>, Taimur Qureshi<sup>c</sup>, Maciej F. Boni<sup>d,e</sup>, Pål Roe Sundsøy<sup>c</sup>, Michael A. Johansson<sup>b,f</sup>, Syed Basit Rasheed<sup>g</sup>, Kenth Engø-Monsen<sup>c</sup>, and Caroline O. Buckee<sup>a,b,1</sup>

<sup>a</sup>Department of Epidemiology, Harvard T. H. Chan School of Public Health, Boston, MA 02115; <sup>b</sup>Center for Communicable Disease Dynamics, Harvard T. H. Chan School of Public Health, Boston, MA 02115; <sup>c</sup>Telenor Research, Telenor Group, N-1360 Fornebu, Norway; <sup>d</sup>Oxford University Clinical Research Unit, Wellcome Trust Major Overseas Programme, Ho Chi Minh City, Vietnam; <sup>e</sup>Centre for Tropical Medicine, Nuffield Department of Clinical Medicine, University of Oxford, Oxford OX3 7FZ, United Kingdom; <sup>f</sup>Division of Vector-Borne Diseases, Centers for Disease Control, San Juan, Puerto Rico 00920; and <sup>g</sup>Department of Zoology, University of Peshawar, Peshawar 25120, Pakistan

Mobile phone data helps in predicting long-range introductions during 2013 dengue epidemic

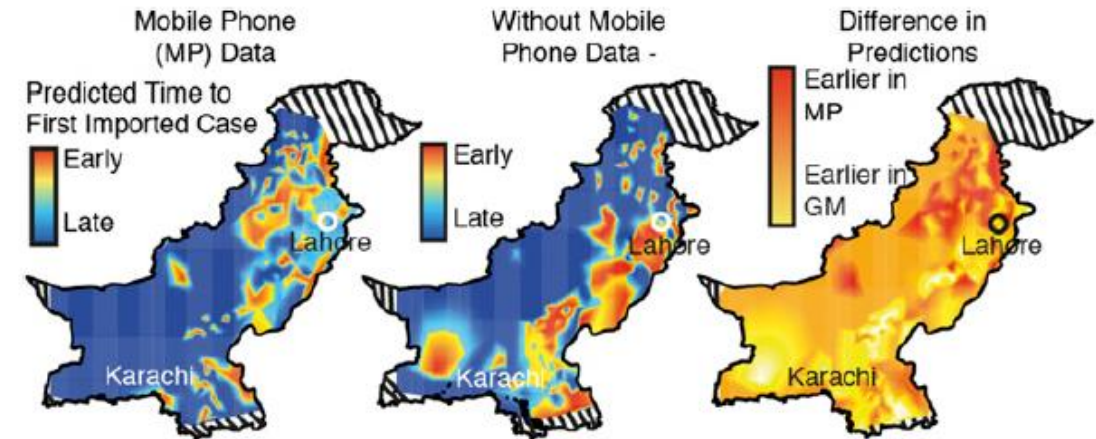


# One emerging solution: mobile data



**But...**

- *Challenging and slow to access*
- *Spatially/temporally restricted (e.g. within country or few years)*
- *Privacy and consent concerns*



## Impact of human mobility on the emergence of dengue epidemics in Pakistan

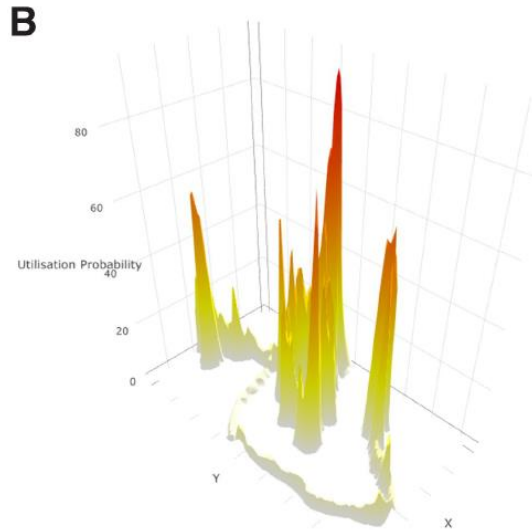
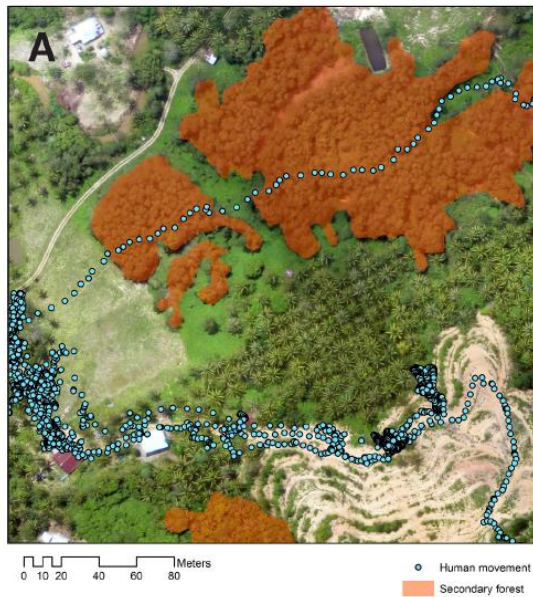
Amy Wesolowski<sup>a,b</sup>, Taimur Qureshi<sup>c</sup>, Maciej F. Boni<sup>d,e</sup>, Pål Roe Sundsøy<sup>c</sup>, Michael A. Johansson<sup>b,f</sup>, Syed Basit Rasheed<sup>g</sup>, Kenth Engø-Monsen<sup>c</sup>, and Caroline O. Buckee<sup>a,b,1</sup>

<sup>a</sup>Department of Epidemiology, Harvard T. H. Chan School of Public Health, Boston, MA 02115; <sup>b</sup>Center for Communicable Disease Dynamics, Harvard T. H. Chan School of Public Health, Boston, MA 02115; <sup>c</sup>Telenor Research, Telenor Group, N-1360 Fornebu, Norway; <sup>d</sup>Oxford University Clinical Research Unit, Wellcome Trust Major Overseas Programme, Ho Chi Minh City, Vietnam; <sup>e</sup>Centre for Tropical Medicine, Nuffield Department of Clinical Medicine, University of Oxford, Oxford OX3 7FZ, United Kingdom; <sup>f</sup>Division of Vector-Borne Diseases, Centers for Disease Control, San Juan, Puerto Rico 00920; and <sup>g</sup>Department of Zoology, University of Peshawar, Peshawar 25120, Pakistan

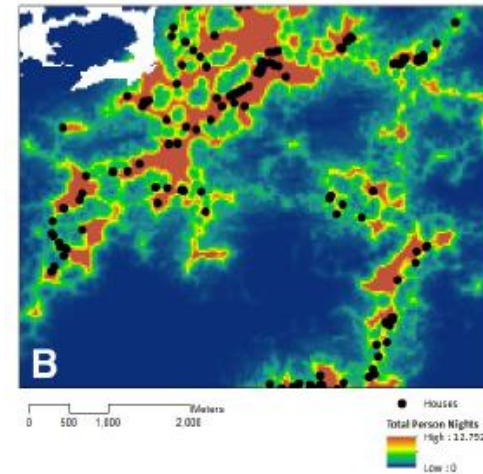
Mobile phone data helps in predicting long-range introductions during 2013 dengue epidemic

# Another solution: GPS or other devices

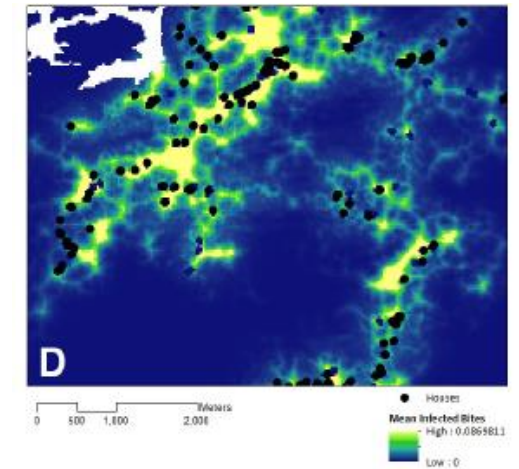
Individual activity spaces characterized using GPS...



Predicted overall distribution of human activity



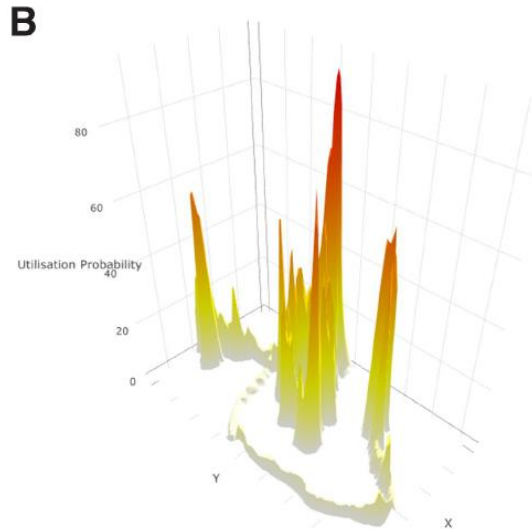
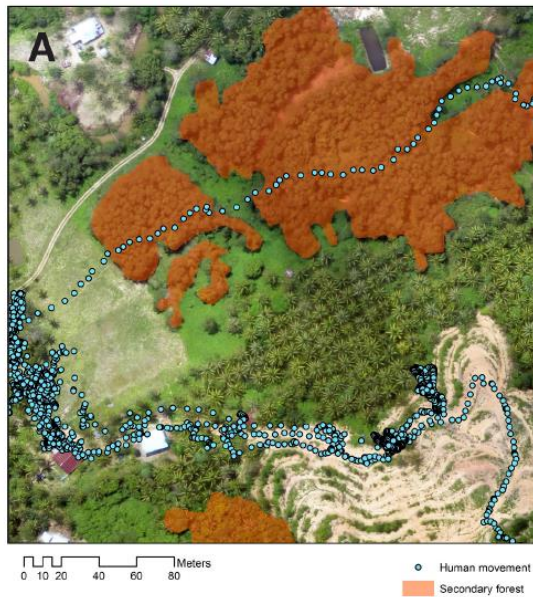
Predicted distribution of infectious mosquito bites (*P. knowlsei*)



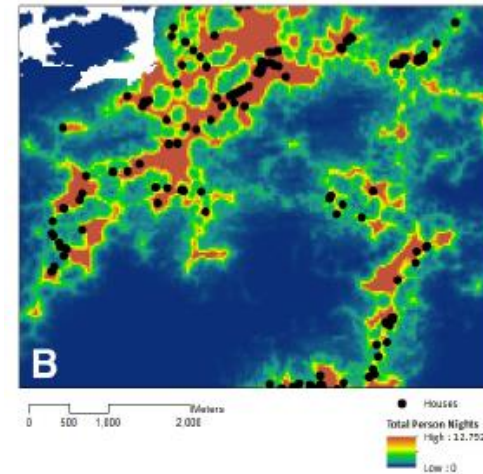


# Another solution: GPS or other devices

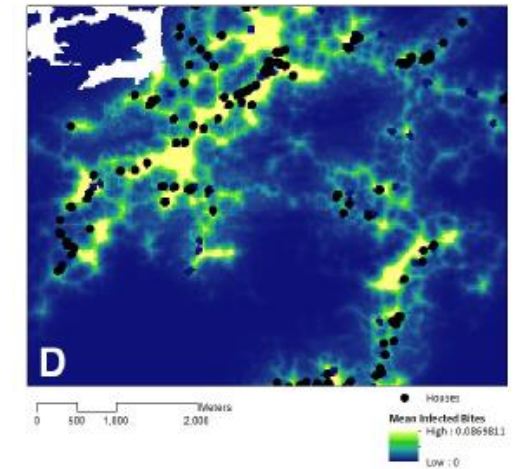
Individual activity spaces characterized using GPS...



Predicted overall distribution of human activity



Predicted distribution of infectious mosquito bites (*P. knowlsei*)



But...

- *Expensive and labour-intensive to collect*
- *So generally small-scale and short-term – appropriate for landscape studies but not necessarily large-scale epidemiological work*

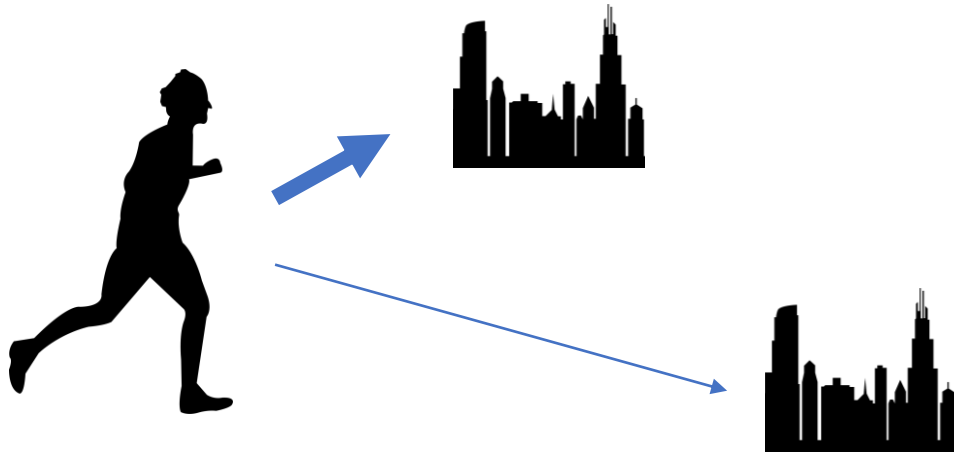


Are there general “rules” of movement governing the likelihood of individuals moving from one location to another?

(Movement ecologists measure and predict these sorts of rules for wildlife, based on tracking or capture data – we tend to call them “resource selection functions”)

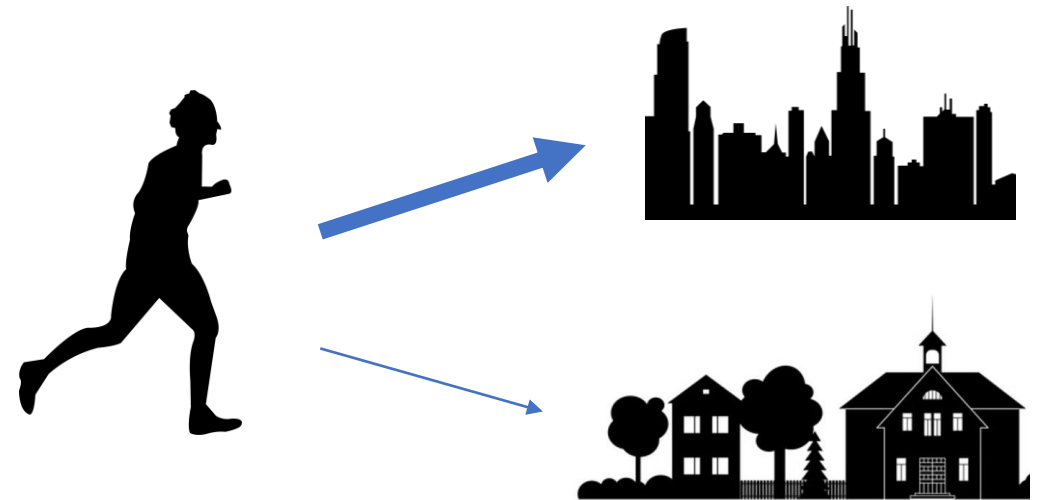
# Some assumptions underpinning general human movement models

## Proximity



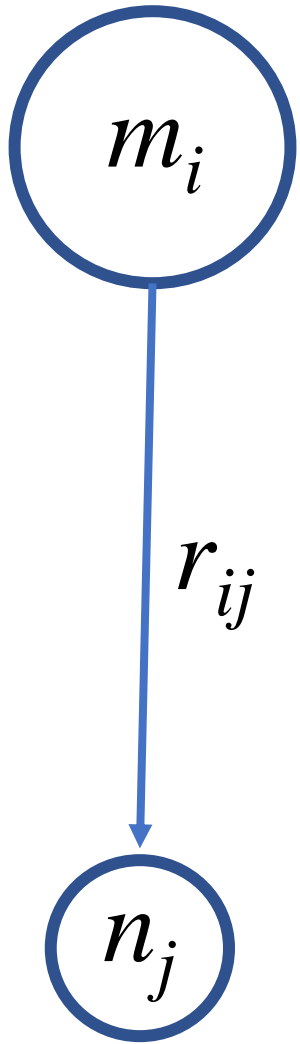
All else being equal, people are more likely to travel to more nearby locations

## Attractiveness



People are more likely to travel to more populated locations, due to greater economic and social opportunities

# The gravity model



$$T_{ij} = \frac{m_i^\alpha n_j^\beta}{f(r_{ij})} = \frac{\text{PopulationSource}^\alpha * \text{PopulationDest}^\beta}{f(\text{Distance})}$$

Simplest formalization of the two assumptions: **the relative flux (or probability of movement) between two locations is proportional to some power of source and destination populations, penalized by a function of the distance between them**

Fast, flexible and widely used across economics, migration and epidemiology settings, *but* requires setting-specific mobility data to estimate attractiveness and distance-decay parameters (or some substantial assumptions)

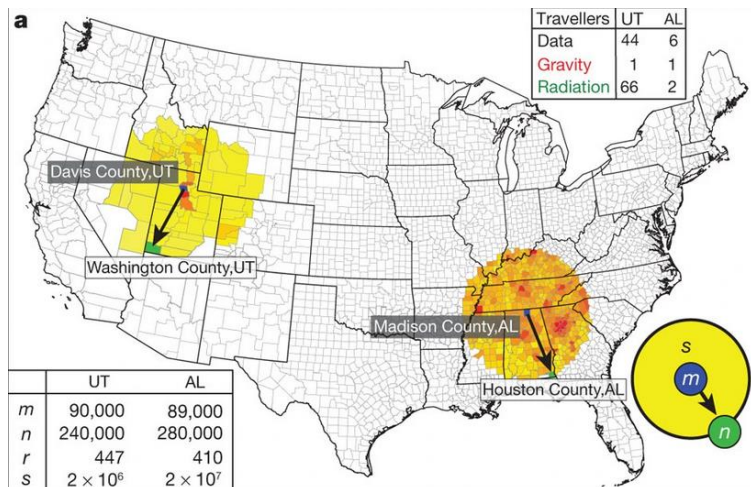
# The radiation model

Total population within the radius  $r_{ij}$

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}$$

## A universal model for mobility and migration patterns

Filippo Simini<sup>1,2,3</sup>, Marta C. González<sup>4</sup>, Amos Maritan<sup>2</sup> & Albert-László Barabási<sup>1,5,6</sup>



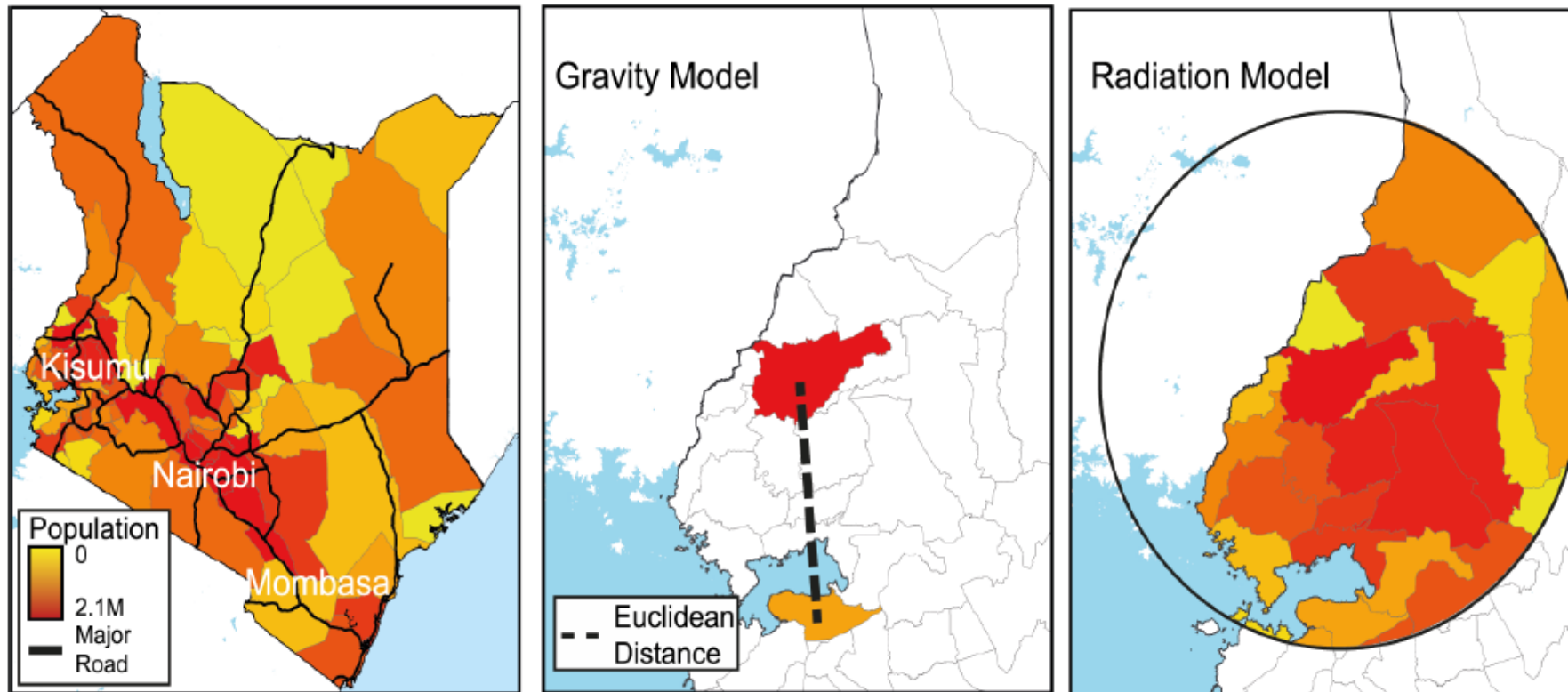
Based on the same principles as the gravity model, but **also accounts for the competitive pull of other densely populated areas more nearby than the destination.**

Relative fluxes between destinations are parameter-free – so can be applied without using context-specific data.

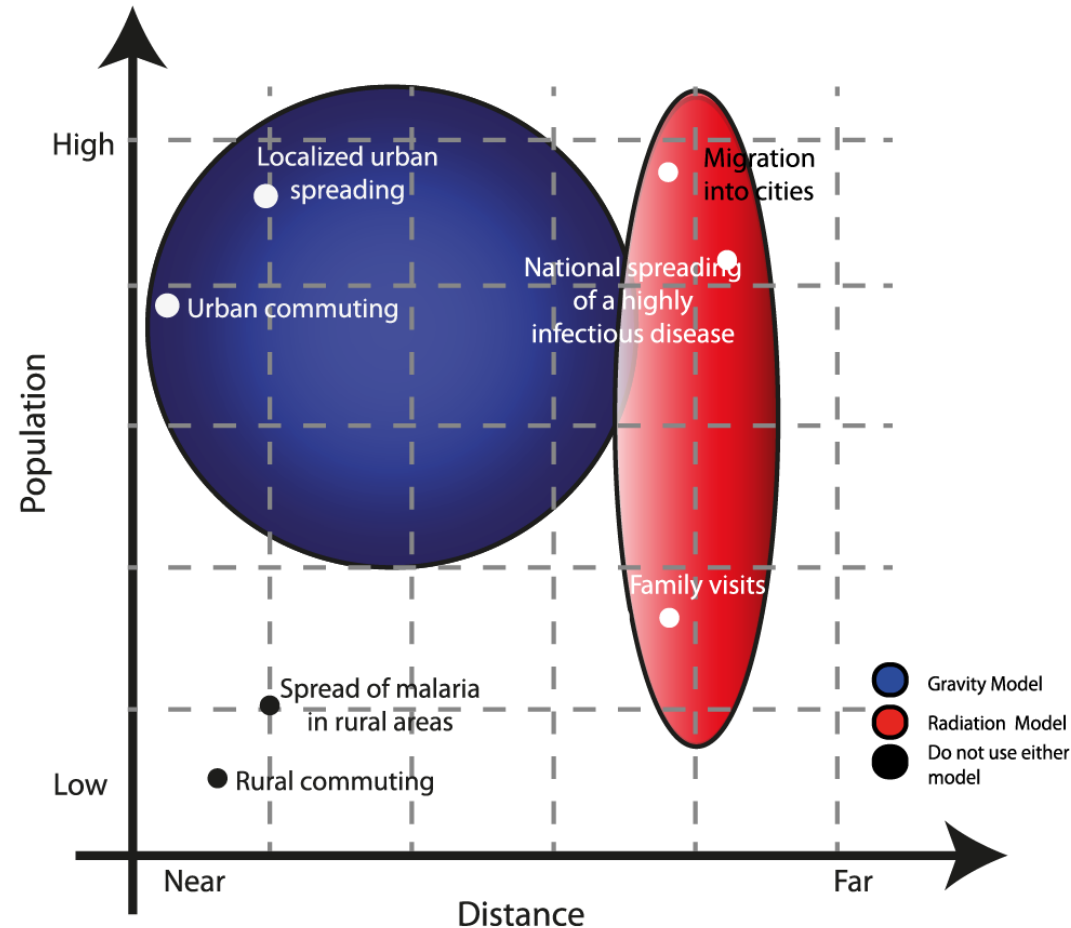
However, developed and validated against USA mobility information – how generalisable?



# Comparative schematic of gravity and radiation models



# A comparison of gravity and radiation model applications in LMIC settings



General guidance based on comparison of performance against mobile phone data in several African countries (but may be difficult to apply in practice)

# More proposed “universal” laws of mobility..

Article

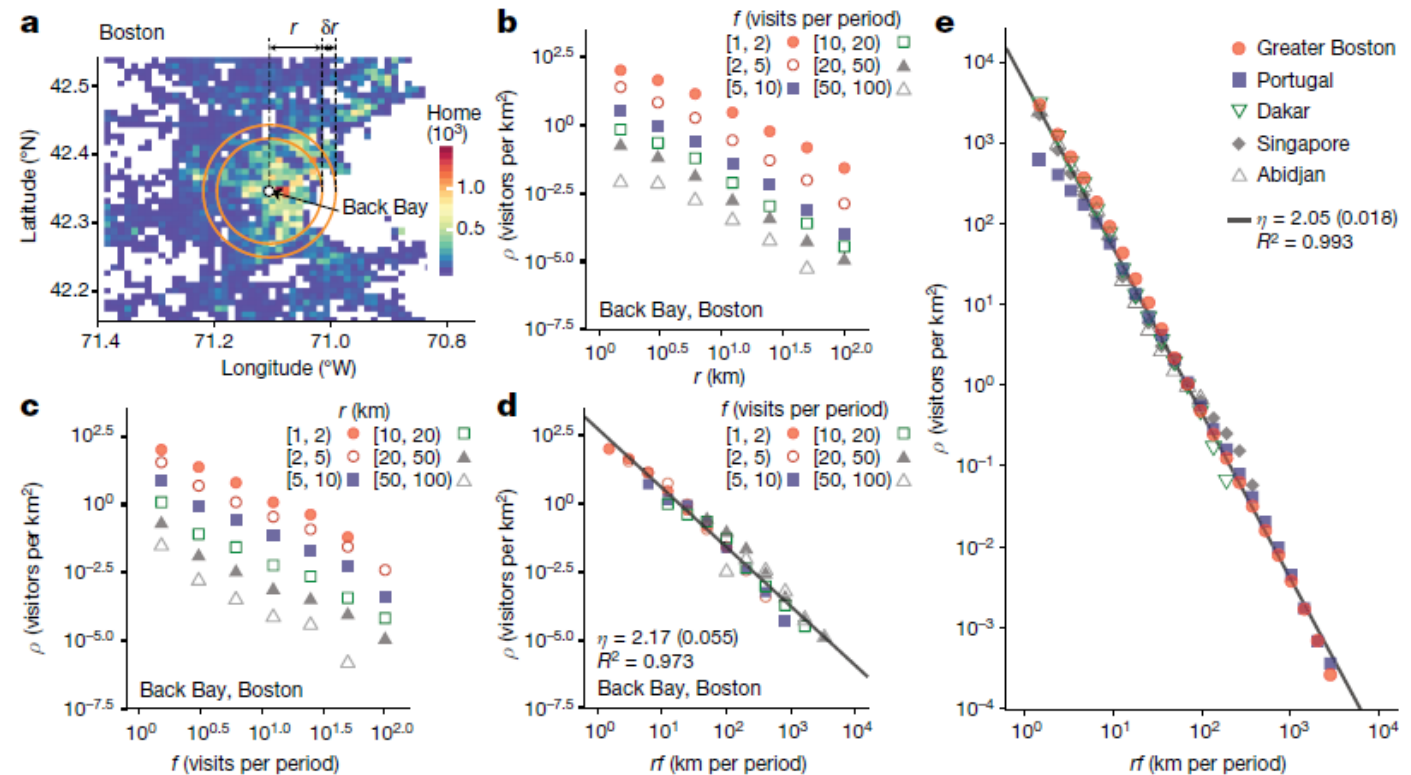
## The universal visitation law of human mobility

<https://doi.org/10.1038/s41586-021-03480-9>

Received: 30 May 2017

Accepted: 22 March 2021

There are likely to be many useful forms of human mobility models – in many cases incorporating *some* mobility proxies may be better than including *none*



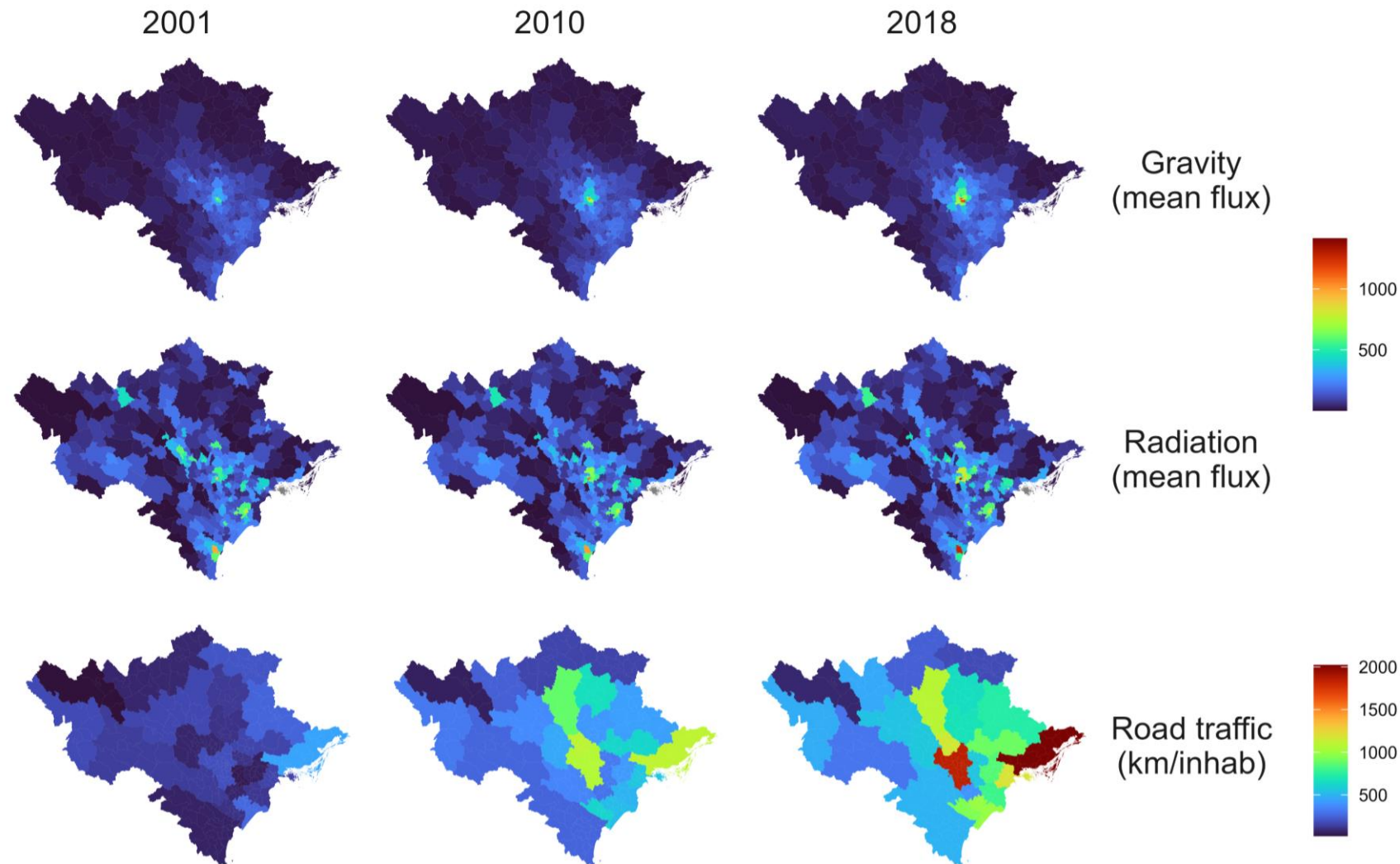
# Advantages and disadvantages of different mobility models

**I ran out of time to do this.**

If it is useful, I can do this and add it to the GitHub repo – let me know.



# Example: long term mobility trends in north Vietnam



Some tutorial code in R