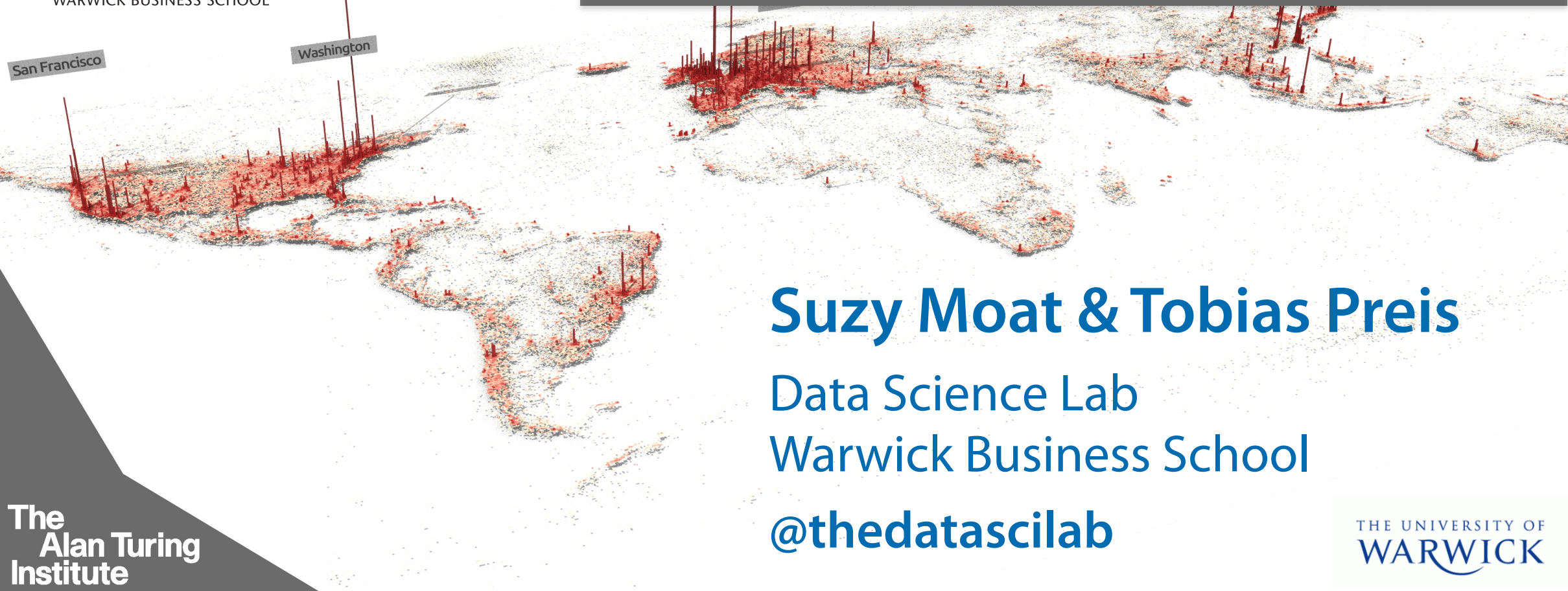


Sensing human behaviour using online data



Suzy Moat & Tobias Preis

Data Science Lab

Warwick Business School

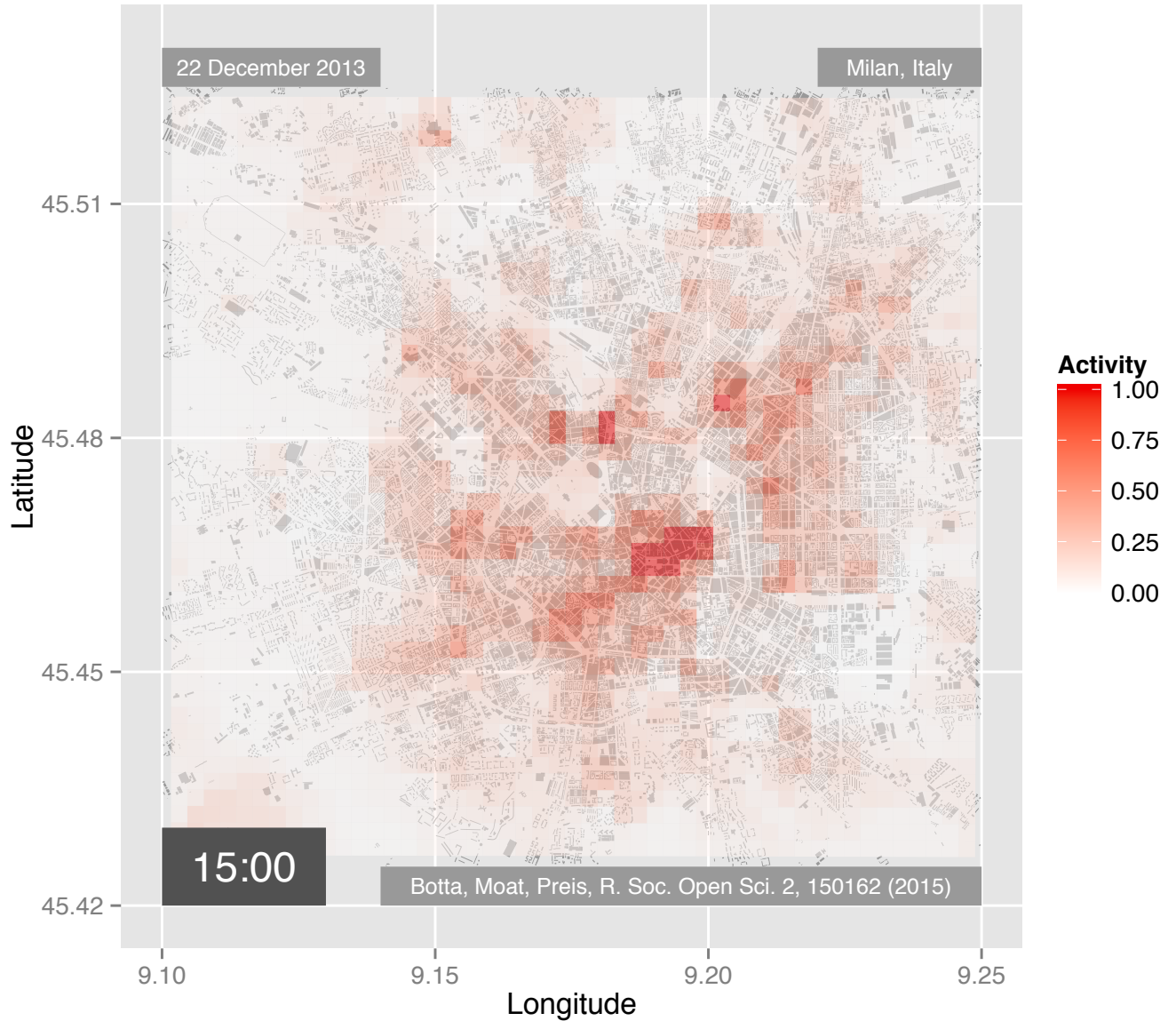
@thedatascilab



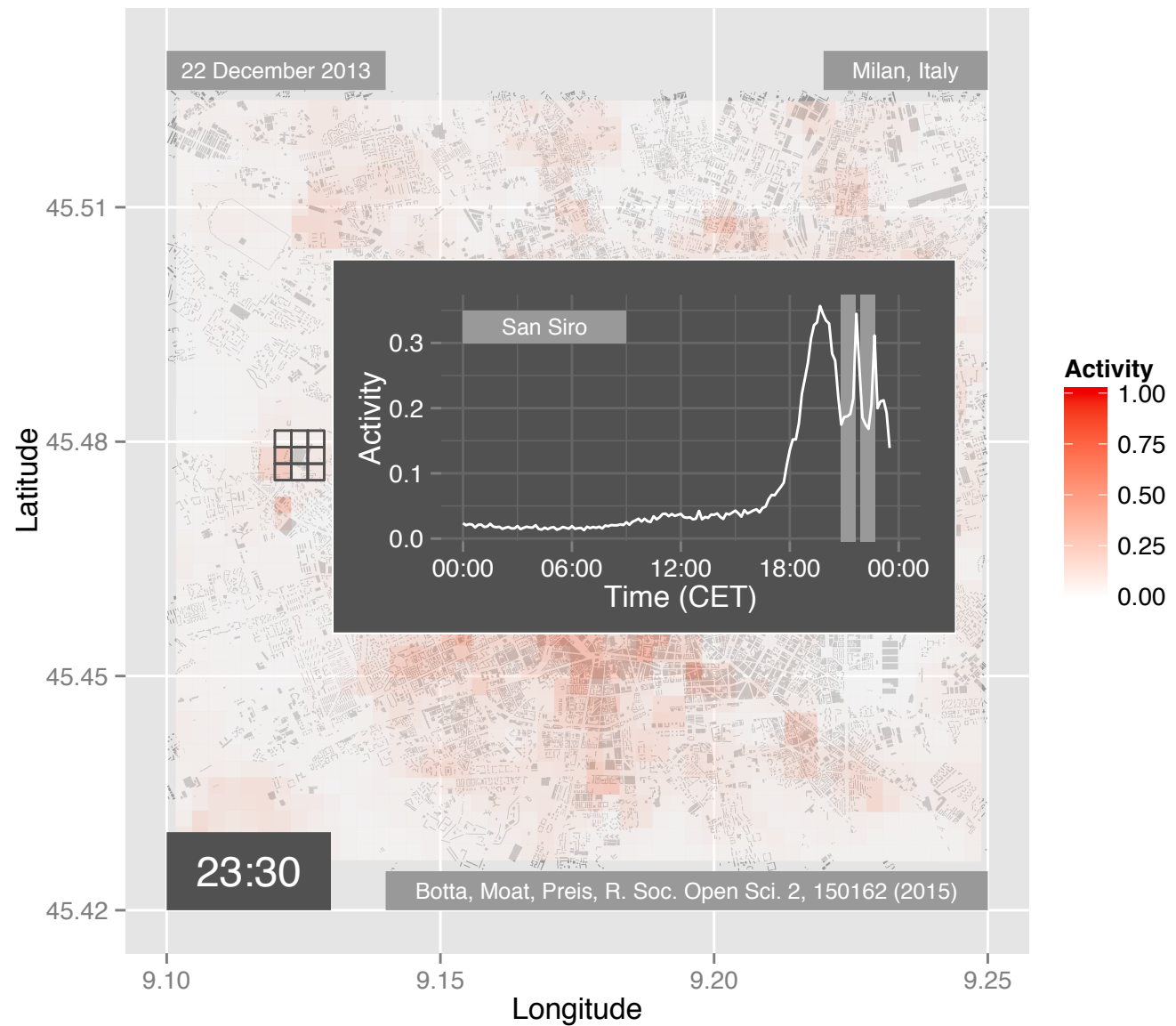
Photo: Reuters



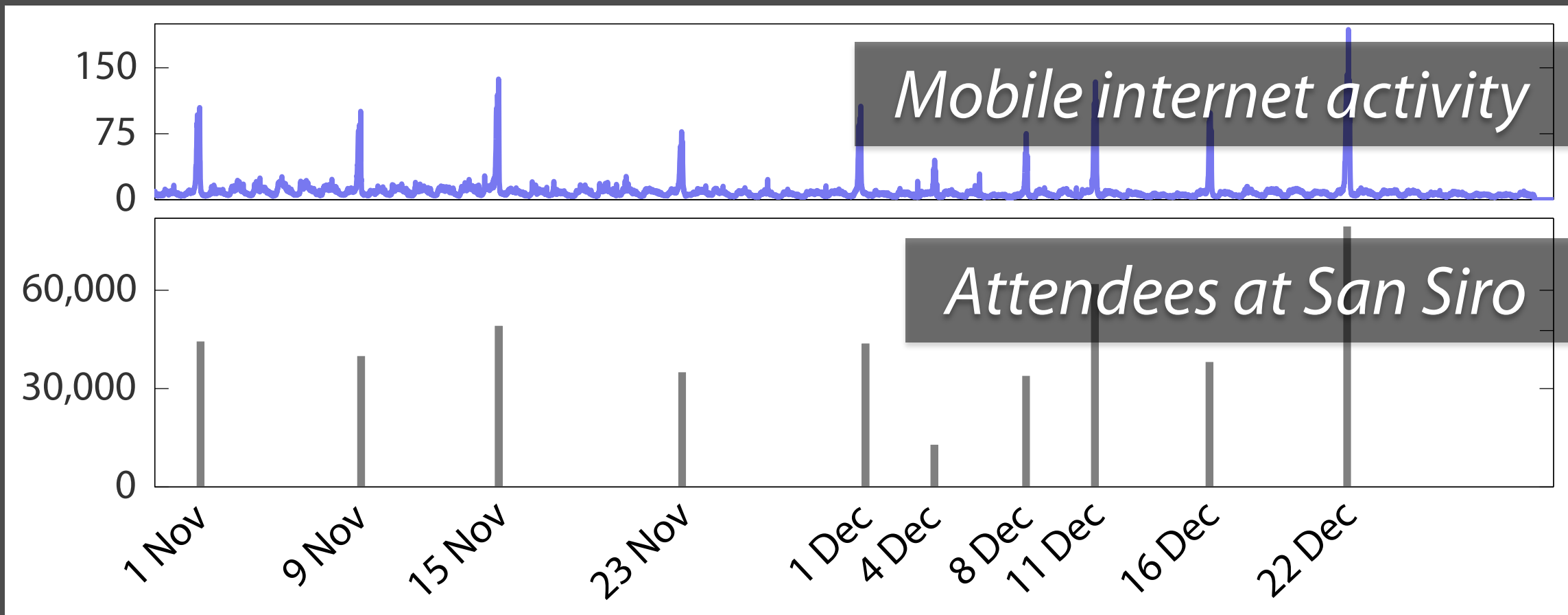
Photo: Kris Krüg



Milan
December 2013



Milan
December 2013

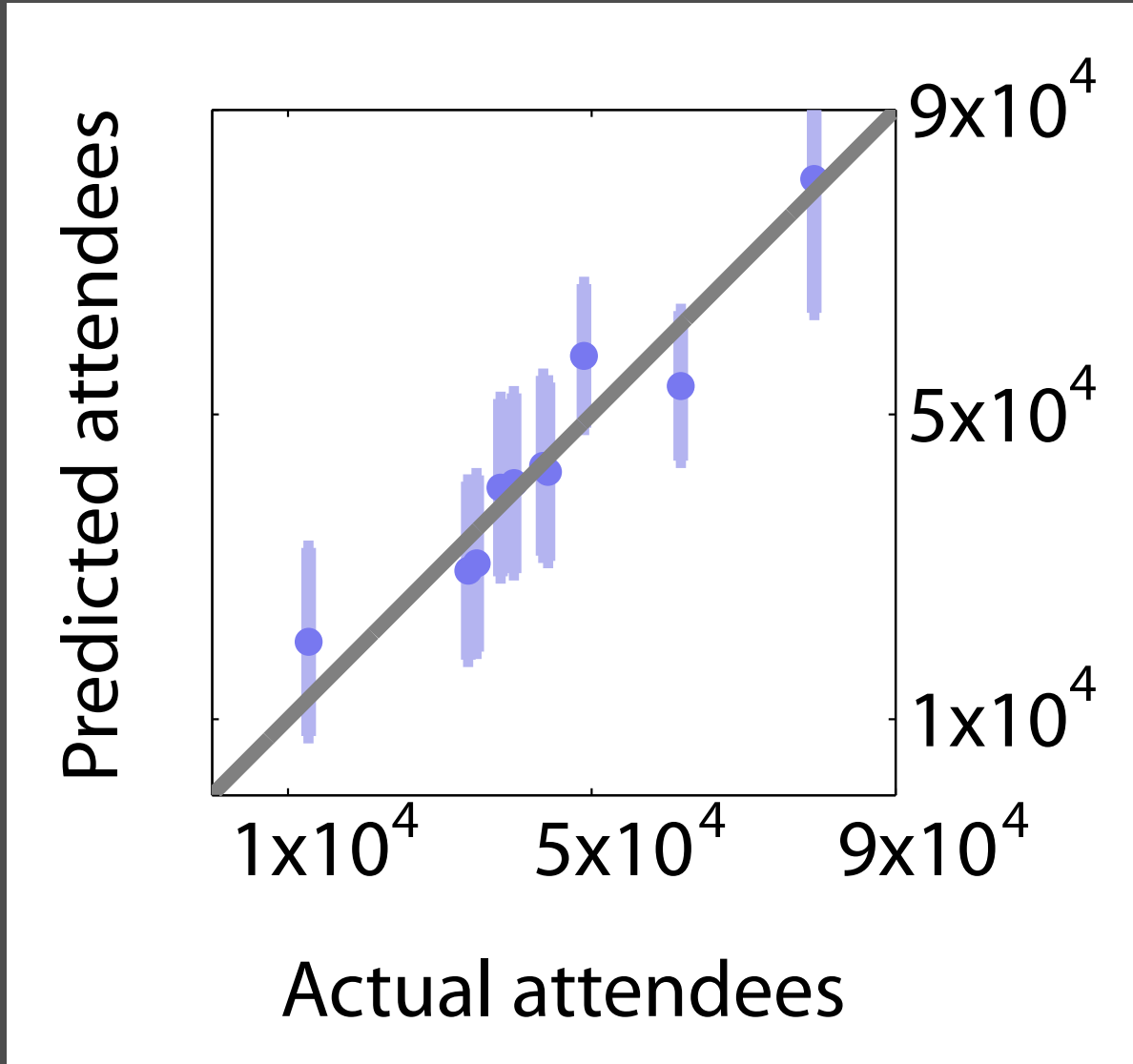


Botta, Moat & Preis (2015)



Match attendance estimated from phone activity

Botta, Moat & Preis (2015)





Beijing

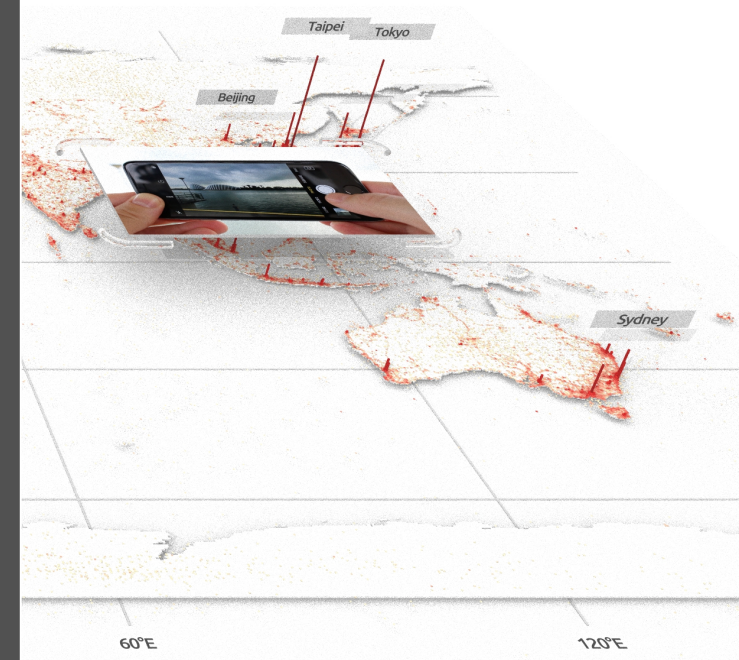
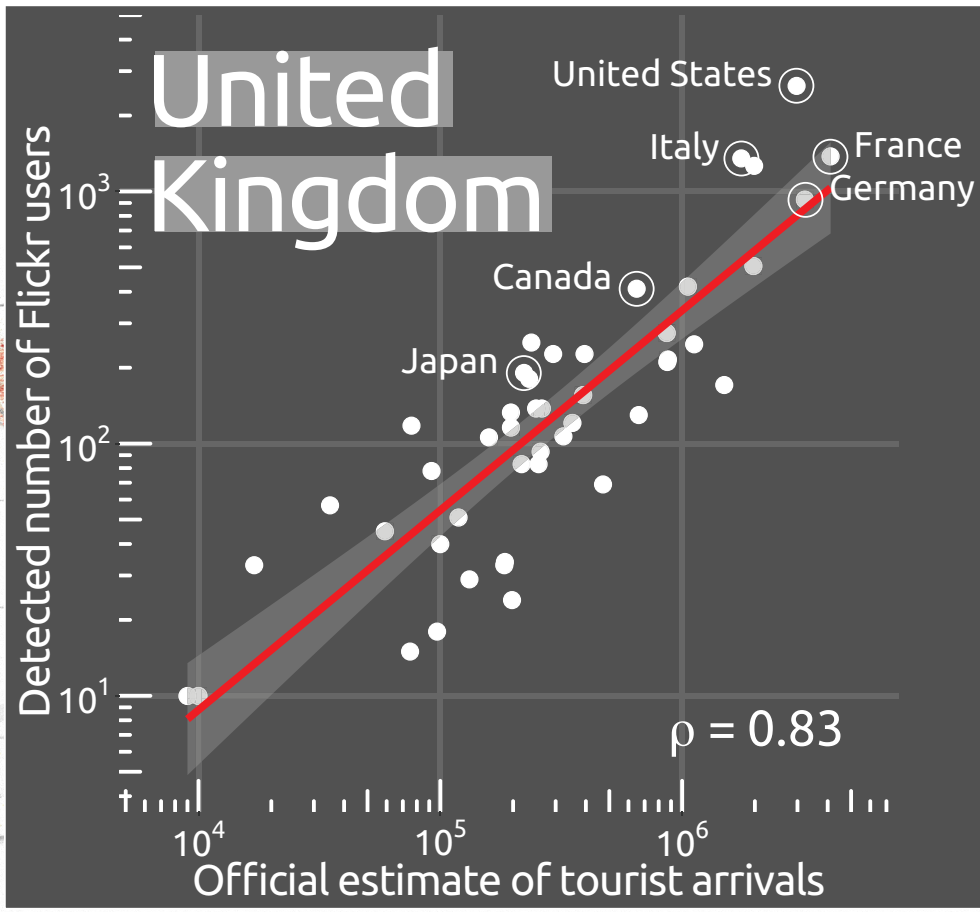
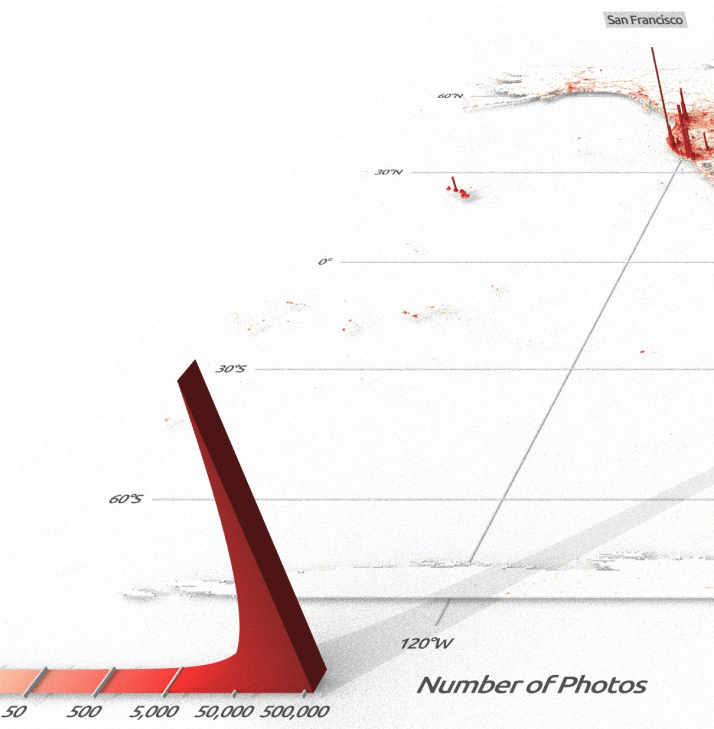
Tokyo

Taipei



HDR

30-MO VIDEO PHOTO SQUARE PAN

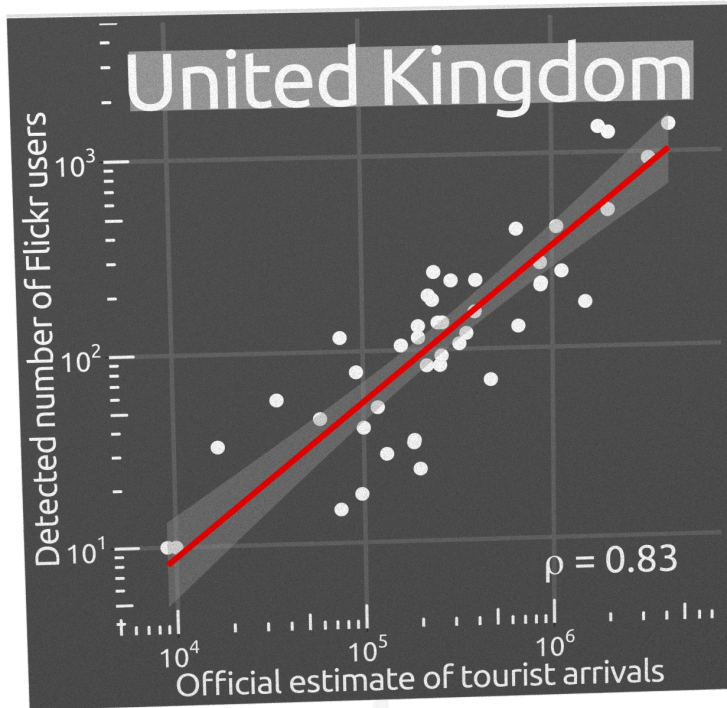


Estimating Tourism Statistics in G7 Countries Using Flickr Photos

Barchiesi, Moat, Alis, Bishop & Preis (2015)

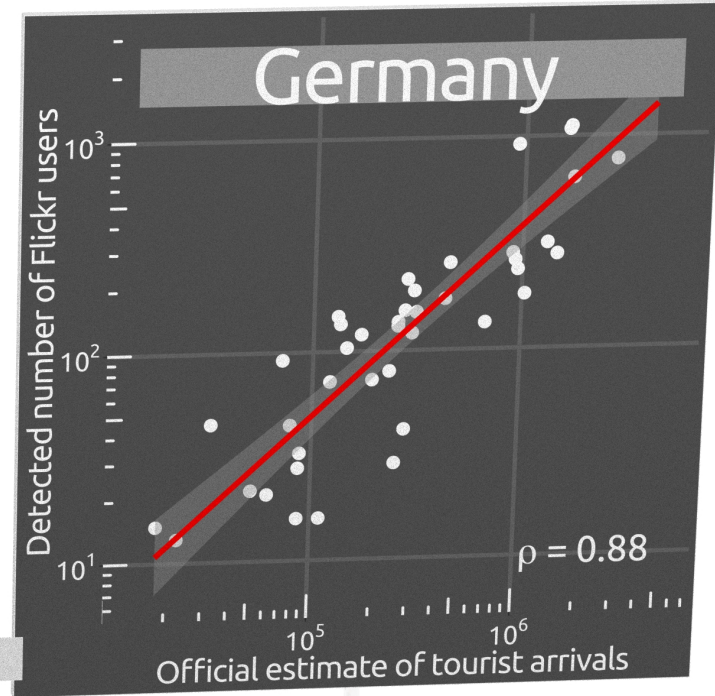
10⁶

New York



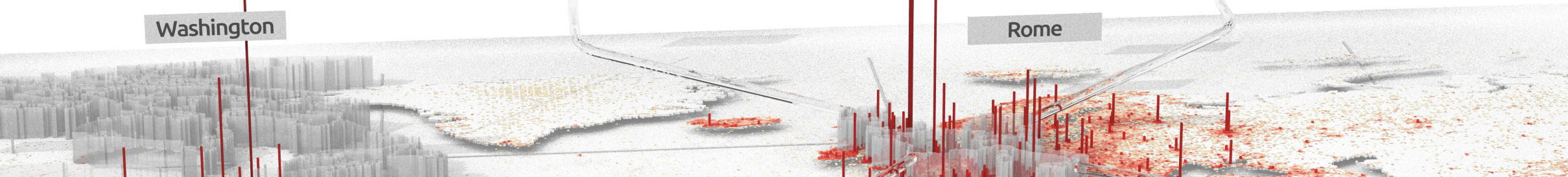
London

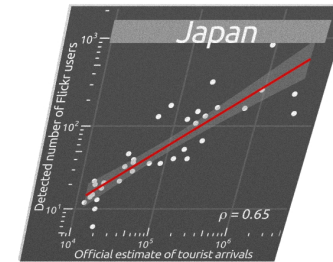
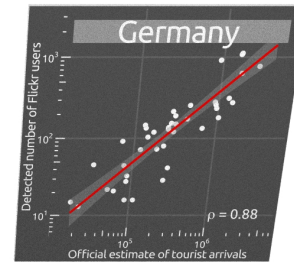
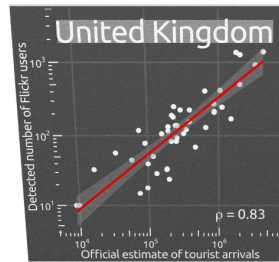
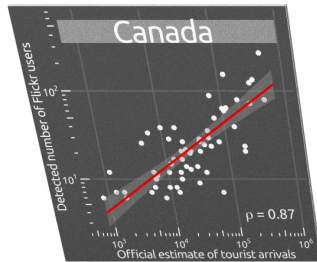
Paris



Washington

Rome





New York

London

Paris

San Francisco

Washington

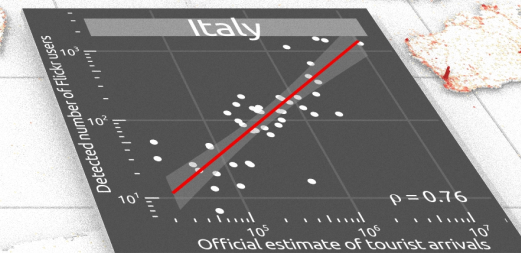
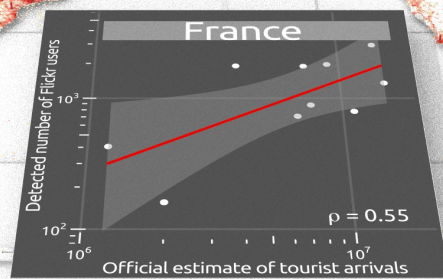
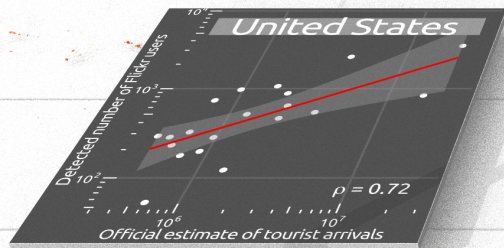
Rome

Taipei

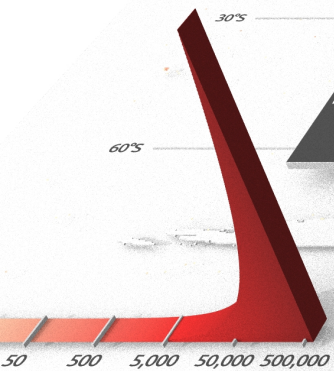
Tokyo

Beijing

Rio de Janeiro



Sydney

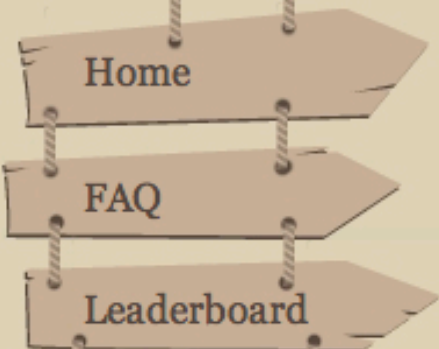


Number of Photos

Estimating Tourism Statistics in G7 Countries Using Flickr Photos



Photo: Tom Richardson

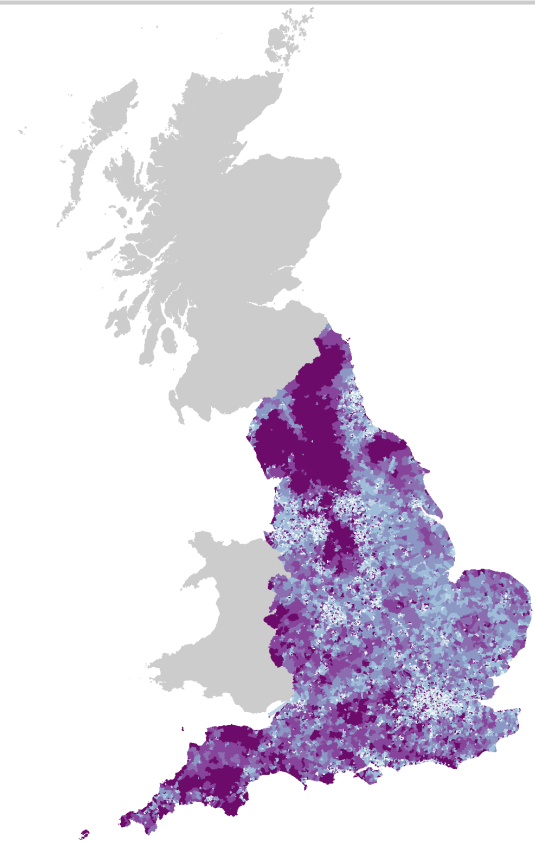


ScenicOrNot helps you to explore every corner of England, Scotland and Wales, all the while comparing your aesthetic judgements with fellow players.

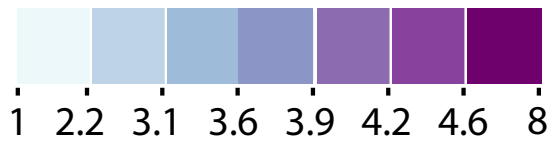


Photo by [David Wild](#) (Licence)

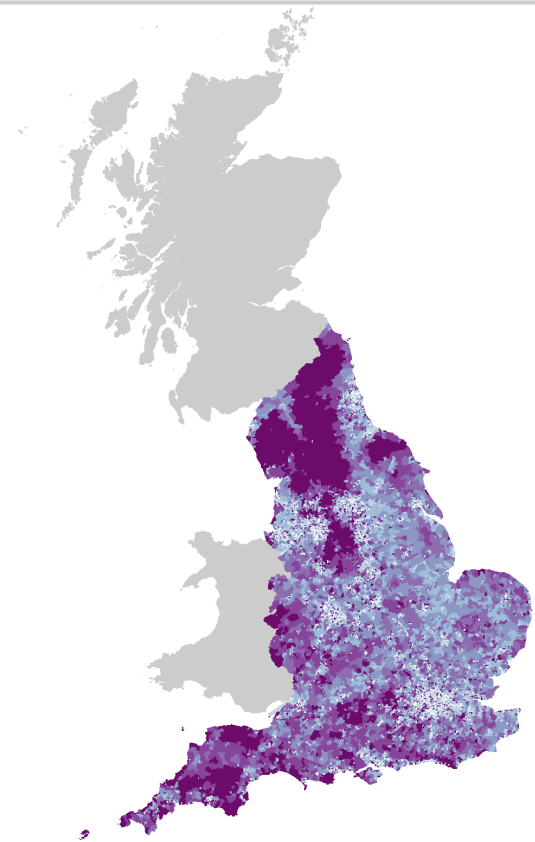
SCENICNESS



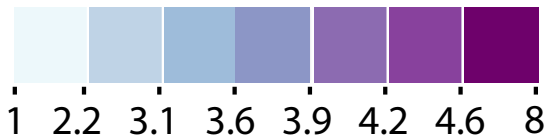
Average scenic rating



SCENICNESS



Average scenic rating

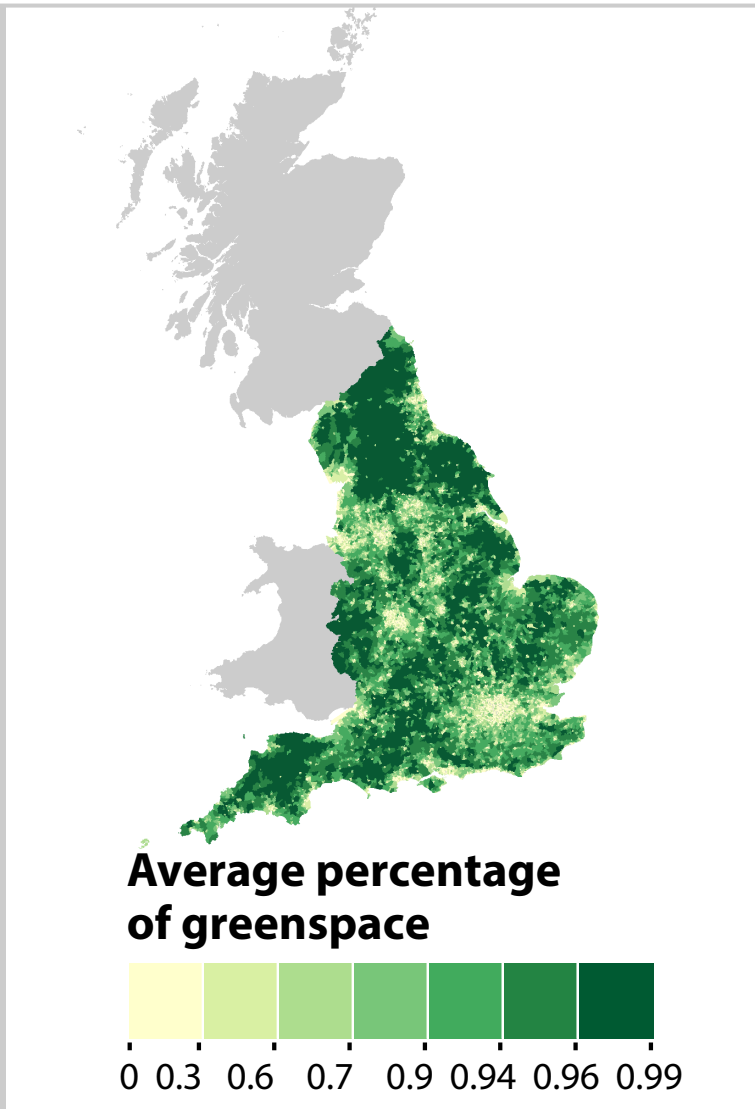


People who live
in more scenic
locations
report
better health

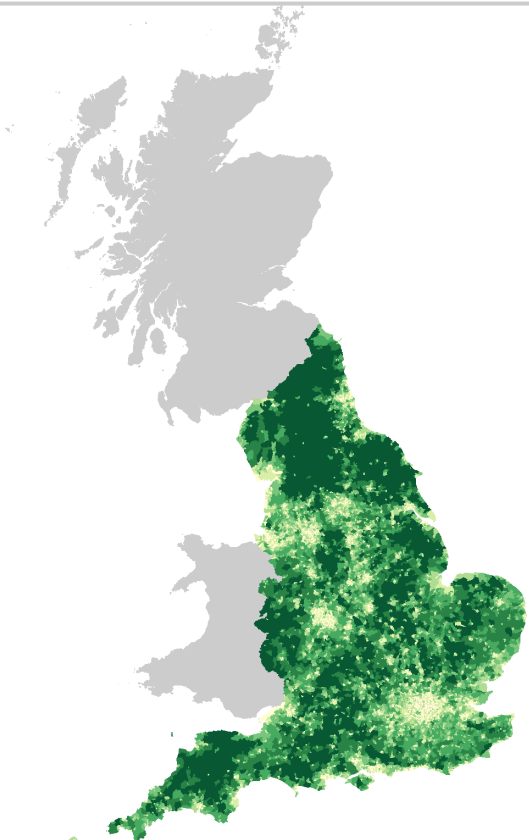
Seresinhe, Preis & Moat (2015)



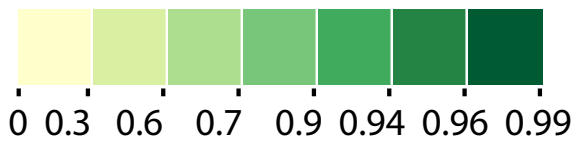
GREENSPACE



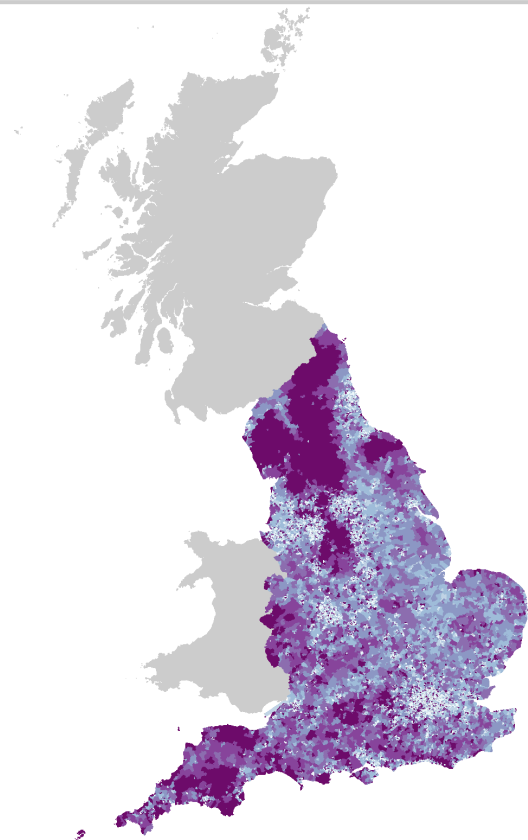
GREENSPACE



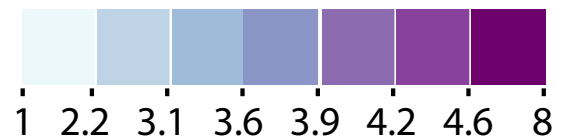
Average percentage of greenspace



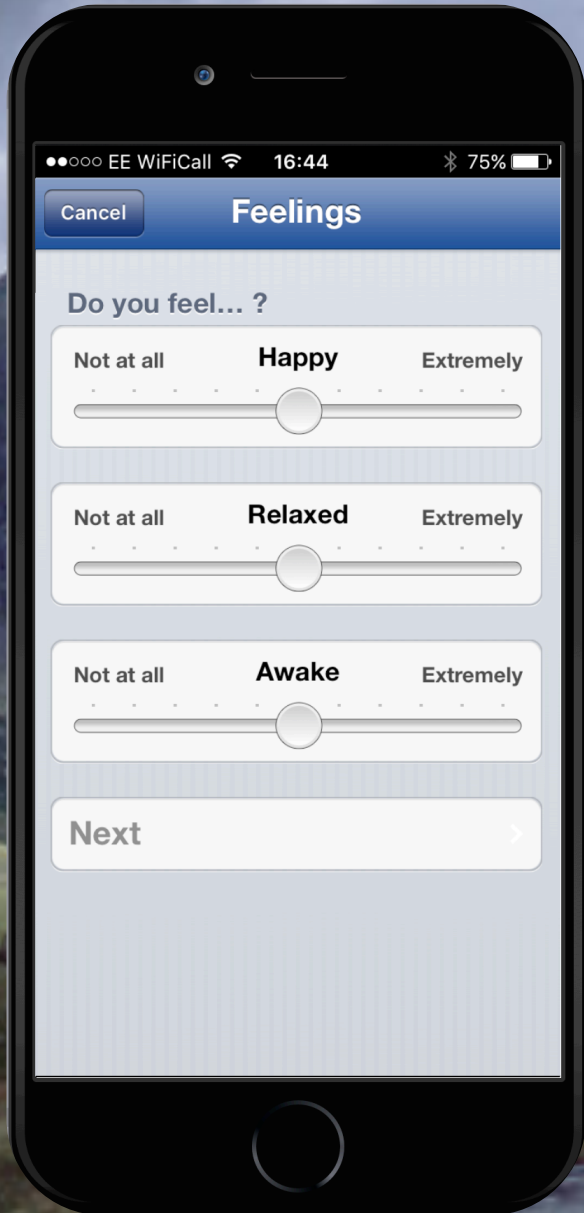
SCENICNESS



Average scenic rating

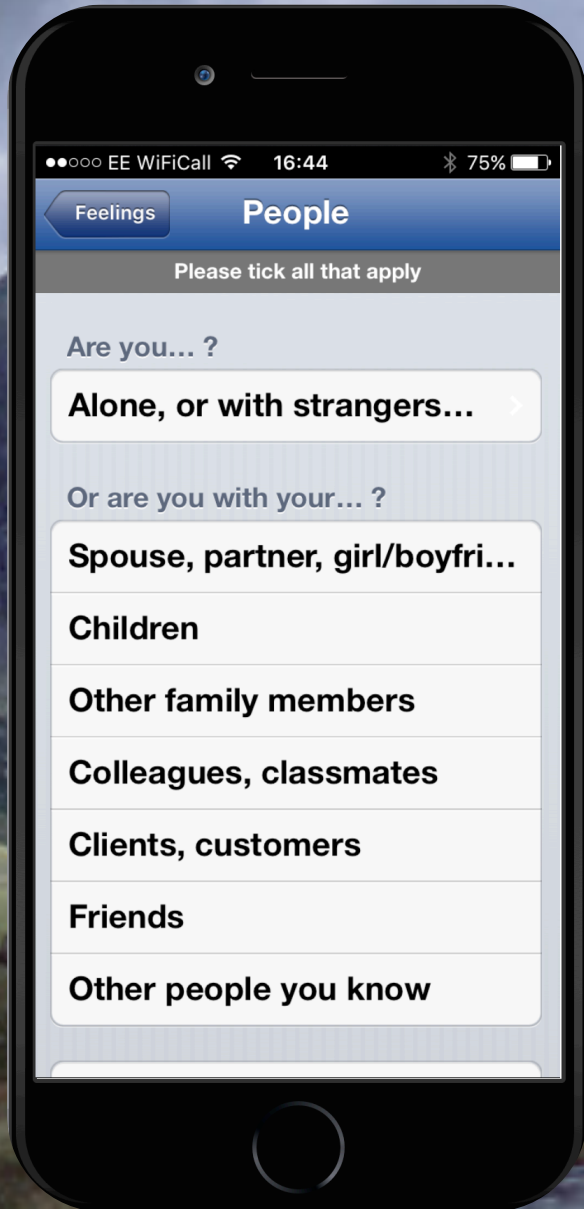






George MacKerron's Mappiness

mappiness.org.uk



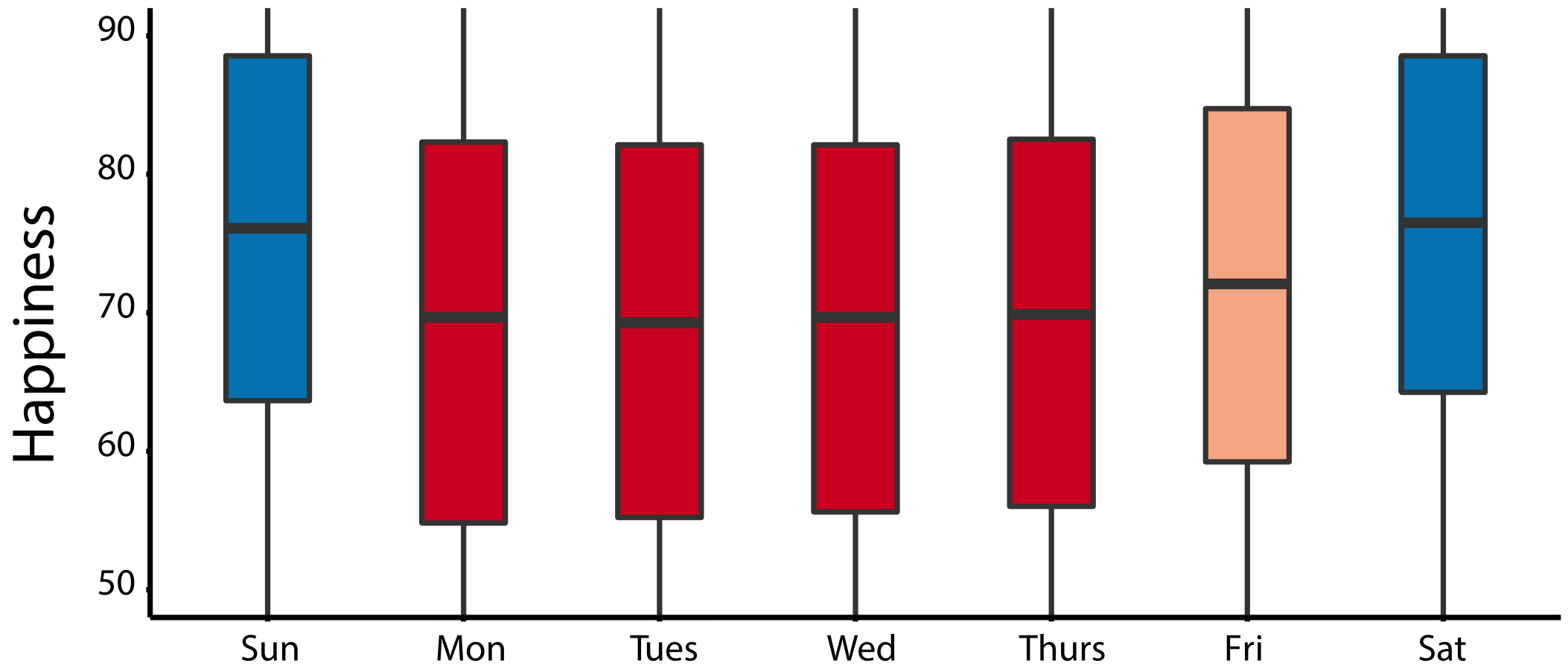
George MacKerron's Mappiness

mappiness.org.uk

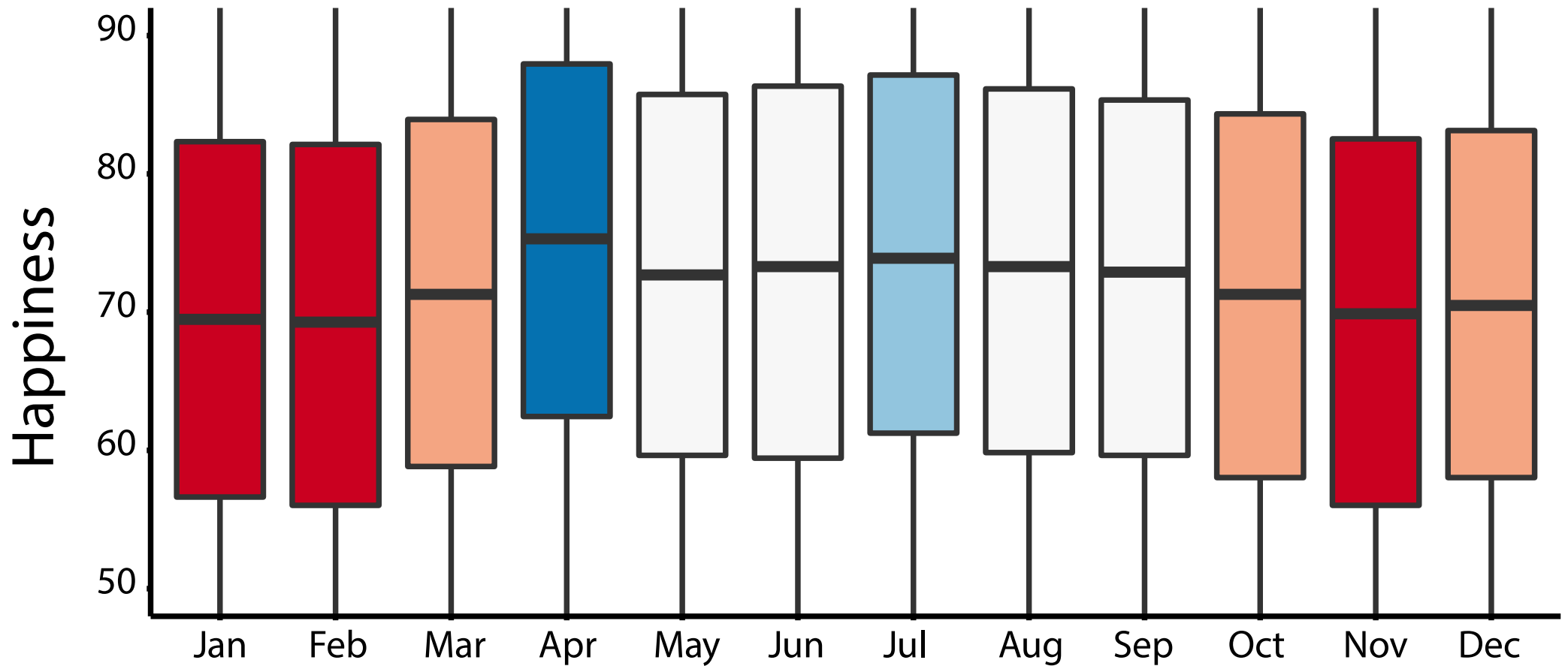


George MacKerron's Mappiness

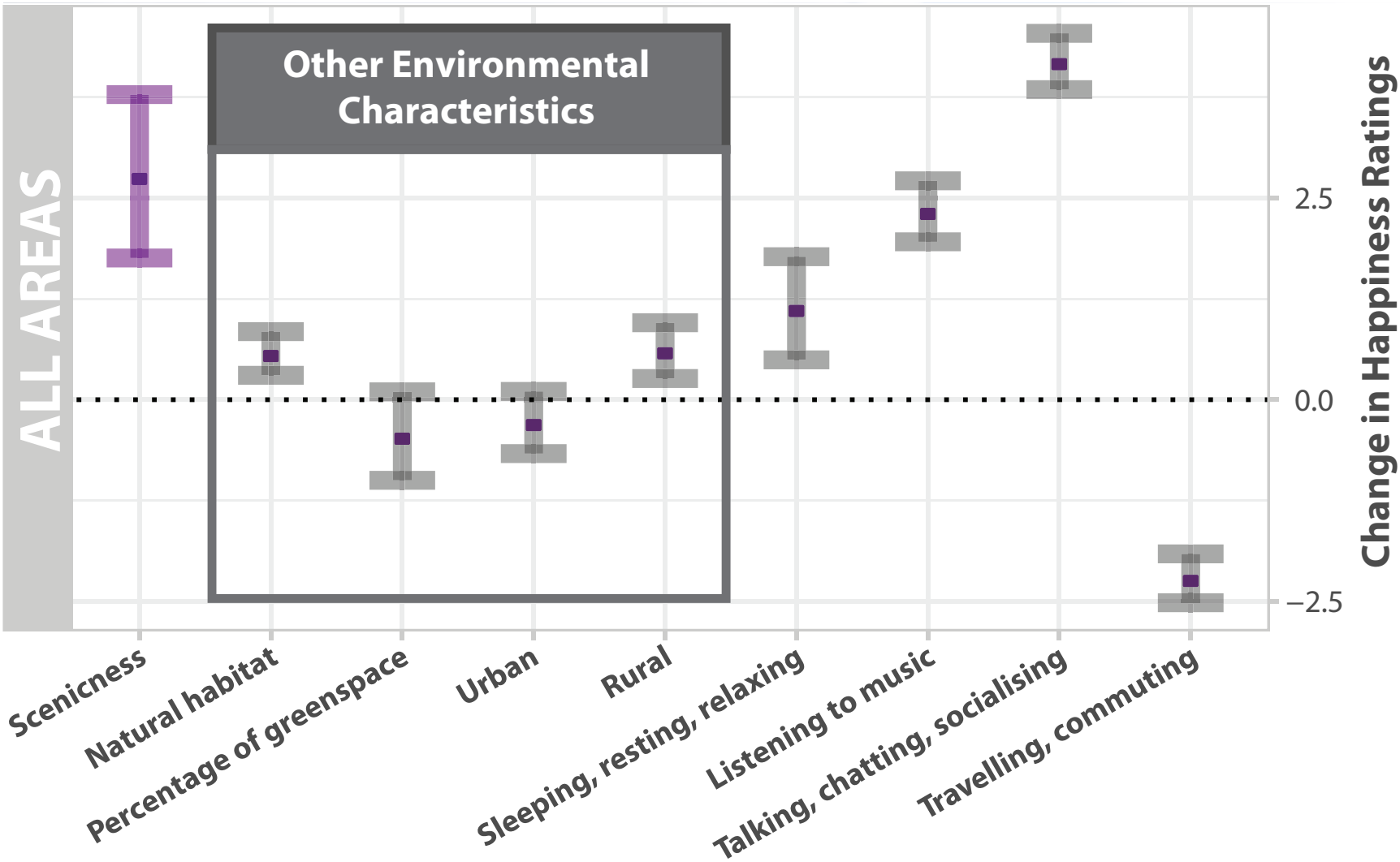
mappiness.org.uk



Seresinhe, Preis, MacKerron & Moat (under review)



Seresinhe, Preis, MacKerron & Moat (under review)



Seresinhe, Preis, MacKerron & Moat (under review)





Places365

0.293 Valley

Categories

0.203 Lake Natural

0.128 Mountain

SUN Scene

0.856 Natural Light

Attributes

0.081 Open Area

0.058 Sailing / Boating



Seresinhe, Preis & Moat (2017)

Lake natural



Seresinhe, Preis
& Moat (2017)

Lake natural



Valley



Seresinhe, Preis
& Moat (2017)

Lake natural



Industrial area



Valley



Seresinhe, Preis
& Moat (2017)

Lake natural



Industrial area



Valley



Hospital



Seresinhe, Preis
& Moat (2017)

Cottage



Seresinhe, Preis
& Moat (2017)

Cottage



Viaduct



Seresinhe, Preis
& Moat (2017)

Cottage



Trees



Viaduct



Seresinhe, Preis
& Moat (2017)

Cottage



Trees



Viaduct

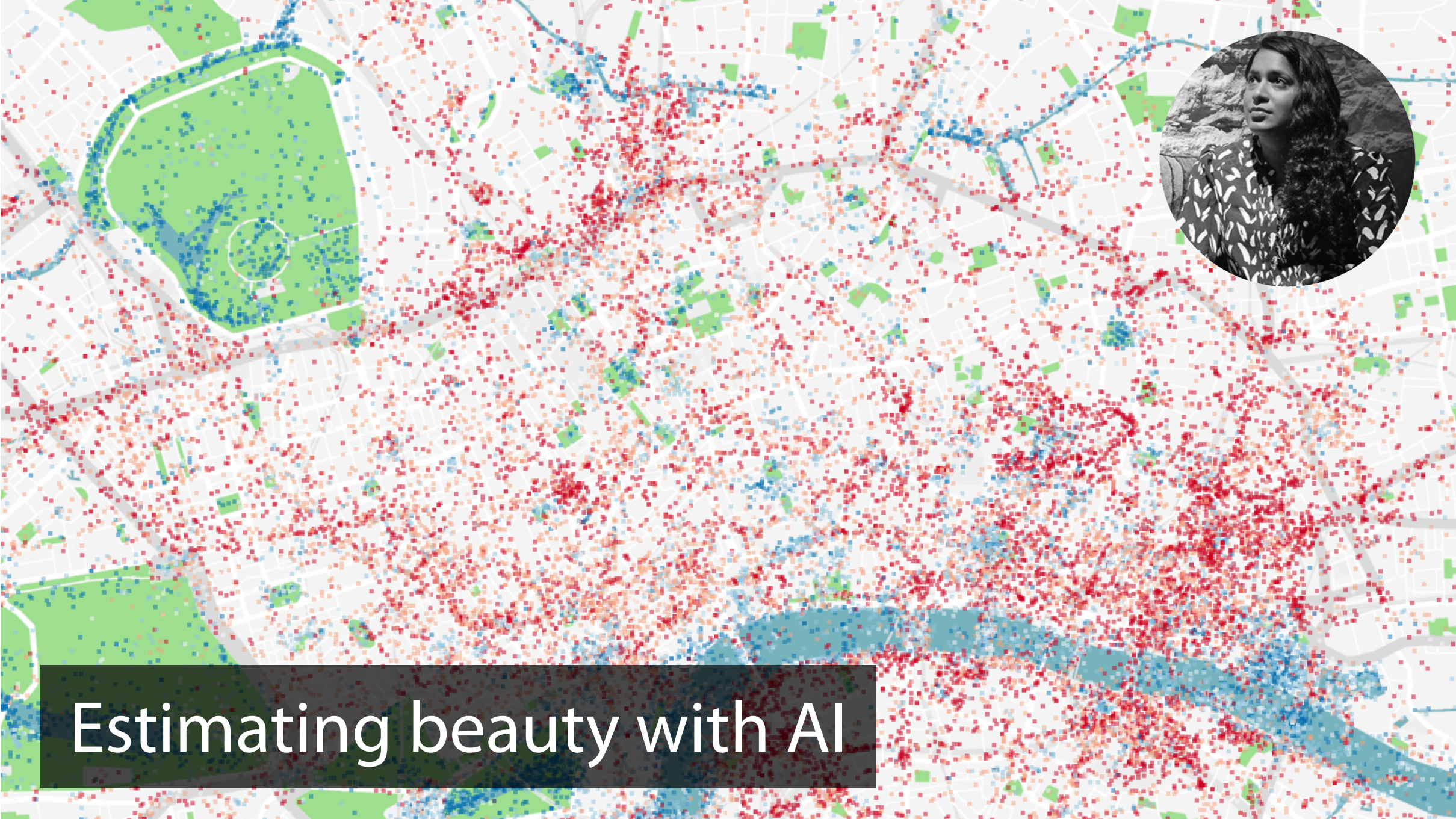


Grass

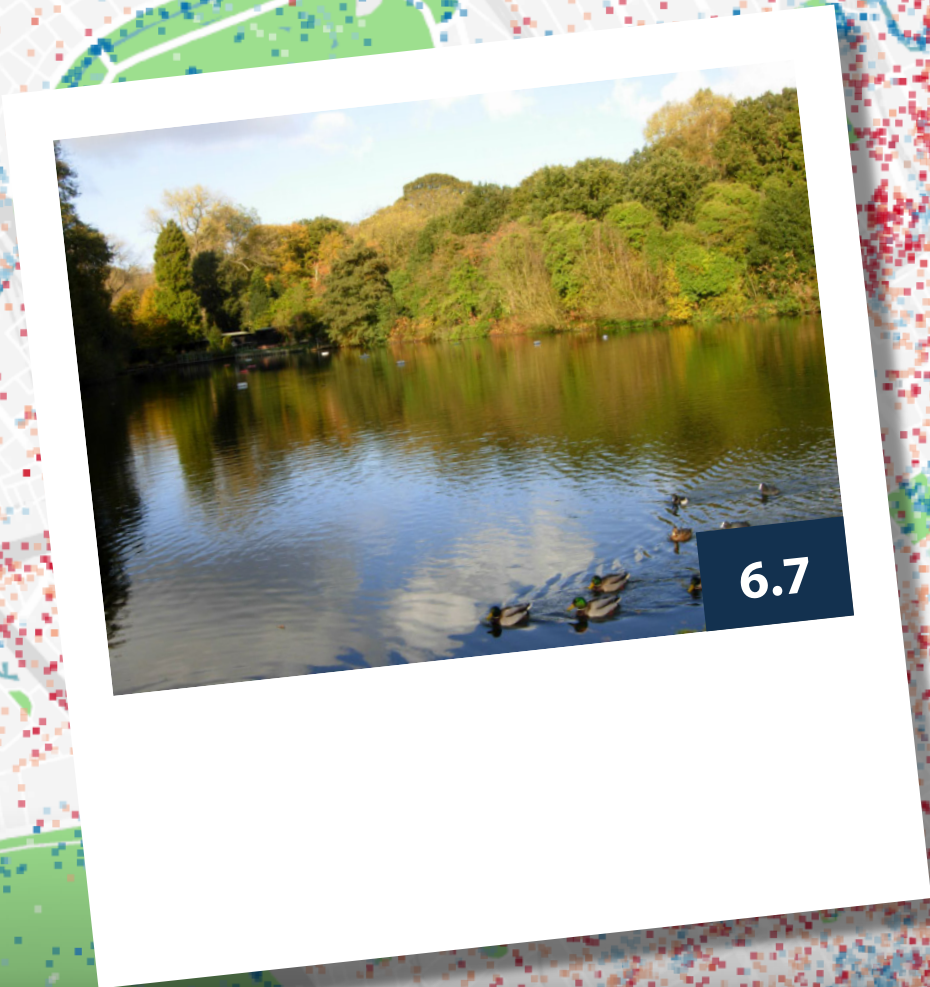


Seresinhe, Preis
& Moat (2017)





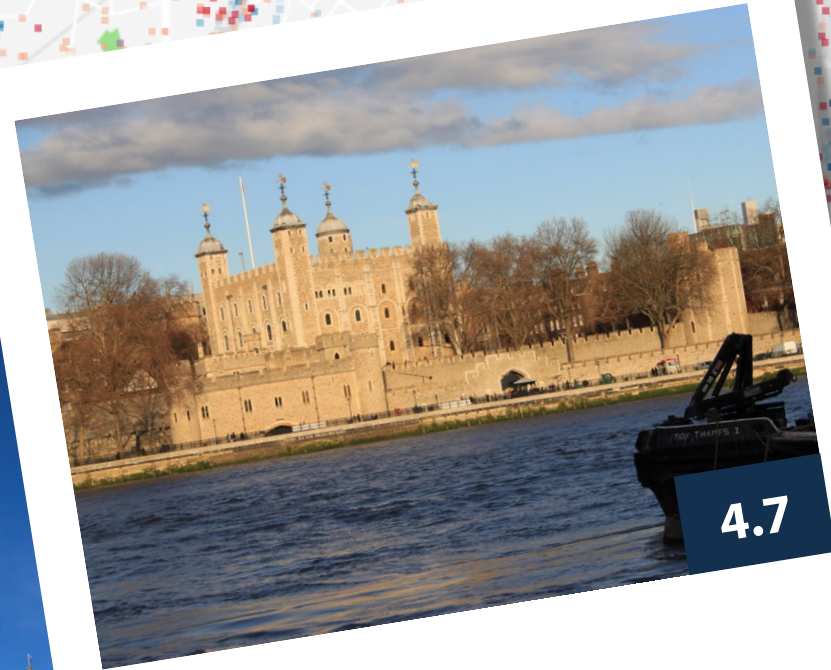
Estimating beauty with AI



Seresinhe, Preis & Moat (2017)



Seresinhe, Preis &
Moat (2017)



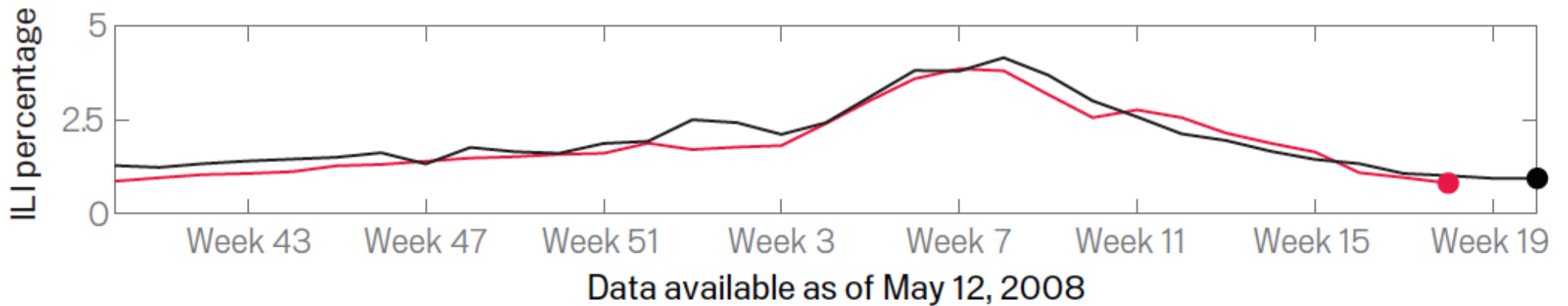
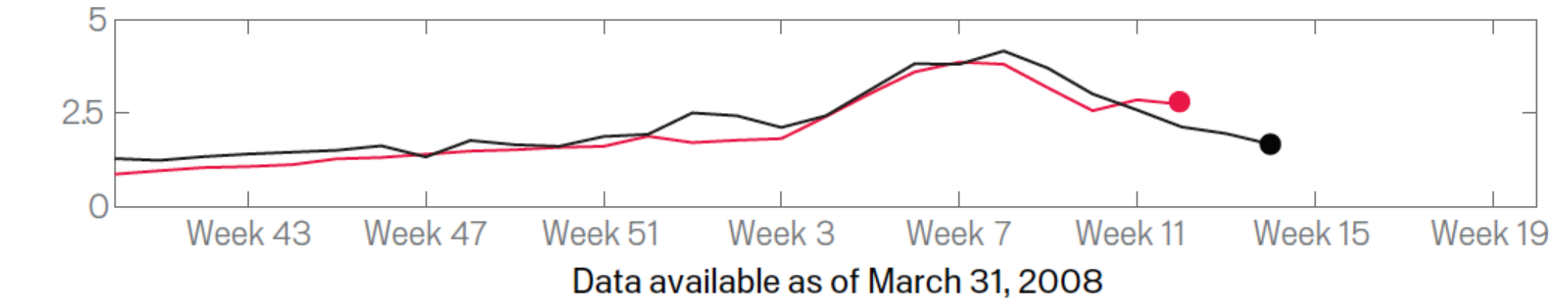
4.7

Seresinhe, Preis &
Moat (2017)

Google
UK

MacBook Pro

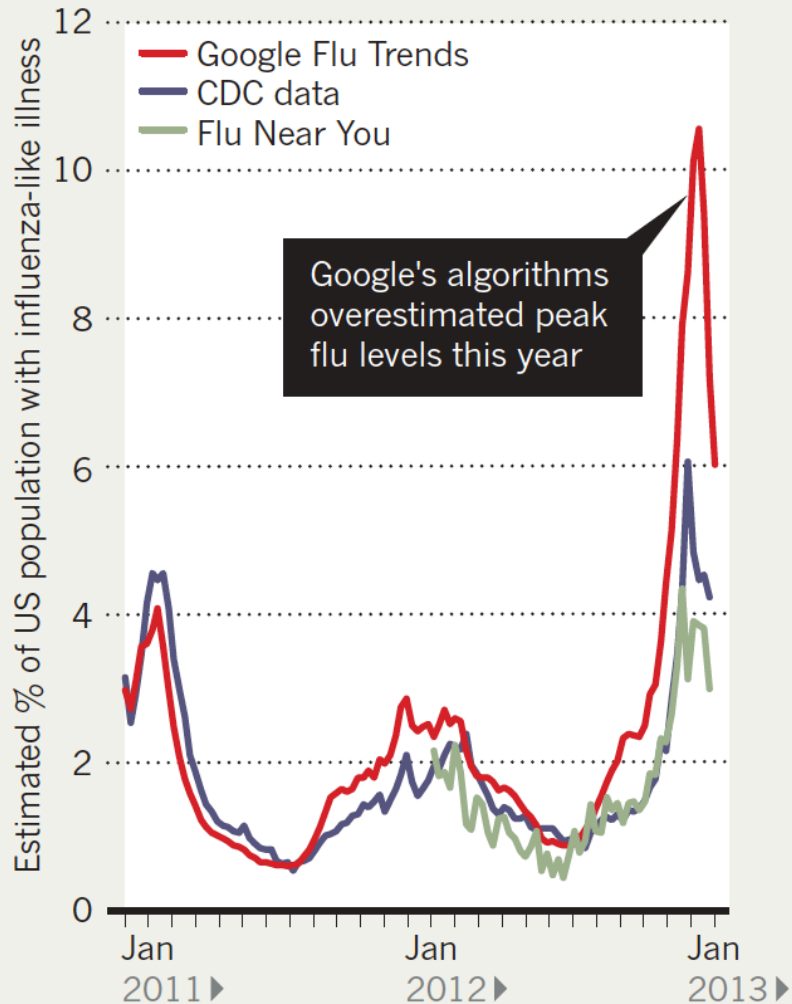




- Flu data
- Google Trends estimate

FEVER PEAKS

A comparison of three different methods of measuring the proportion of the US population with an influenza-like illness.



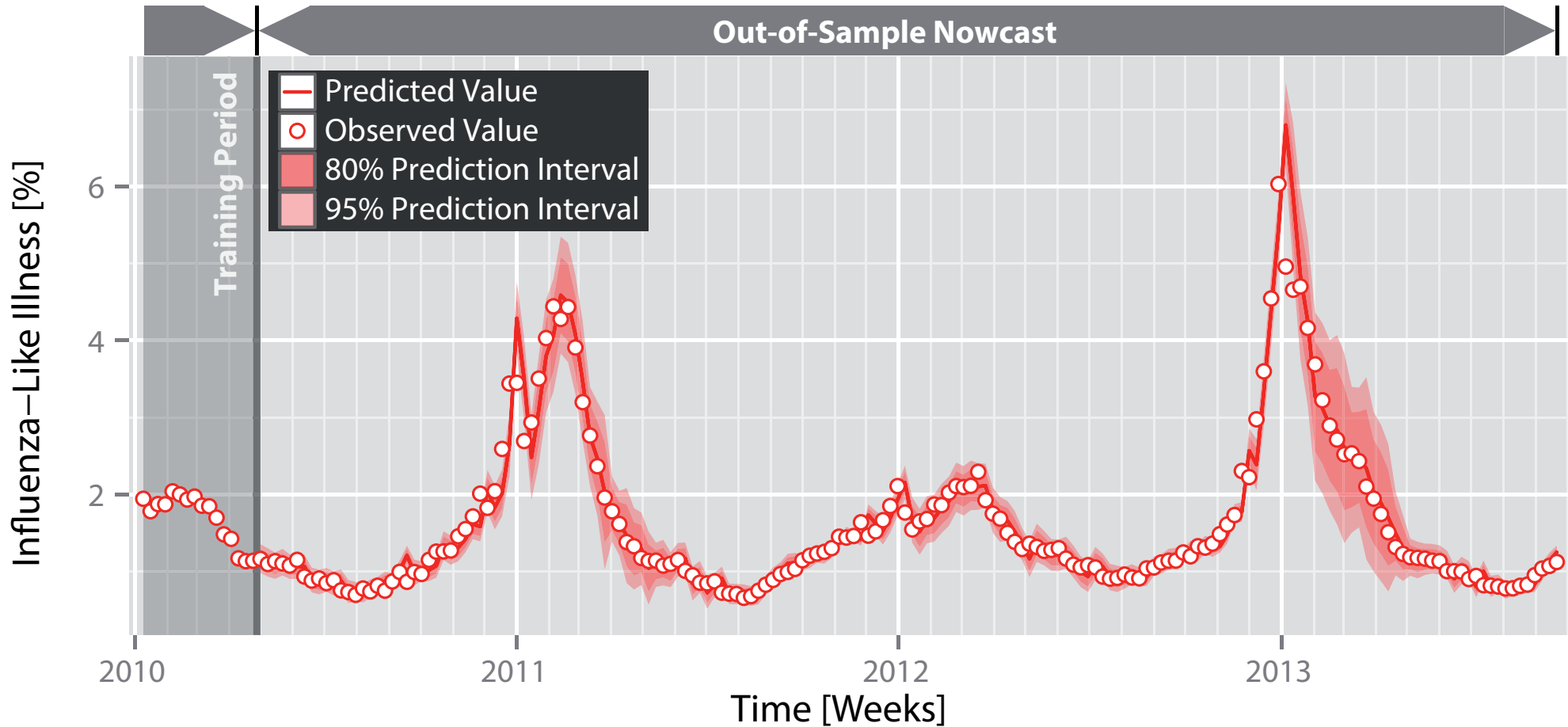
EPIDEMIOLOGY

When Google got flu wrong

US outbreak foxes a leading web-based method for tracking seasonal flu.

“The press reports may have triggered many flu-related searches by people who were not ill.”

Butler, *Nature* **494**, 155 (2013)

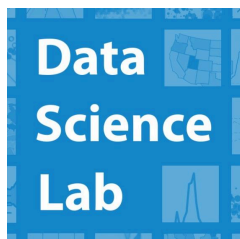


**Flu estimate errors reduced
by between 16% and 53%.**

Preis & Moat (2014)



Online data may help us measure behaviour that was previously expensive, time-consuming or impossible to capture



The Alan Turing Institute

