Infectious diseases hazard map for India based on mobility networks

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  DST and SERB Special MATRICS
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  (2020-21)

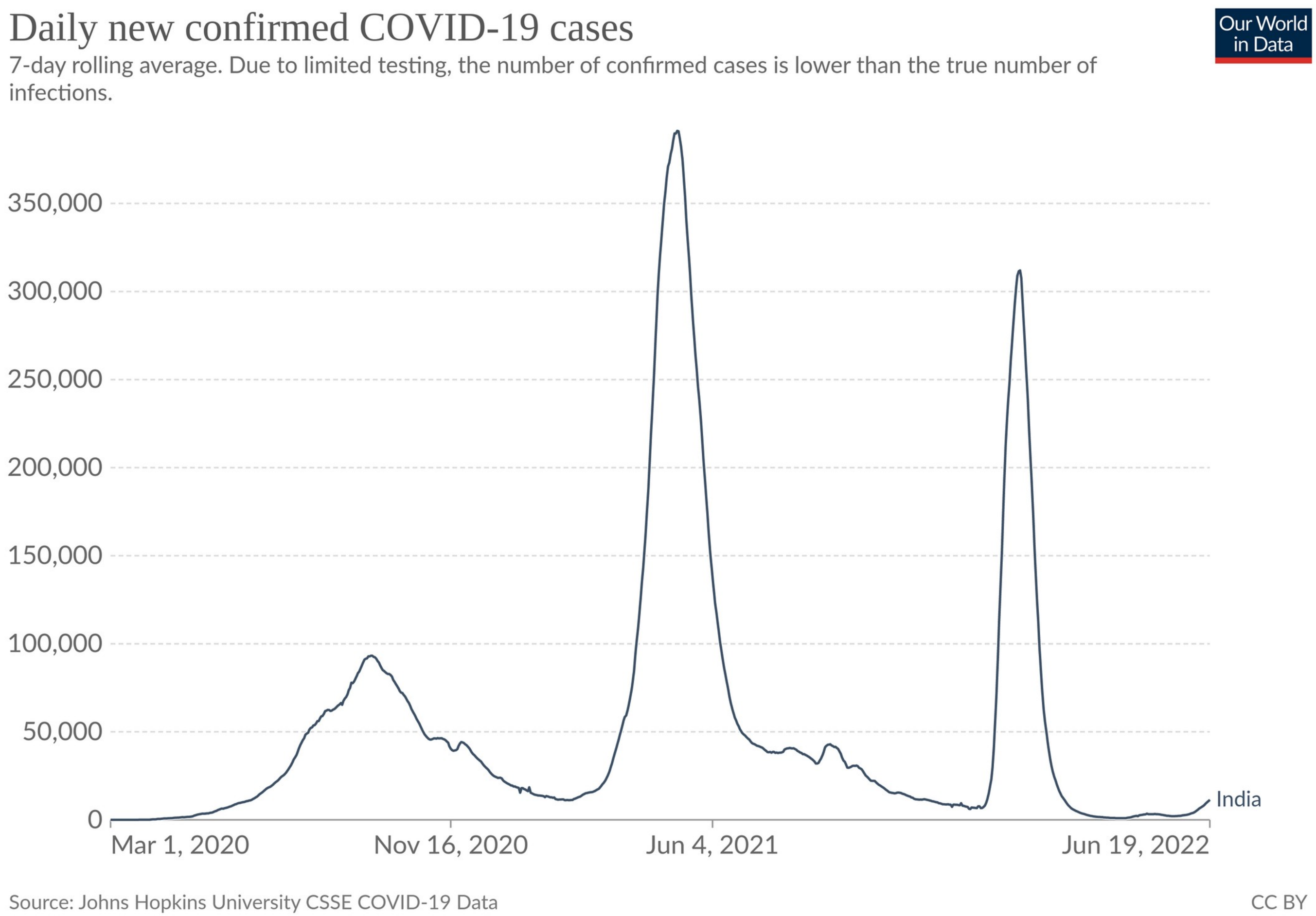
- *Current Science* **121**, 1208 (2021)

On COVID-19 pandemic

First case reported in December 2019 from Wuhan, China.
In India, first few cases started in February, 2020.

Total number cases : 4.33 crores (worldwide : 53.8 crores)

Deaths : 5.24 lakhs (worldwide : 63.2 lakhs)



The arrival of Spanish Flu (1918) in India

“

There is ample evidence during the first epidemic of the introduction of infection into a locality from another infected locality. The railway played a prominent part, as was inevitable. During the panic caused by the epidemic, the trains were filled with emigrants from infected centres, many of them being ill. The Post office also was an important agency in disseminating infection, also very largely through the Railway Postal Service. Lucknow, Lahore, Simla and other cities are said to have been infected in this manner

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there is ample evidence to prove that infection in India during the second epidemic was carried from province to province and place to place within each province by travellers by rail, riverboats, carts and on foot

“

ANNUAL REPORT

OF THE

SANITARY COMMISSIONER WITH THE GOVERNMENT OF INDIA

FOR

1918

WITH

APPENDICES AND RETURNS OF SICKNESS AND MORTALITY AMONG EUROPEAN TROOPS, INDIAN TROOPS, AND PRISONERS IN INDIA FOR THE YEAR.

CALCUTTA
SUPERINTENDENT GOVERNMENT PRINTING, INDIA
1920

Price, Two Rupees Eight Annas.

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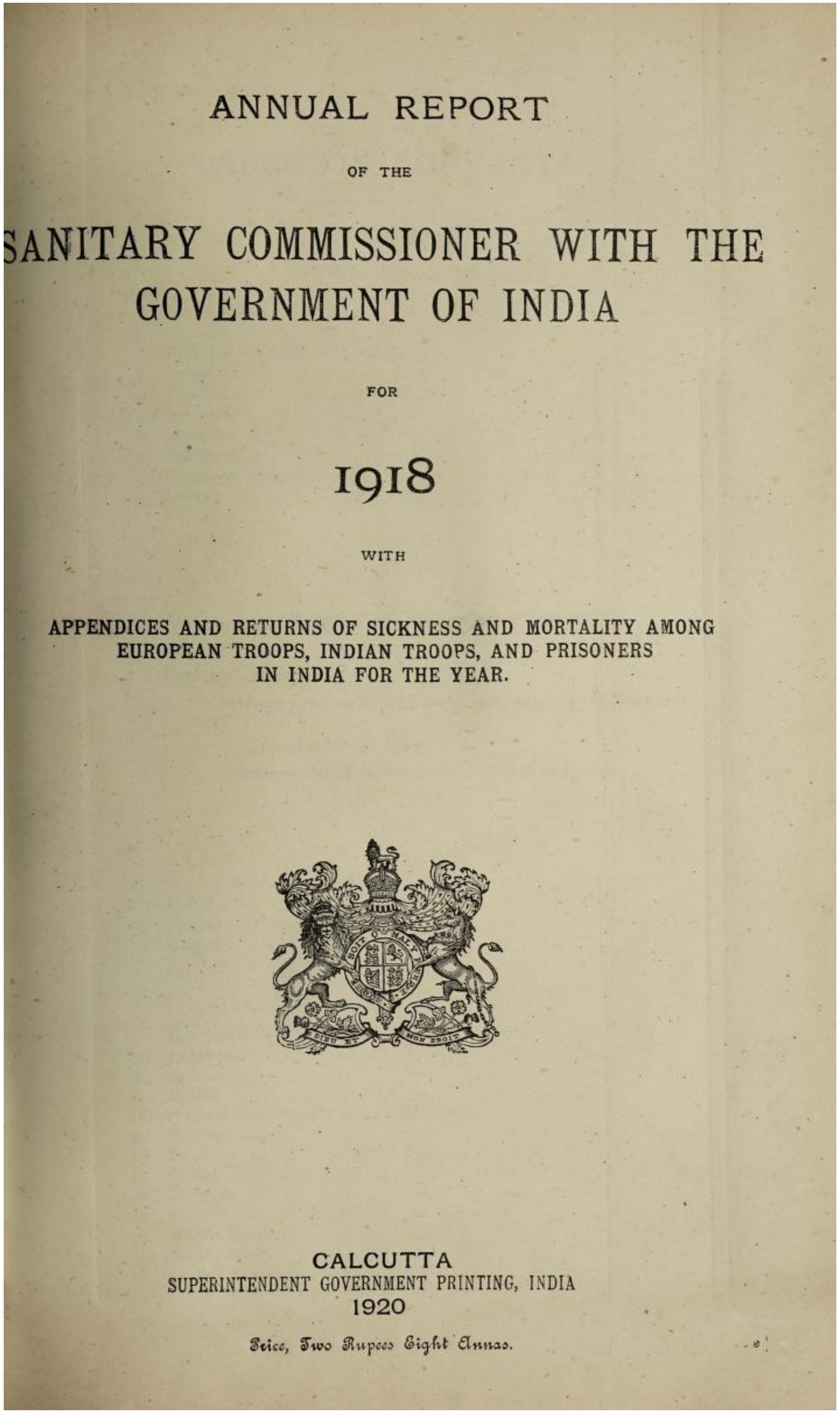

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SUPERINTENDENT GOVERNMENT PRINTING, INDIA
1920

Price, Two Rupees Eight Annas.

A Contribution to the Mathematical Theory of Epidemics.

By W. O. Kermack and A. G. McKendrick.

(Communicated by Sir Gilbert Walker, F.R.S.—Received May 13, 1927.)

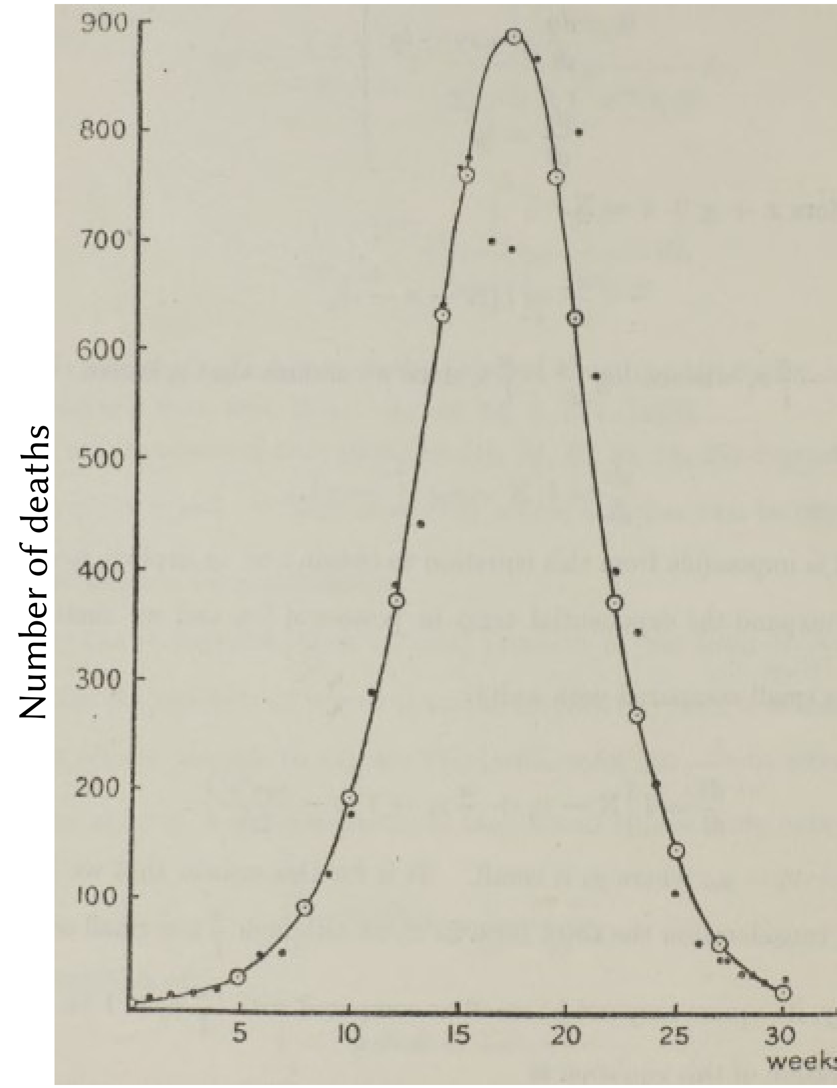
(From the Laboratory of the Royal College of Physicians, Edinburgh.)

Introduction.

(1) One of the most striking features in the study of epidemics is the difficulty of finding a causal factor which appears to be adequate to account for the magnitude of the frequent epidemics of disease which visit almost every population. It was with a view to obtaining more insight regarding the effects of the various factors which govern the spread of contagious epidemics that the present investigation was undertaken. Reference may here be made to the work of Ross

W. O. Kermack and A. G. McKendrick
Proc. Royal. Soc. A **115**, 700 (1927)

Plague in Bombay,
Dec 1905 to Jul 1907



Susceptible-Infected-Recovered (SIR) model

$$I + S \xrightarrow{\alpha} 2I$$

Infection rate α

$$I \xrightarrow{\beta} R$$

Recovery rate β

$$S \xrightarrow{\alpha} I \xrightarrow{\beta} R$$

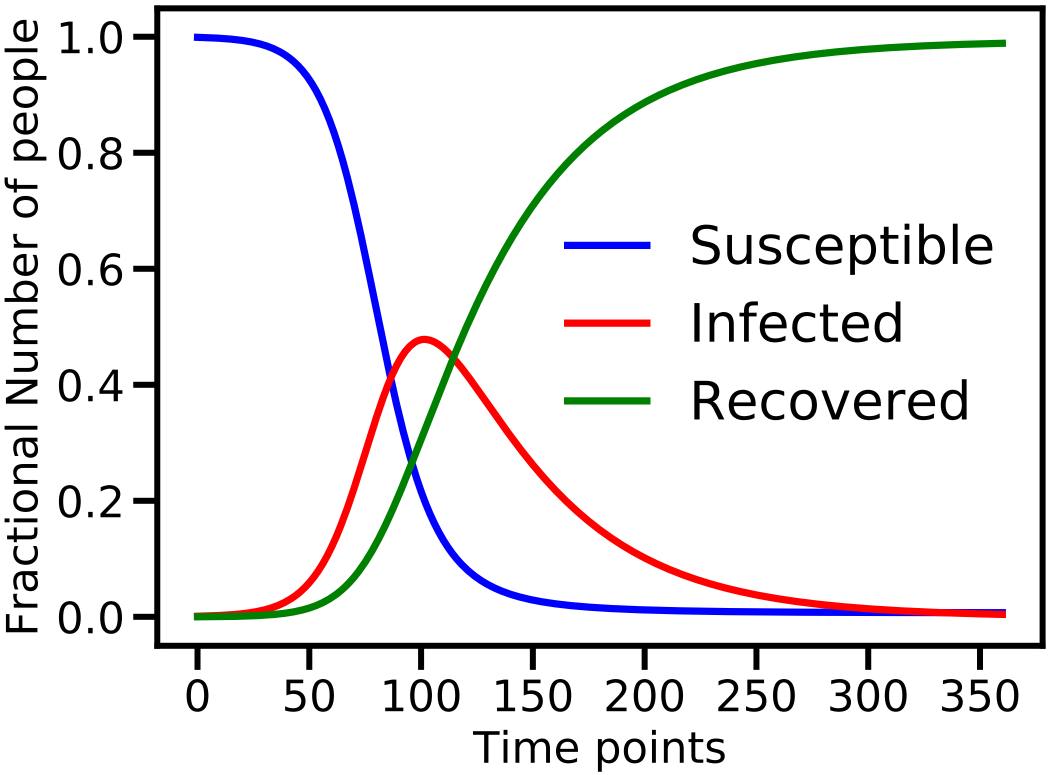
$$\boxed{\begin{aligned} \frac{dS(t)}{dt} &= -\alpha \frac{S(t)I(t)}{N}, \\ \frac{dI(t)}{dt} &= +\alpha \frac{S(t)I(t)}{N} - \beta I(t), \\ \frac{dR(t)}{dt} &= +\beta I(t). \end{aligned}}$$

$$S(t) + I(t) + R(t) = N$$

constant

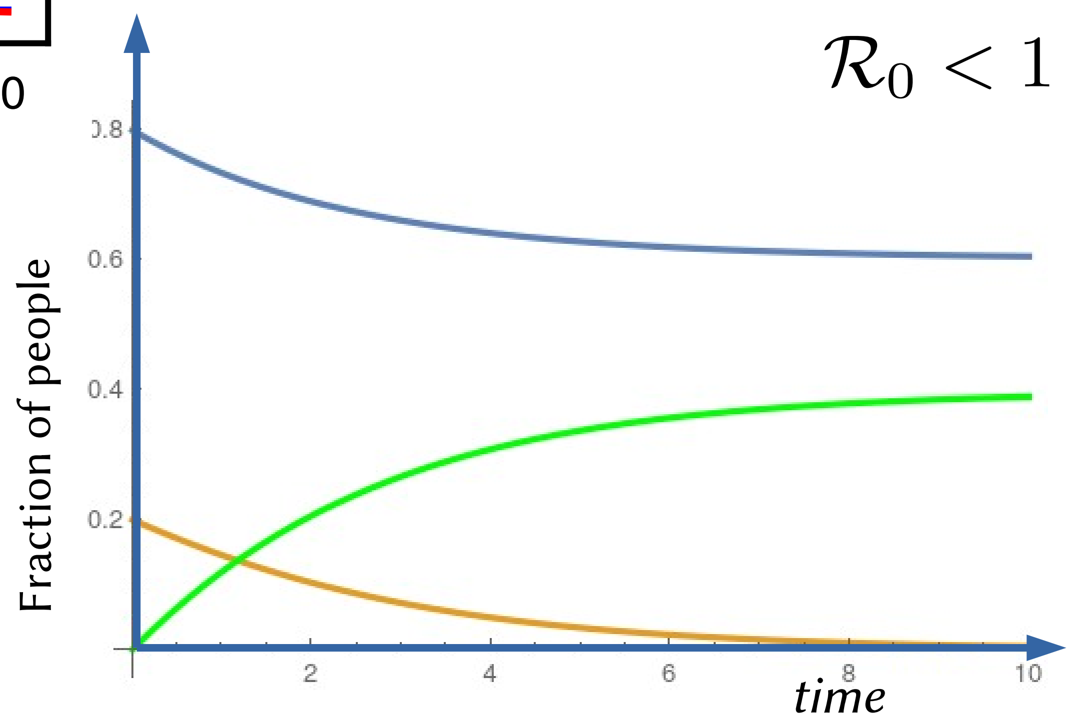
Compartmental model with 3 compartments

Two different scenarios from SIR model : numerical solutions

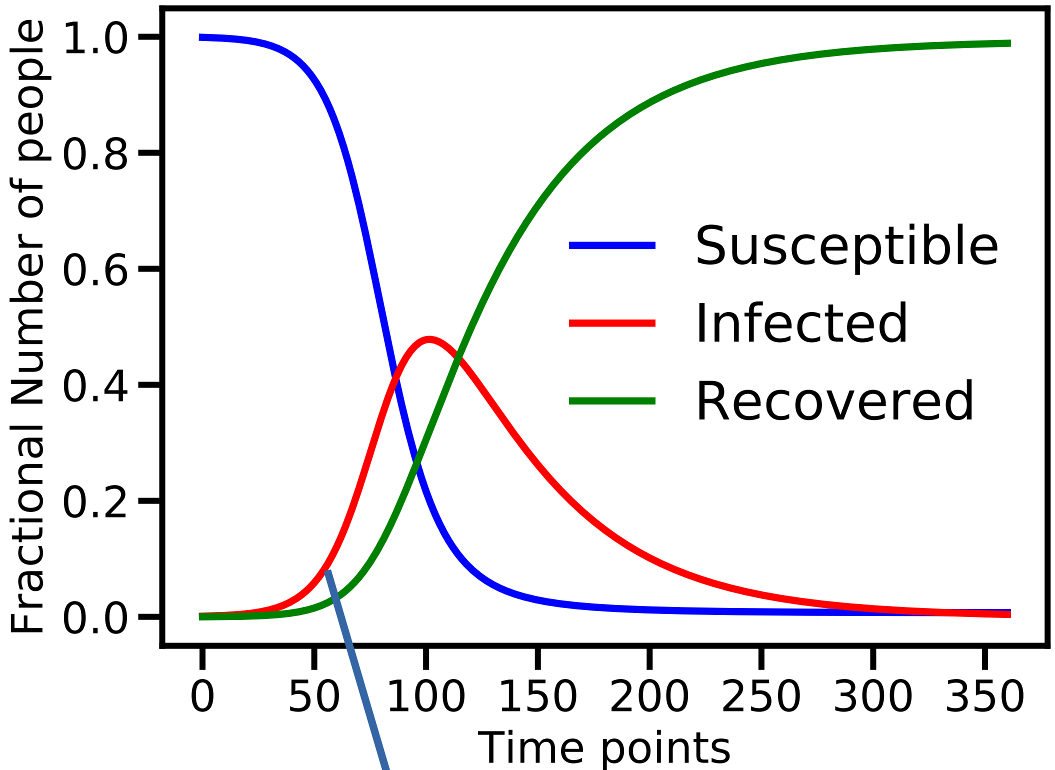


$$\alpha = 1.5, \quad \beta = 0.7$$
$$\mathcal{R}_0 > 1$$

$$\alpha = 0.5, \quad \beta = 1.0$$
$$\mathcal{R}_0 < 1$$



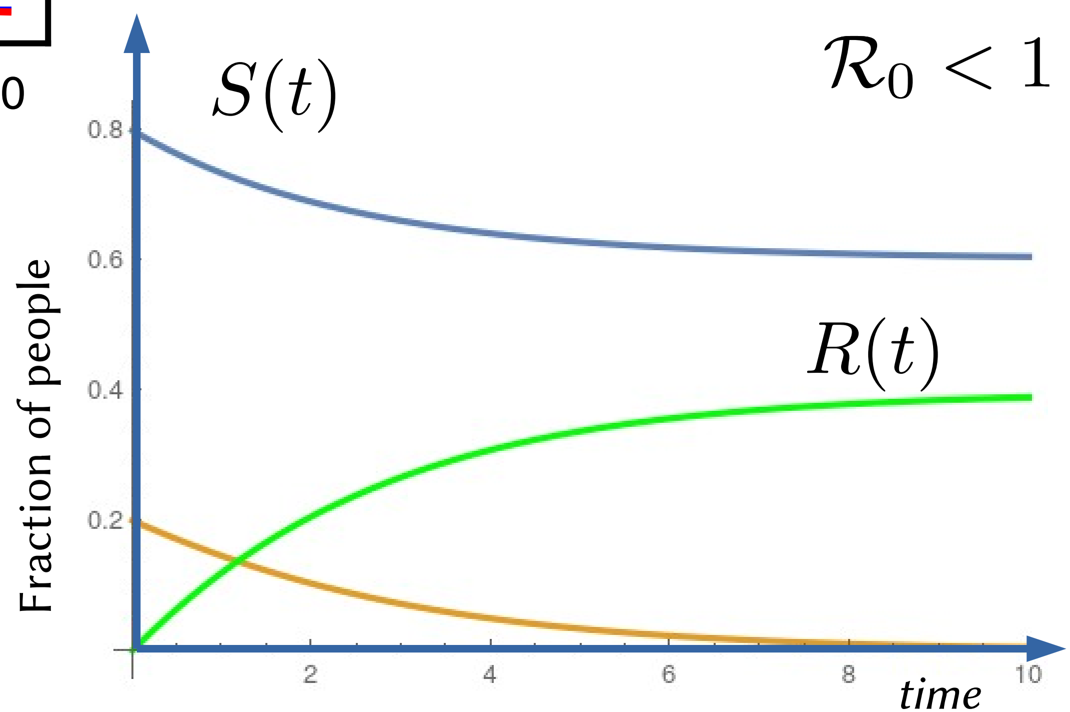
Two different scenarios from SIR model : numerical solutions



$$\alpha = 1.5, \quad \beta = 0.7$$
$$\mathcal{R}_0 > 1$$

Regime of exponential increase

$$\alpha = 0.5, \quad \beta = 1.0$$
$$\mathcal{R}_0 < 1$$



For very short times : $S(t) \approx N$

$$\frac{\partial I(t)}{\partial t} \approx (\alpha - \beta) I(t)$$

$$I(t) \sim I_0 \; e^{(\alpha - \beta)t}$$

$\alpha > \beta$ Exponential increase in infected cases

$\alpha < \beta$ Exponential increase in infected cases

- Reduce SIR model to

$$\frac{dr}{dt} = \beta \left(1 - r - s_0\ r\ e^{-(\alpha/\beta) r}\right) \qquad r = \frac{R}{N}$$

- $t \to \infty, \quad \frac{dr}{dt} \to 0, \quad r_\infty = \text{constant}$

$$\boxed{r_\infty = 1 - e^{-\mathcal{R}_0\ r_\infty},} \qquad \mathcal{R}_0 = \frac{\alpha}{\beta}$$

Basic reproduction number

When does a solution exist ?

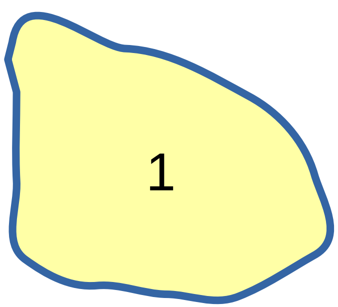
$$r_\infty = 1 - e^{-R_0 \; r_\infty}, \qquad R_0 = \frac{\alpha}{\beta}$$

- No epidemic (decay of infections)

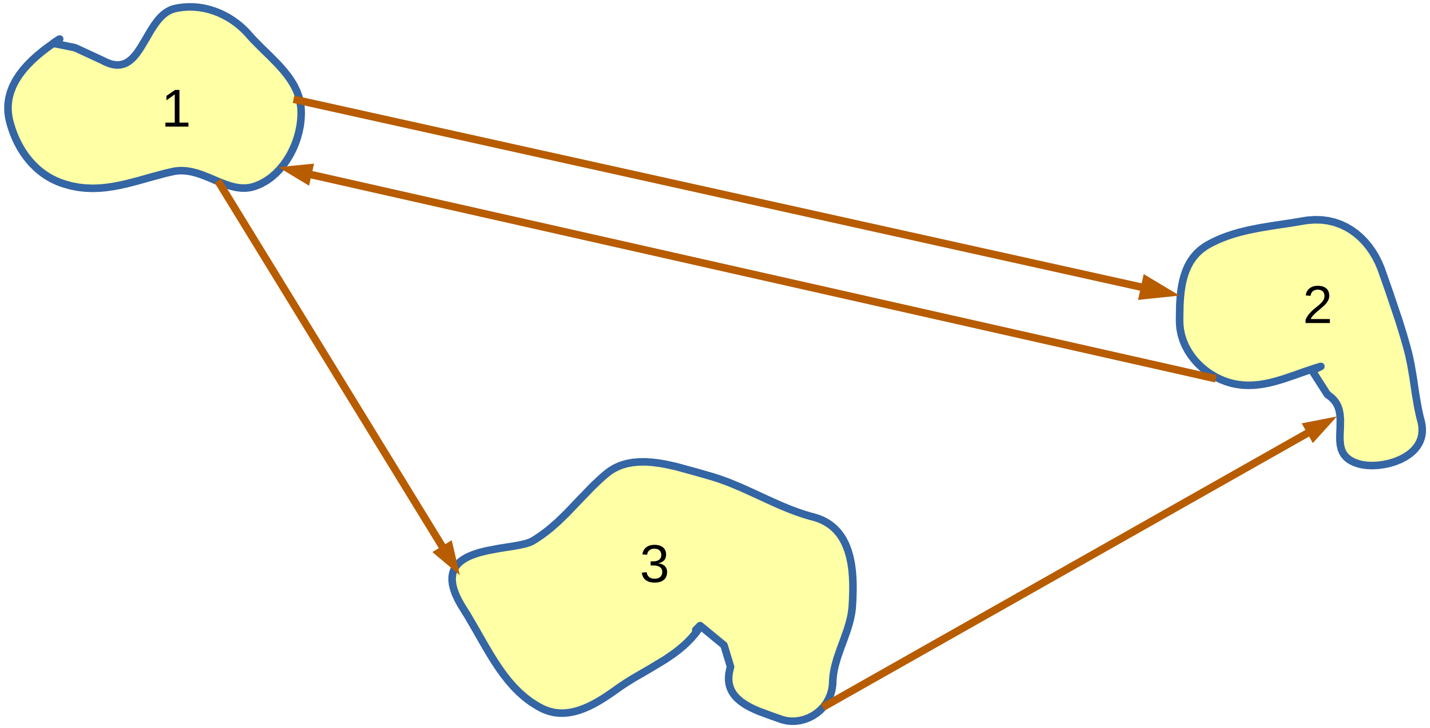
$$R_0 < 1, \qquad \alpha < \beta, \qquad r_\infty \to 0$$

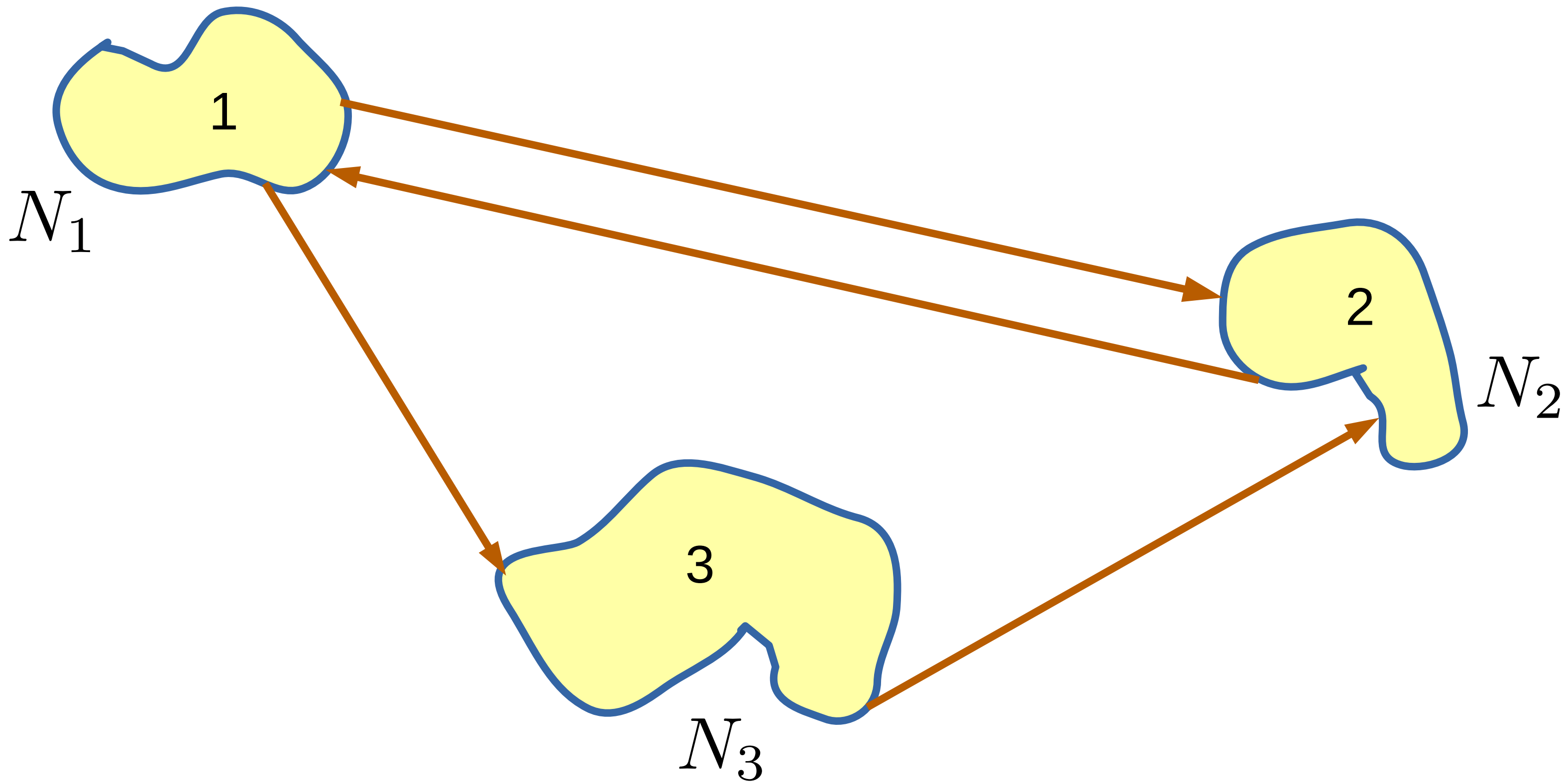
- Epidemic (infections increasing)

$$R_0 > 1, \qquad \alpha > \beta, \qquad r_\infty \to \text{constant} > 0$$



Well-mixed population within one city or town


1
2
3



nodes	1,	2,	3,	... ...	M
population	N_1	N_2	N_3		N_M

total population $N = N_1 + N_2 + \dots N_M$

- **Characterization of the second wave of COVID-19 in India**

Rajesh Ranjan[1,*], Aryan Sharma[2] and Mahendra K. Verma[2]
[1]Department of Aerospace Engineering, Indian Institute of Technology, Kanpur 208 016, India
[2]Department of Physics, Indian Institute of Technology, Kanpur 208 016, India

Current Science (2021)

- **Dynamical modelling and analysis of COVID-19 in India**

R. Gopal[1], V. K. Chandrasekar[1,*] and M. Lakshmanan[2]
[1]Centre for Nonlinear Science and Engineering, School of Electrical and Electronics Engineering, SASTRA Deemed University, Thanjavur 613 401, India
[2]Department of Nonlinear Dynamics, School of Physics, Bharathidasan University, Tiruchirappalli 620 014, India

- Modelling and forecasting of COVID-19 pandemic in India
  Chaos, Solitons and Fractals 139, 110049 (2020).

PAPER

- Digital herd immunity and COVID-19

Vir B Bulchandani[1,2], Saumya Shivam[3], Sanjay Moudgalya[3,4,5] and S L Sondhi[6,3]

Published 23 June 2021 • © 2021 IOP Publishing Ltd
Physical Biology, Volume 18, Number 4

The basic premise is that irrespective of the severity of the infectious disease, its spread is caused by the mobility of the people via the transportation networks.

- Central question :

In a network of N cities/towns given by $X_1, X_2, X_3, \cdots X_N$, and if the infection outbreak location is declared to be X_1, can a hazard value be assigned to all other cities/towns reflecting their risk of catching the infection ?

This is not about predicting the infection case loads and its evolution.

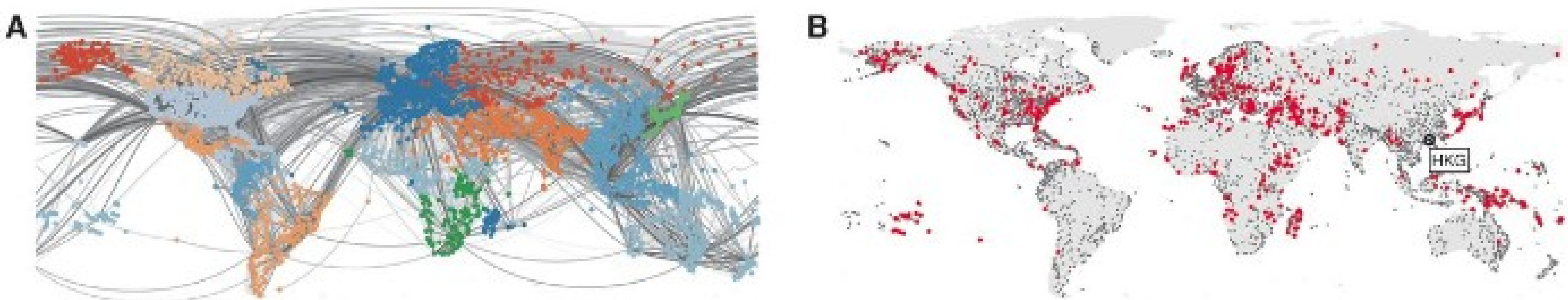

Display top 30 connections
EpiRisk
GLEAM
PROJECT
City
Country
Infected basins
London (UK)
Add a source basin
Number of infected individuals
5000
use detailed distribution
Month of travel
January
Restrict travels by 0%
Days to onset of symptoms
1
EXPORTED CASES
RELATIVE RISK
DATA
ABOUT
Top destinations ranked according to the relative risk of case importation.
Southampton
4.5%
ARABIAN SEA
mapbox
© Mapbox © OpenStreetMap Improve this map

epirisk.net

The Hidden Geometry of Complex, Network-Driven Contagion Phenomena

DIRK BROCKMANN AND DIRK HELBING

SCIENCE • 13 Dec 2013 • Vol 342, Issue 6164 • pp. 1337-1342 • DOI: 10.1126/science.1245200



D. Brockmann and D. Helbing,
Science **342**, 1337 (2013)

F. Iannelli, *Phys. Rev. E* **95**, 012313 (2017)

Movement kinetics

$$\frac{\partial X_n}{\partial t} = \sum_{m \neq n} \mu_{nm} \, X_m - \mu_{mn} \, X_n \qquad X = S, I, R$$

Mobility rate for travelling from city *m* to *n*

- F_m^n → Number of people going from city *m* to *n* in unit time
- $F_m = \sum_n F_m^n$ → Total outflux from city m
- $P_m^n = \frac{F_m^n}{F_m}$ → Probability for an individual to go from city *m* to city *n*

SIR model augmented with mobility

$$\frac{\partial S_n(t)}{\partial t} = -\alpha \frac{S_n(t) I_n(t)}{N_n} + \sum_m \left[\frac{F_m^n}{N_m} S_m(t) - \frac{F_n^m}{N_n} S_n(t) \right]$$

$$\frac{\partial I_n(t)}{\partial t} = +\alpha \frac{S_n(t) I_n(t)}{N_n} - \beta I_n(t) + \sum_m \left[\frac{F_m^n}{N_m} I_m(t) - \frac{F_n^m}{N_n} I_n(t) \right]$$

$$\frac{\partial R_n(t)}{\partial t} = +\beta I_n(t) + \sum_m \left[\frac{F_m^n}{N_m} R_m(t) - \frac{F_n^m}{N_n} R_n(t) \right]$$

$\alpha \longrightarrow$ Infection rate

$\beta \longrightarrow$ Recovery rate

$$n, m = 1, 2, 3 \ldots M$$

$$N = S(t) + I(t) + R(t)$$

SIR model augmented with mobility

$$\frac{\partial S_n(t)}{\partial t} = -\alpha \frac{S_n(t) I_n(t)}{N_n} + \boxed{\sum_m \left[\frac{F^n_m}{N_m} S_m(t) - \frac{F^m_n}{N_n} S_n(t) \right]}$$

$$\frac{\partial I_n(t)}{\partial t} = +\alpha \frac{S_n(t) I_n(t)}{N_n} - \beta I_n(t) + \boxed{\sum_m \left[\frac{F^n_m}{N_m} I_m(t) - \frac{F^m_n}{N_n} I_n(t) \right]}$$

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$$n, m = 1, 2, 3 \ldots M$$

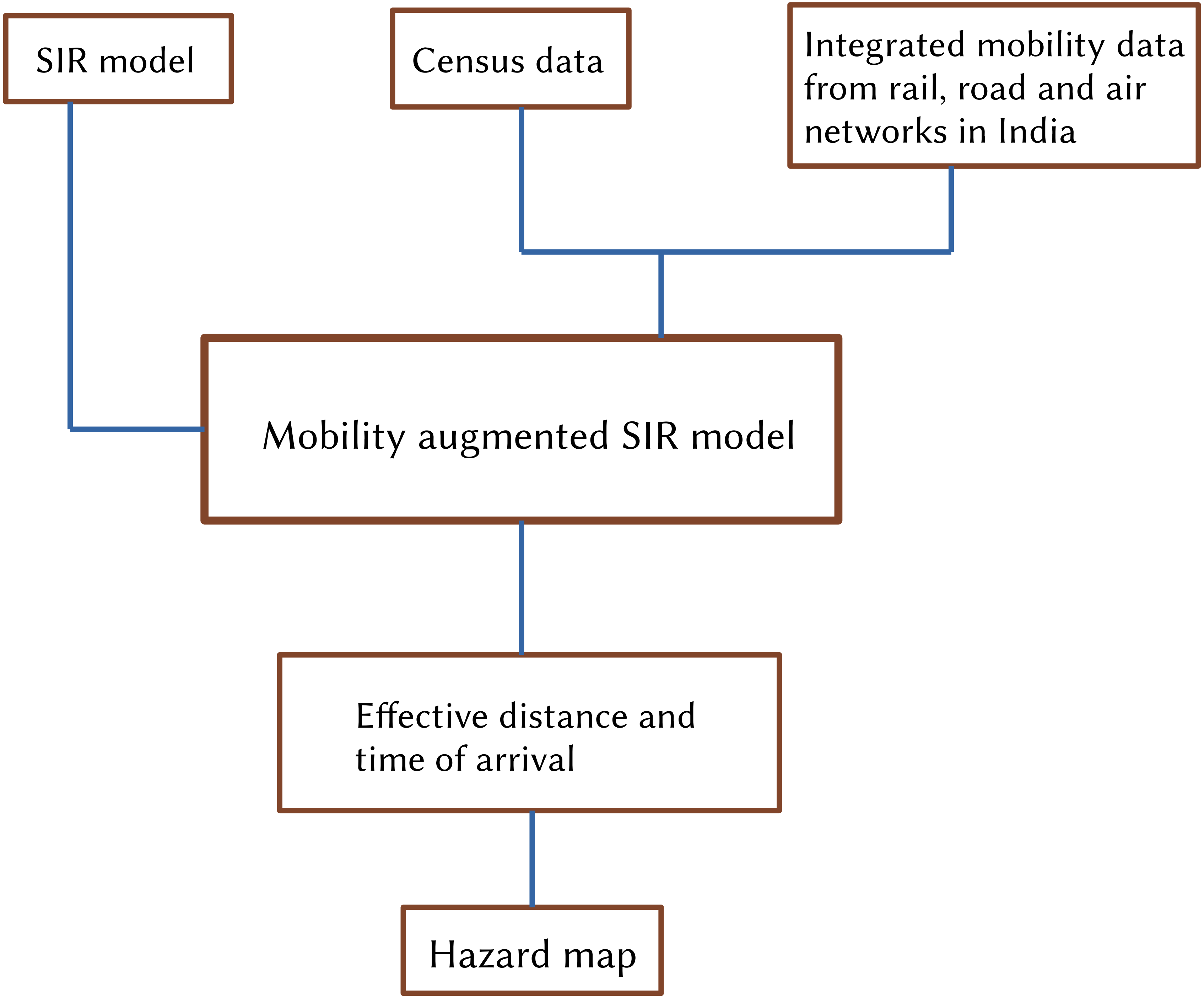
SIR model

Information about infection

Mobility information

Information about geographical spread of infection

algorithm behind the hazard map : top level view



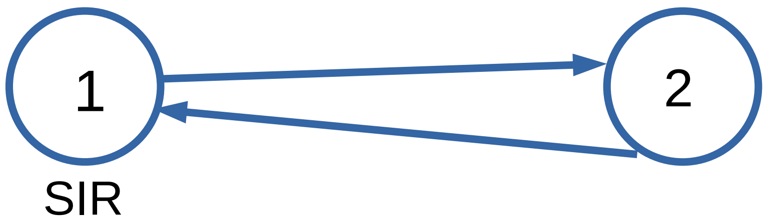
effective distance

- Effective distance
  between *i*-th and *j*-th
  cities

$$D_{\text{eff}}^{i \to j} = 1 - \log P_i^j = 1 - \log(\underbrace{F_i^j / F_i}_{\text{mobility data}})$$

One-step conditional probability that a person leaving city i travels to city j

Two-city model



α Infection rate

Q → transition rate from 1 to 2

What is the distribution of first arrival time of infection ?

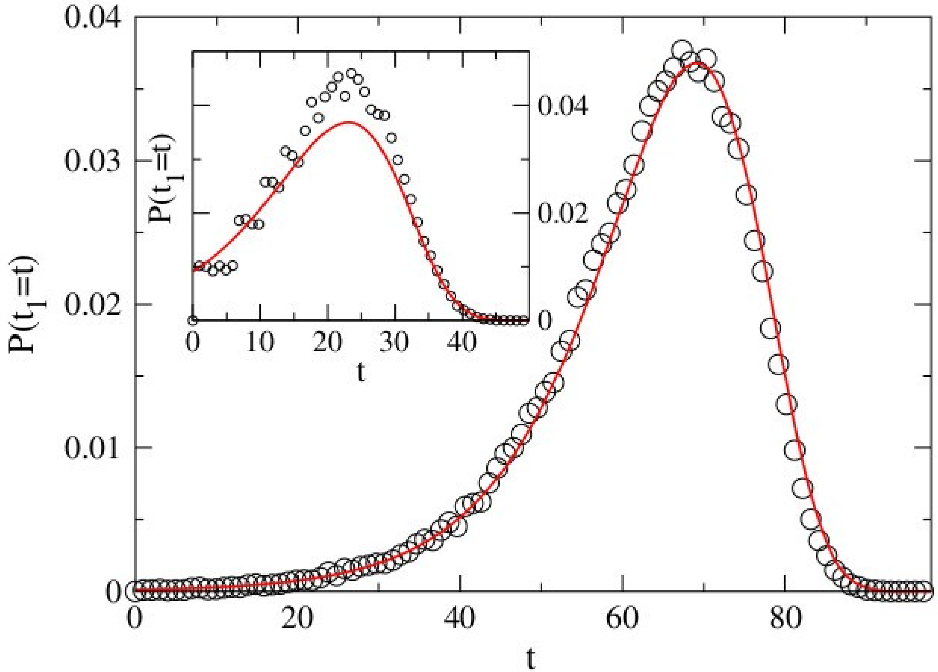
Gumbel distribution.

$$P(t) = Q\ \exp\left(\alpha t - \frac{Q}{\alpha} e^{\alpha t}\right)$$

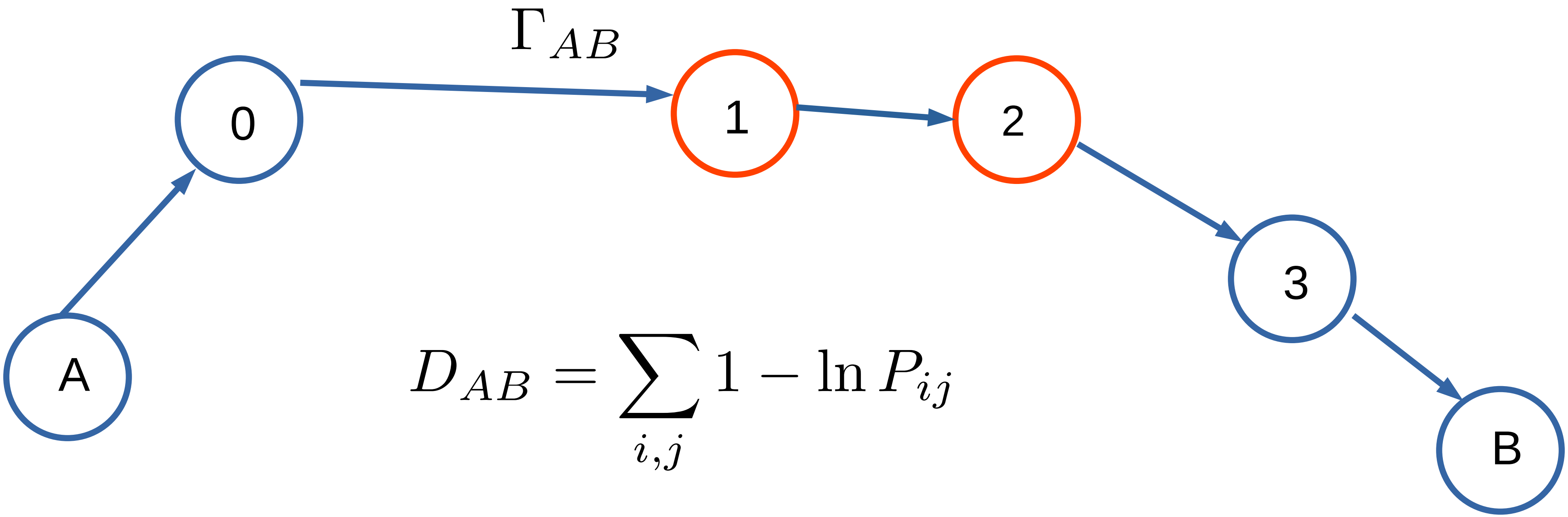
Mean hitting time

$$\langle t \rangle = \frac{1}{\alpha}\left(\ln\frac{\alpha}{Q} - \gamma\right)$$

$$D = 1 - \ln P_{ij}$$

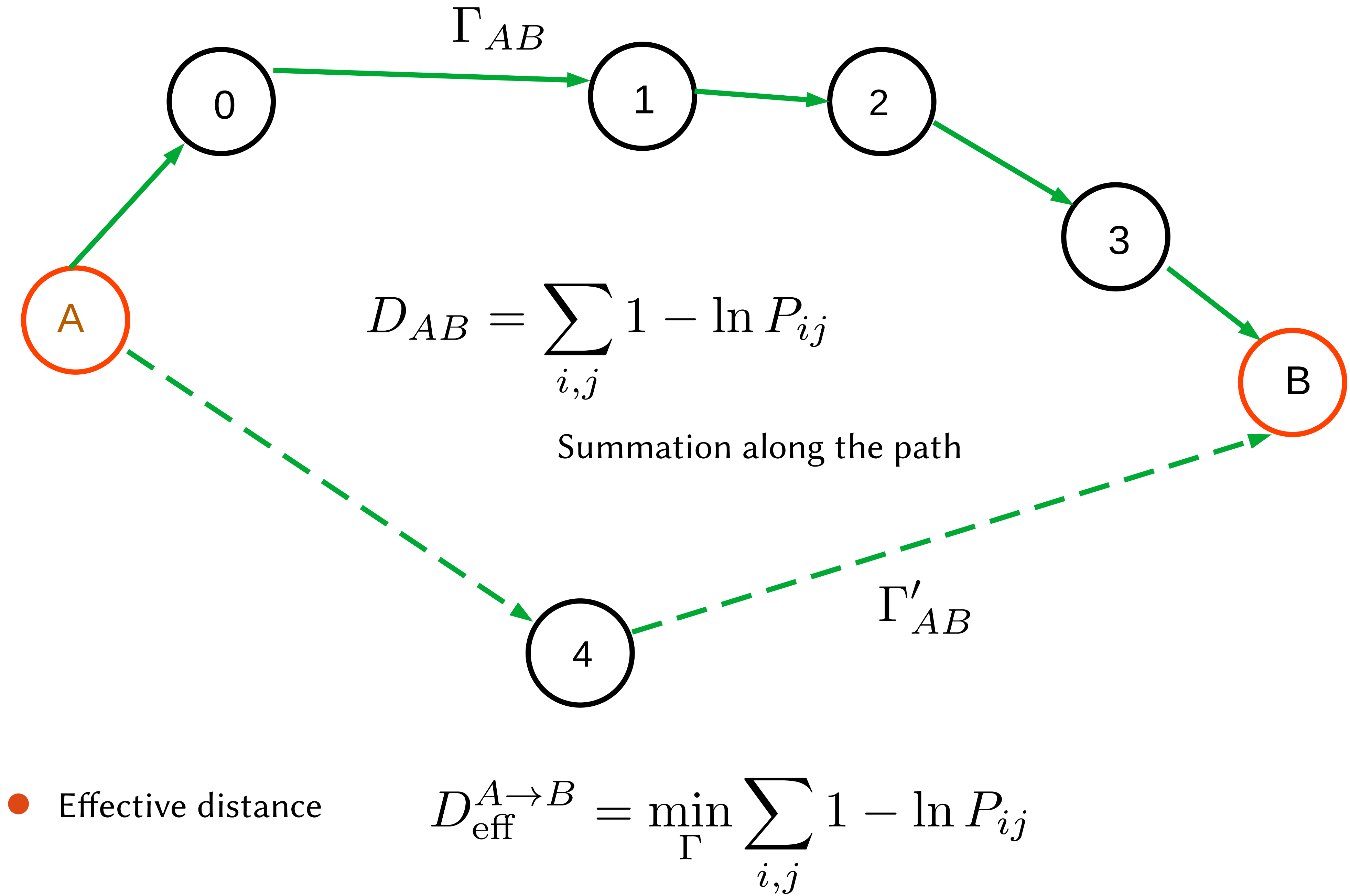


Gautreau, Barrat, Barthelemy, *J. Stat. Mech.* L09001 (2007)



$$D_{AB} = \sum_{i,j} 1 - \ln P_{ij}$$

Summation along the path Γ_{AB}


Γ_{AB}
0
1
2
3
A
B
4
$D_{AB} = \sum_{i,j} 1 - \ln P_{ij}$
Summation along the path
Γ'_{AB}
Effective distance
$D_{\text{eff}}^{A \to B} = \min_{\Gamma} \sum_{i,j} 1 - \ln P_{ij}$

effective distance and ToA

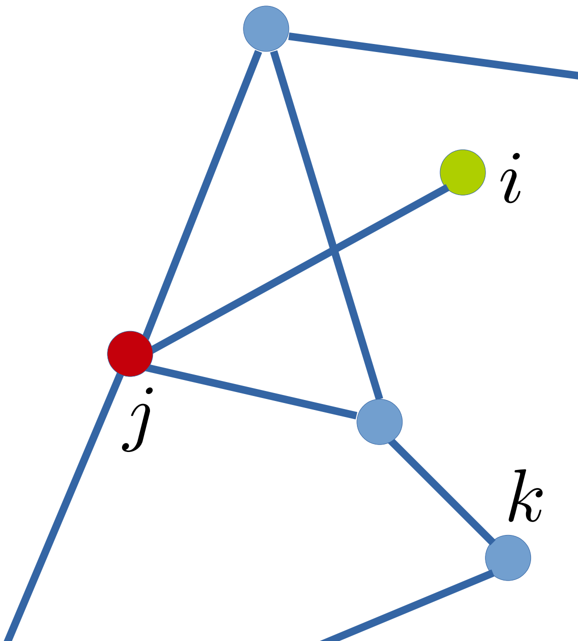
- Effective distance between *i*-th and *j*-th cities

$$D_{\text{eff}}^{i\to j} = 1 - \log P_i^j = 1 - \log(\underbrace{F_i^j / F_i}_{\text{mobility data}})$$

One-step conditional probability that a person leaving city i travels to city j

- Time of arrival of an infection is when the infection cases $I(t)$ exceed a threshold value for the first time

$$\text{At} \quad t = T_A, \quad I(t) > I_c$$



$$\boxed{\text{Central result :} \qquad T_A \propto D_{\text{eff}}^{i\to j}}$$

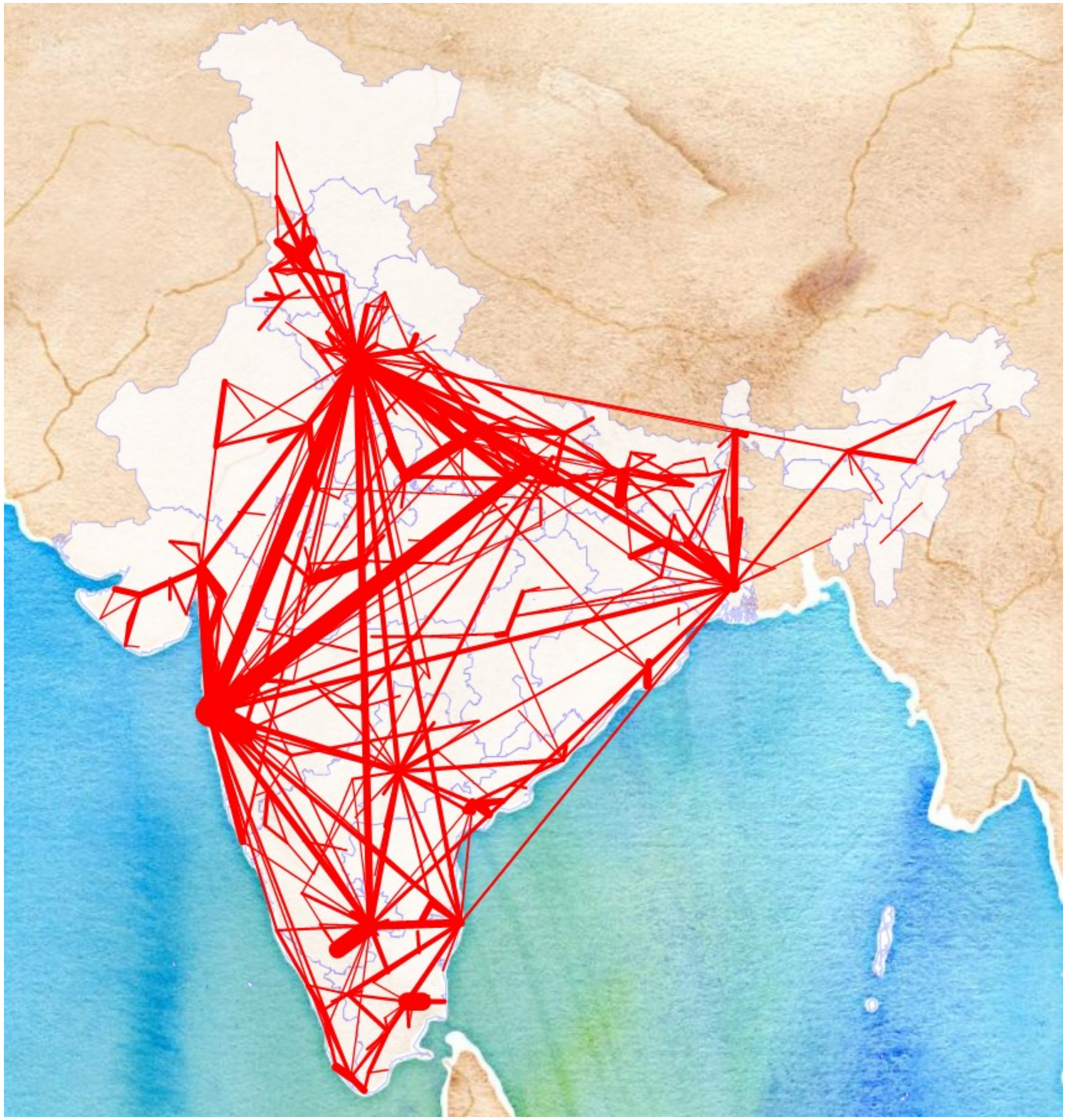
network and mobility data

- 446 cities/towns in India with a population of 1 lakh or more (based on 2011 census).
- Data of train, air and road traffic considered.
- Train data for 435 cities/towns collected. Data from Indian Railway time table, Live train status websites used.
- Flight schedules and passenger data from airline websites used.
- NHAI website data was used for road traffic. Gaps in road traffic data. Estimated used.
- Geographical location of cities obtained using python library *geopy*.
- All local mobility discarded. For instance, Mumbai local train passengers ignored.

How India travels ....
(A statistical summary)

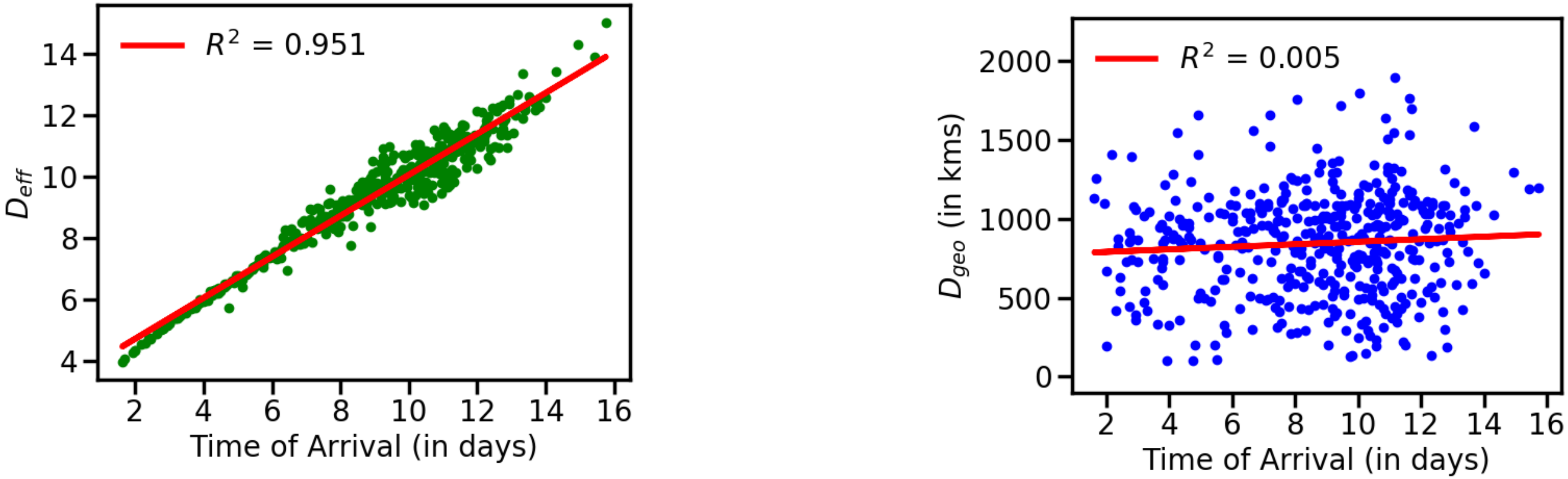
Property	Airway	Railway	Roadway	Combined
Number of Nodes	85	435	446	446
Number of Edges	1182	41594	9128	46448
Average Degree	13	95	20	104
Route symmetry index	1	0.9875	1	0.9878
Locality of Mobility	Same	Different	Same	Different
Passengers/day	7.5×10^5	8.8×10^6	2.5×10^6	1.2×10^7
Fraction of total	0.06	0.73	0.21	1.0

How India travels ....

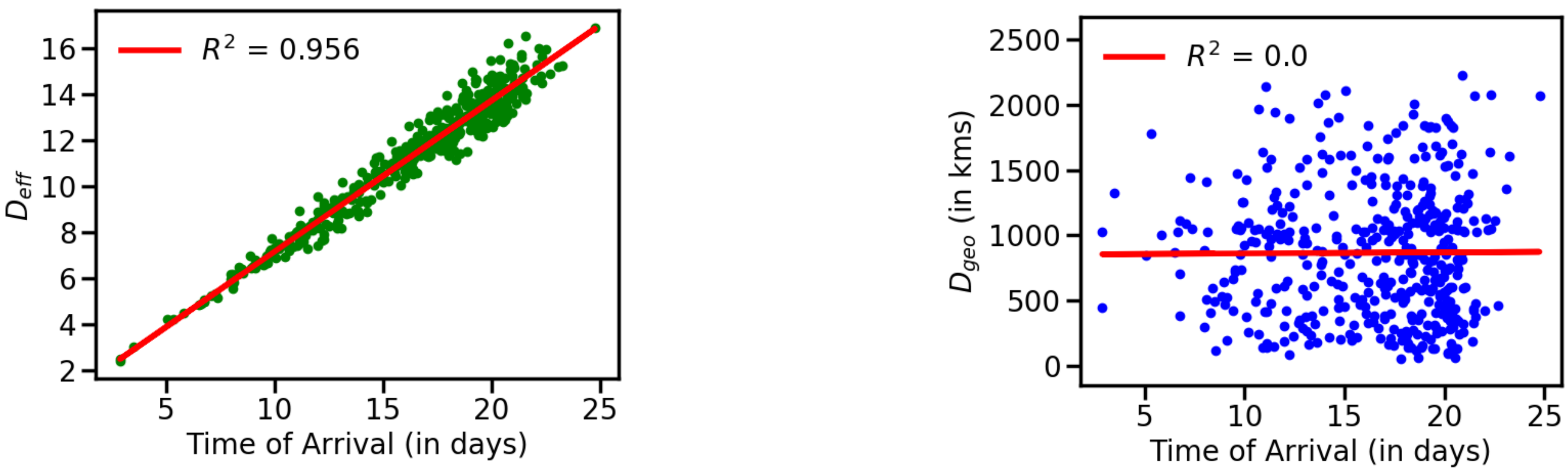


- Data from rail, road and air. Top 500 of 23224 connections shown here. Thicker lines indicate more mobility of people in that route.

Outbreak location : *Delhi*



Outbreak location : *Tirupati*



$$T_A \propto D_{\text{eff}}^{i \to j}$$

The Hidden Geometry of Complex, Network-Driven Contagion Phenomena

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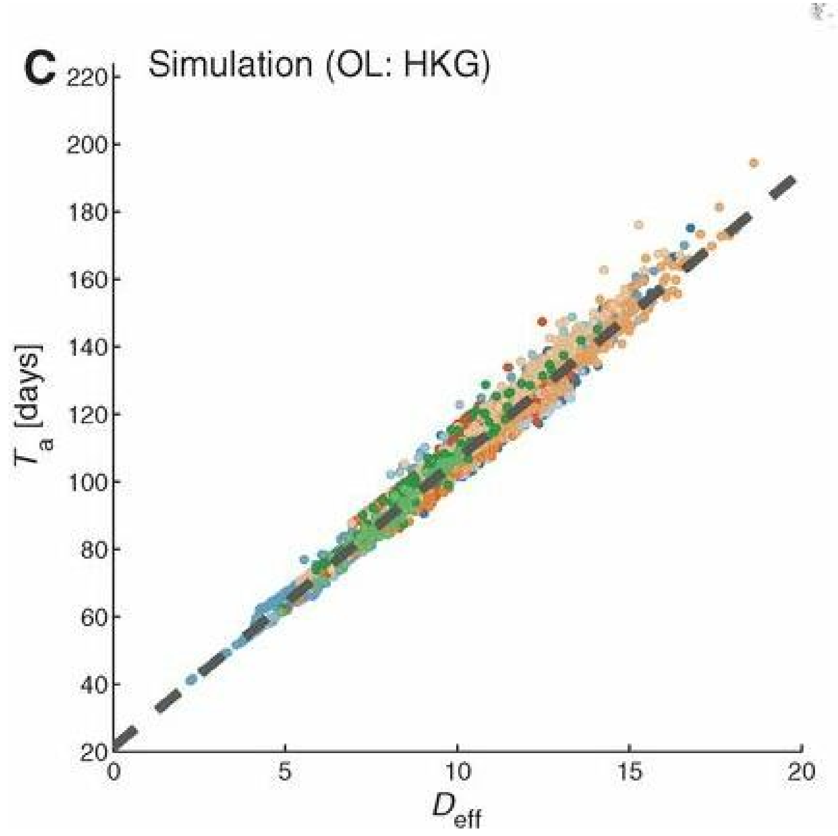
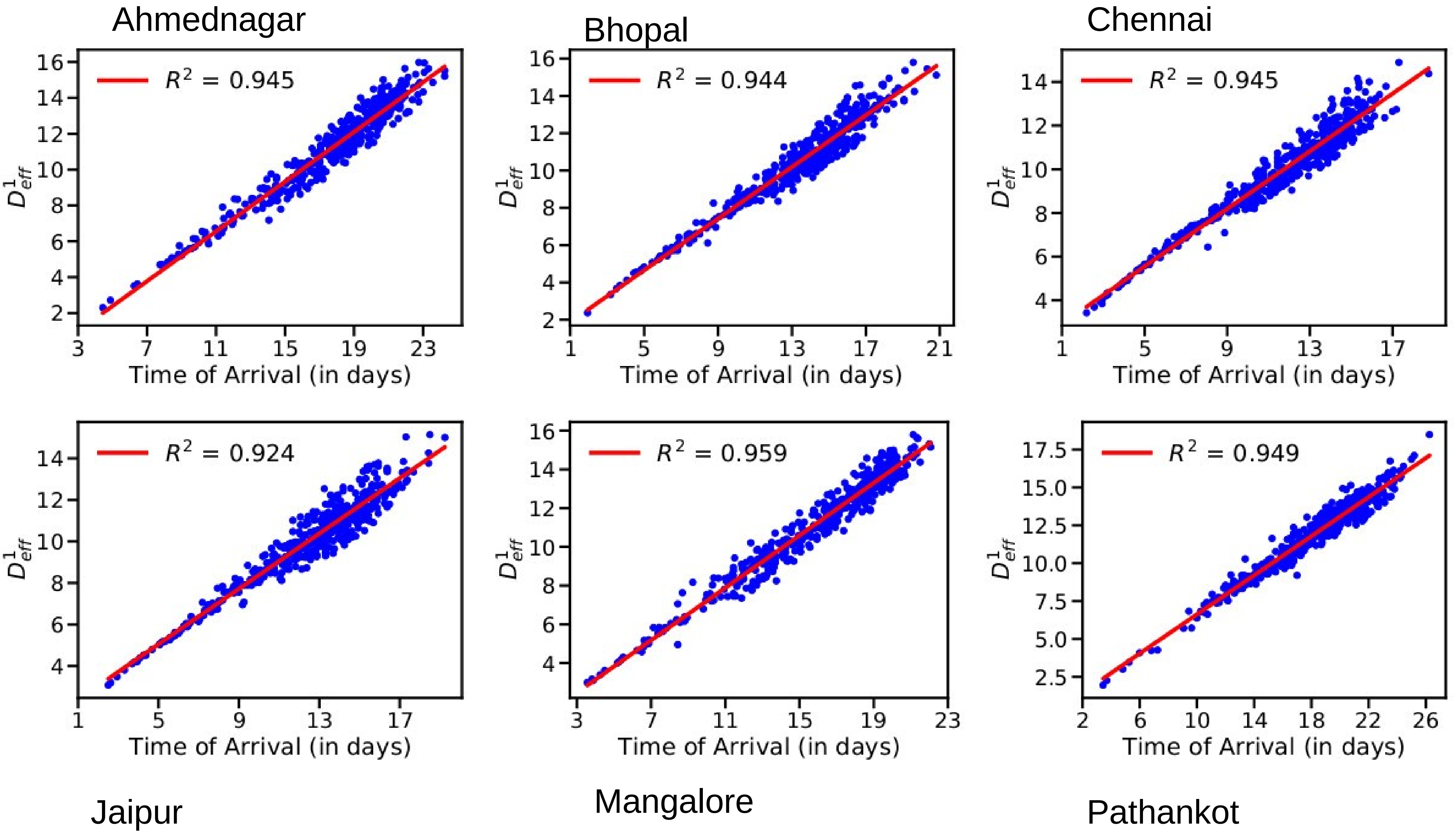
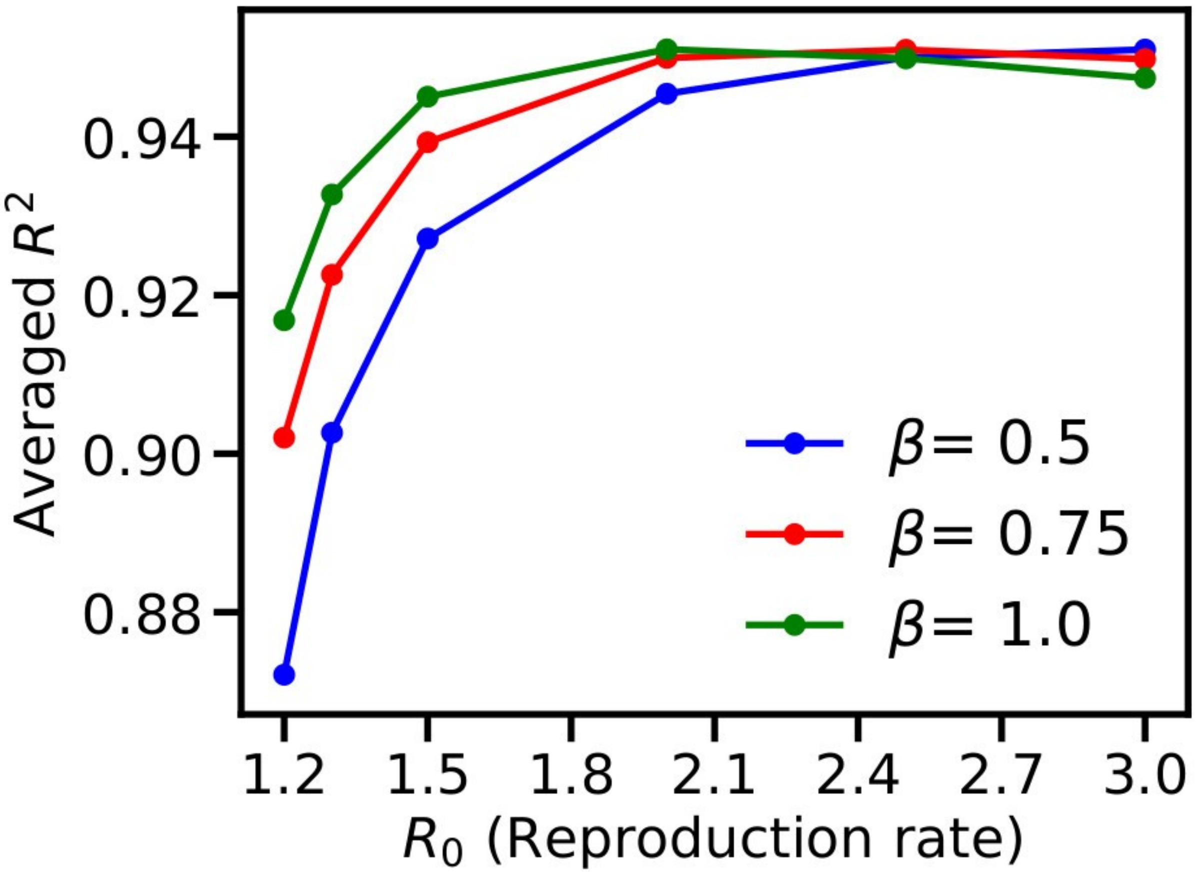
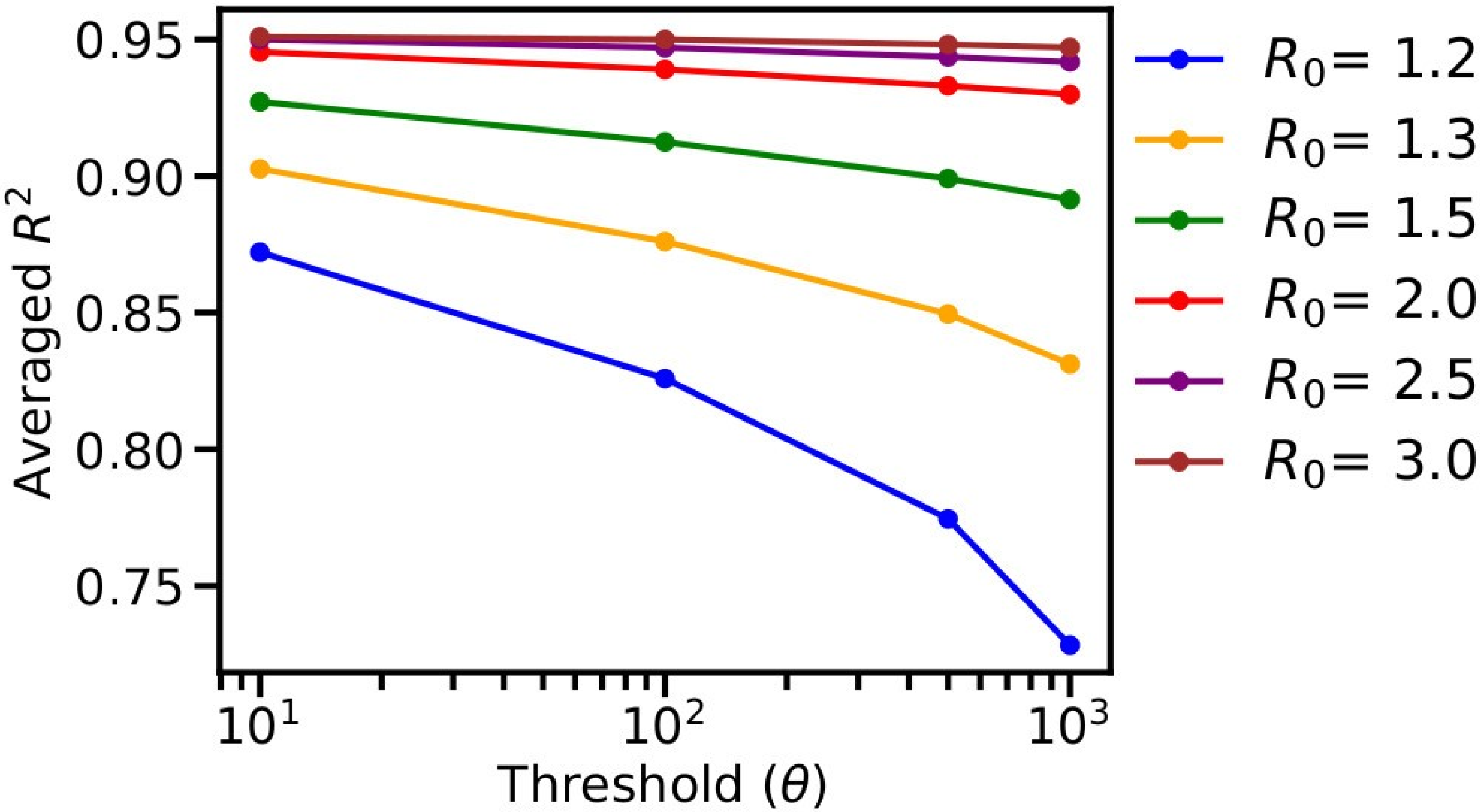


Based on airline traffic data


Ahmednagar
$R^2 = 0.945$
Bhopal
$R^2 = 0.944$
Chennai
$R^2 = 0.945$
$R^2 = 0.924$
$R^2 = 0.959$
$R^2 = 0.949$
D_{eff}^1
Time of Arrival (in days)
Jaipur
Mangalore
Pathankot



Averaged over all outbreak locations as a function of α and β.



Averaged over all outbreak locations as a function of α and β.

hazard value

$$h = \exp(-D_{\text{eff}})$$

Given an outbreak location, if effective distance is small, infection arrives faster. Hence higher hazard.

Patna	
City	TOA
Gaya	2.06
Dinapur Nizamat	2.50
Arrah	2.75
Delhi	2.81
Bhagalpur	3.25
Kolkata	3.25
Darbhanga	3.88
Biharsharif	3.94
Jehanabad	3.94
Begusarai	4.00
Muzaffarpur	4.06
Varanasi	4.06

Tirupati	
City	TOA
Chittoor	2.88
Chennai	2.88
Hyderabad	3.50
Bangalore	5.06
Vellore	5.31
Tiruvannamalai	5.81
Kadapa	6.50
Vijayawada	6.62
Visakhapatnam	6.75
Anantapur	6.75
Madanapalle	6.75
Nellore	7.06

Mumbai	
City	TOA
Thane	1.00
Pune	1.19
Delhi	1.62
Ahmedabad	2.00
Surat	2.00
Pimpri Chinchwad	2.19
Nashik	2.25
Bangalore	2.38
Vasai	2.38
Hyderabad	2.56
Chennai	2.94
Vasco Da Gama	3.00

TOA in *days*

hazard value

$$h = \exp(-D_{\text{eff}})$$

Given an outbreak location, if effective distance is small, infection arrives faster. Hence higher hazard.

Hazard rank

	Patna	
	City	TOA
1	Gaya	2.06
2	Dinapur Nizamat	2.50
3	Arrah	2.75
4	Delhi	2.81
5	Bhagalpur	3.25
	Kolkata	3.25
	Darbhanga	3.88
	Biharsharif	3.94
	Jehanabad	3.94
	Begusarai	4.00
	Muzaffarpur	4.06
	Varanasi	4.06

	Tirupati	
	City	TOA
1	Chittoor	2.88
2	Chennai	2.88
3	Hyderabad	3.50
4	Bangalore	5.06
5	Vellore	5.31
	Tiruvannamalai	5.81
	Kadapa	6.50
	Vijayawada	6.62
	Visakhapatnam	6.75
	Anantapur	6.75
	Madanapalle	6.75
	Nellore	7.06

	Mumbai	
	City	TOA
1	Thane	1.00
2	Pune	1.19
3	Delhi	1.62
4	Ahmedabad	2.00
5	Surat	2.00
	Pimpri Chinchwad	2.19
	Nashik	2.25
	Bangalore	2.38
	Vasai	2.38
	Hyderabad	2.56
	Chennai	2.94
	Vasco Da Gama	3.00

TOA in *days*

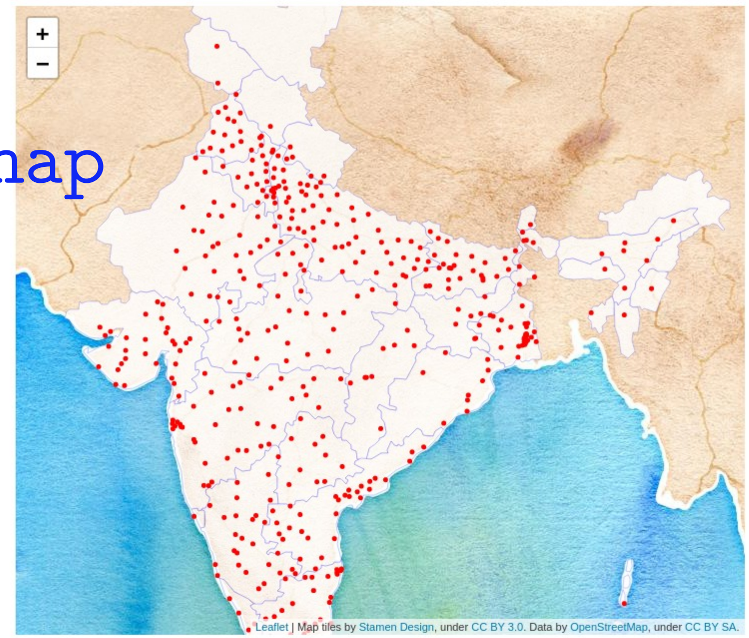
sites.iiserpune.ac.in/~hazardmap

Choose any city/town as outbreak location and see the hazard map.

Hazard Map India   ABOUT   TEAM   DATA   HOW IT WORKS

Welcome to the infectious diseases hazard map project. The map below shows 446 cities/towns in India with a population of more than 1 lakh. Hover the mouse over any red dot to get its average hazard rank. Click on it, and you can make that city/town as the outbreak location for an infectious disease. This will take you to the hazard map with the chosen outbreak location. You can also choose the outbreak location using the following dropdown menu.

Choose a city as the outbreak location: ...



You can get more details here. Average hazard rank indicates the relative risk faced by a city/town due to any infectious disease. Smaller the rank, more the risk. Thus, rank 3 is more at risk compared to rank 4, and so on. For more details, see arXiv/2105.15123. Note that the location of some cities on the map may not be accurate.

Contact: hazardmap@acads.iiserpune.ac.in

Supported by a special MATRICS grant from SERB, Govt. of India, and INSPIRE, DST, Govt. of India and IISER Pune.

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in the national pages of media

Dainik Jagran
11.6.2021

Well-connected metros more likely to spread infectious diseases: study

ANJALI MARAR
PUNE, JUNE 11

A HAZARD map of Indian cities, accounting for the potential of spreading infectious diseases from typical outbreak locations through inter-city travel, has placed Delhi, Mumbai, Kolkata, Bengaluru, Hyderabad, Chennai, Ahmedabad, Lucknow, Jhansi, Pune and Jaipur in top positions.

Researchers at Indian Institute of Science Education and Research (IISER), Pune, after studying 446 cities with over one lakh population, have linked the transport modes and its usage frequency to understand the spread of infectious diseases from a host city reporting an outbreak and its spread.

Amreli, Gangtok, Shimla, Kannur, Tezpur, Osmanabad, Jorhat and Junagad remained among the cities that had least hazard at the time of an outbreak. The researchers made use of air, rail and road transport between these cities to bring out this hazard map for the country and compared them with the spread of Covid-19 cases reported between March and July 2020.

"Suppose there is an infectious disease outbreak in a particular city, this map provides a lead time informing how long the disease will take to travel to other parts of the country. With this information, government agencies can stay prepared and plan travel restrictions accordingly," said MS Santhanam, professor, Department of Physics at IISER.

In India, railways account for the bulk of long-distance traffic ferrying about 88 lakh people per day, followed by road – 25 lakh and air – 7.5 lakh. As a result, trains not only are infection carriers but also do so over long distances in a country like India, the researchers said.

The IISER scientists concluded that it is not the geographical proximity, which plays the deciding factor in a disease spread. Instead, a metric based on frequency of travel on key travel routes is a better predictor of the risks to cities.

For example, Osmanabad (ranked 435) in Maharashtra may be geographically located closer to Mumbai. But, in the event of an outbreak in Mumbai, due to better air and rail connectivity and the sheer number of travellers, the disease will reach Delhi or Kolkata sooner.

TRANSMISSION IN TRANSIT

If metros are outbreak locations, the infection swiftly reaches far corners of the country. For instance, an infection at Tirupati will reach Bengaluru in about 5 days. But if Mumbai or Delhi is the epicentre, the infection spreads to Bengaluru in just about 2.5 days.

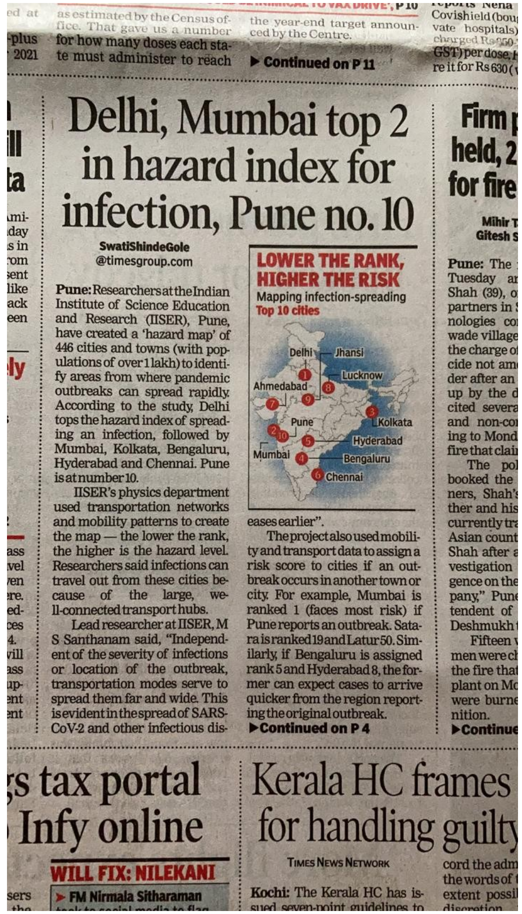
Source: Study at IISER, Pune

Brooms, threats, rumours: Bihar's Tika Express runs into hurdles

SANTOSH SINGH
PATNA, JUNE 11

THE 'TIKA Express' drive launched by Chief Minister Nitish Kumar on June 3 is making slower progress than the Bihar government perhaps expected. While the initiative

Indian Express
12.6.2021



Delhi, Mumbai top 2 in hazard index for infection, Pune no. 10

SwatiShindeGole
@timesgroup.com

Pune: Researchers at the Indian Institute of Science Education and Research (IISER), Pune, have created a 'hazard map' of 446 cities and towns (with populations of over 1 lakh) to identify areas from where pandemic outbreaks can spread rapidly. According to the study, Delhi tops the hazard index of spreading an infection, followed by Mumbai, Kolkata, Bengaluru, Hyderabad and Chennai. Pune is at number 10.

IISER's physics department used transportation networks and mobility patterns to create the map — the lower the rank, the higher is the hazard level. Researchers said infections can travel out from these cities because of the large, well-connected transport hubs.

Lead researcher at IISER, M S Santhanam said, "Independent of the severity of infections or location of the outbreak, transportation modes serve to spread them far and wide. This is evident in the spread of SARS-CoV-2 and other infectious diseases earlier".

The project also used mobility and transport data to assign a risk score to cities if an outbreak occurs in another town or city. For example, Mumbai is ranked 1 (faces most risk) if Pune reports an outbreak. Satara is ranked 19 and Latur 50. Similarly, if Bengaluru is assigned rank 5 and Hyderabad 8, the former can expect cases to arrive quicker from the region reporting the original outbreak.

▶Continued on P 4

LOWER THE RANK, HIGHER THE RISK
Mapping infection-spreading Top 10 cities

's tax portal Infy online

WILL FIX: NILEKANI

Kerala HC frames for handling guilty

TIMES NEWS NETWORK

Kochi: The Kerala HC has issued seven-point guidelines to

Times of India
9.6.2021

संक्रमण के जोखिम में शीर्ष पर दिल्ली

राज्य ब्यूरो, नई दिल्ली: पुणे स्थित भारतीय विज्ञान शिक्षा संस्थान (आइआइएसईआर) के शोधकर्ताओं ने एक लाख से अधिक जनसंख्या वाले 446 शहरों में संक्रमण फैलने के जोखिम का नक्शा तैयार किया है। नक्शे से इस बात का पता चलता है कि किन शहरों में कितनी तेजी से कोई संक्रामक महामारी फैल सकती है। शोधकर्ताओं के मुताबिक तेजी से संक्रमण फैलने के जोखिम की सूची में दिल्ली शीर्ष पर है। दिल्ली के बाद इस सूची में मुंबई, कोलकाता, बेंगलुरु, हैदराबाद और चेन्नई का स्थान है, वहीं पुणे 10वें स्थान पर है।

शहरों में संक्रमण का जोखिम	
दिल्ली	1
मुंबई	2
कोलकाता	3
बेंगलुरु	4
हैदराबाद	5
चेन्नई	6
अहमदाबाद	7
लखनऊ	8
झांसी	9
पुणे	10

दिल्ली में संक्रमण से इन शहरों को खतरा	
कानपुर	1
मुंबई	2
गुरुग्राम	3
लखनऊ	4
फरीदाबाद	5
झांसी	6
रोहतक	7
मुरादाबाद	8
लुधियाना	9
बेंगलुरु	10

दिल्ली के संक्रमण का इन स्थानों पर भी होगा व्यापक असर

लोनी	नोएडा	सोनीपत	मोदीनगर
मेरठ	खोड़ा	बहादुरगढ़	बुलंदशहर

LokSatta
11.6.2021

WWW.LOKSATTA.COM
शुक्रवार, ११ जून २०२१

वि वि धा | लोकसत्ता

'हॅझार्ड मॅप'ची निर्मिती; 'आयसर पुणे'च्या संशोधन गटाचे संशोधन

साथरोगांवर नियंत्रणासाठी सतर्कता नकाशा

लोकसत्ता प्रतिनिधी

धोका असलेली दहा शहरे

महत्त्व काय?

खासगी विद्यापीठांतील प्रवेशांसाठीची 'पेरा सीईटी' १६ ते १८ जुलैदरम्यान

लोकसत्ता प्रतिनिधी

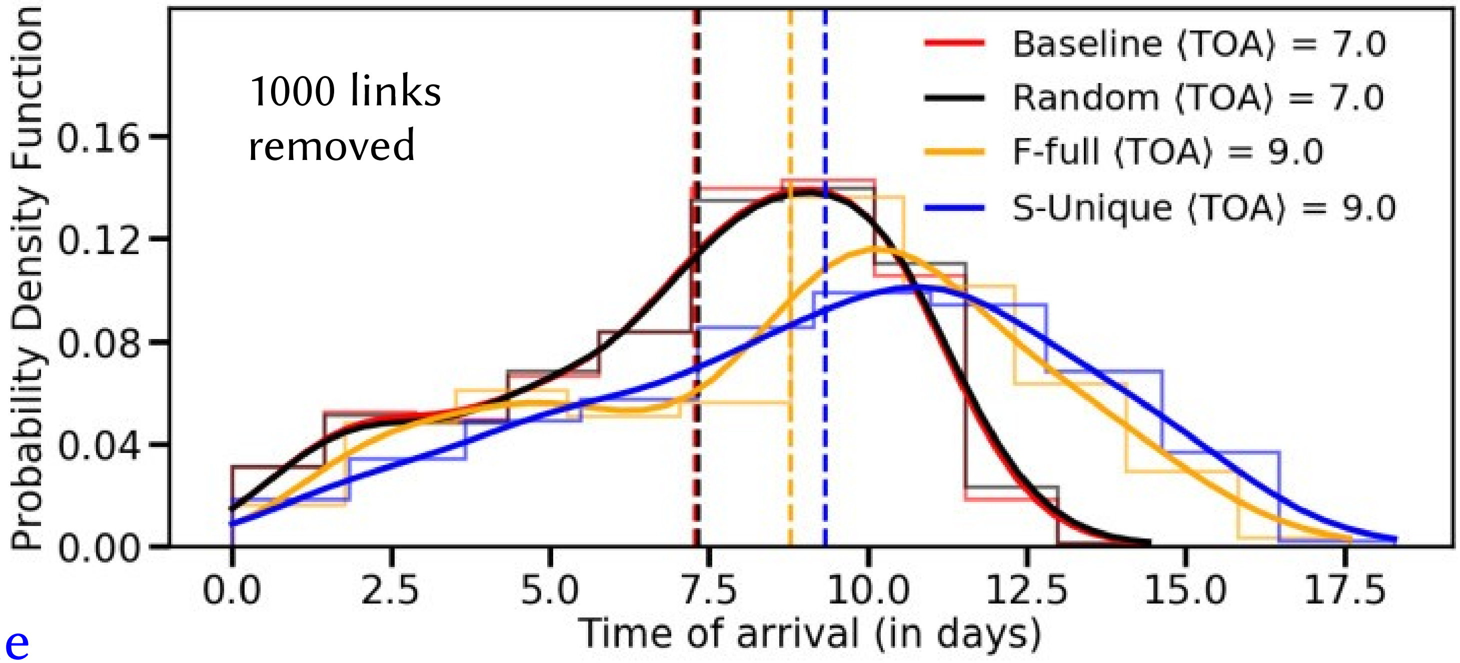
Fri, 11 June 2021

comparison with real data

Based on observed data
From March – June 2020

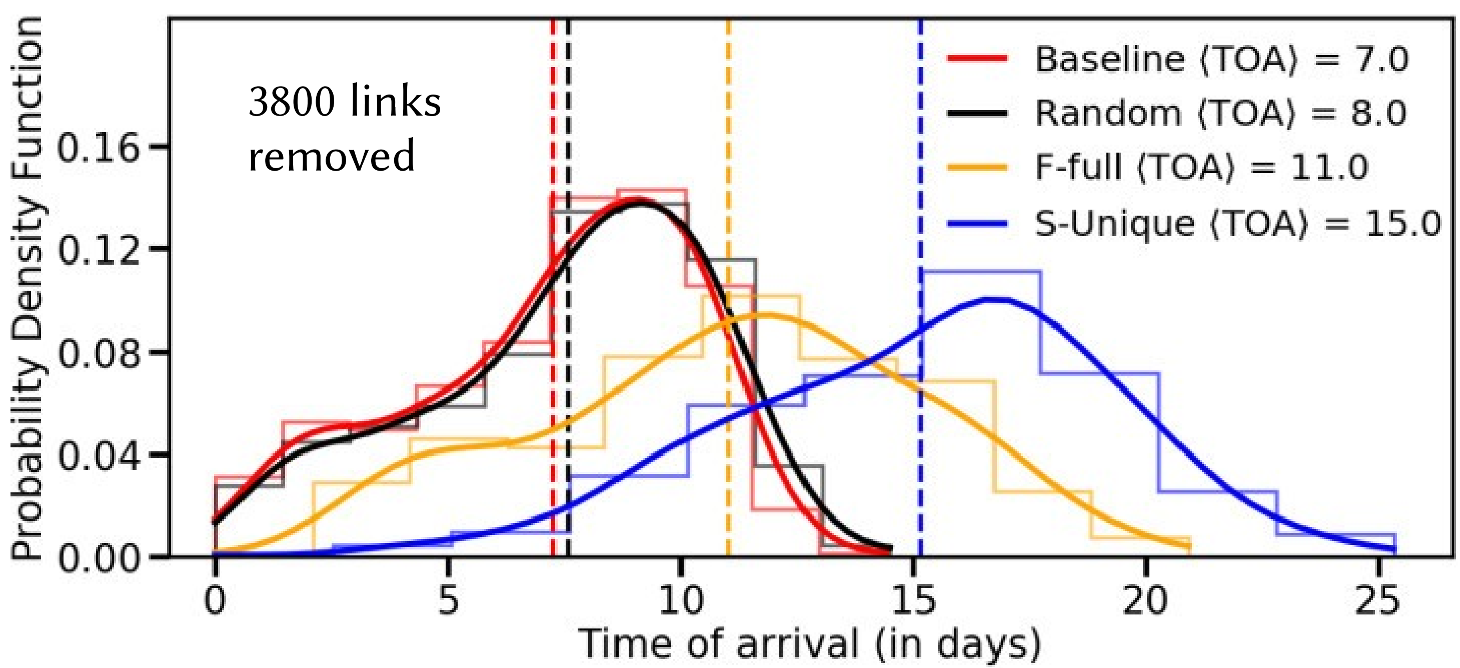
City	Simulation TOA	City	Real TOA
Mumbai	1	Mumbai	1
Pune	22	Delhi	11
Thane	23	Ahmedabad	13
Delhi	25	Chennai	16
Ahmedabad	26	Thane	25
Surat	26	Pune	46
Bangalore	27	Hyderabad	57
Pimpri Chinchwad	28	Bangalore	65
Hyderabad	29	Guwahati	70
Nashik	29	Kolkata	79
Vasai	30	Nashik	85
Chennai	31	Guntur	88

9 out of 12 cities are common to both the lists.



Can we slow down the spread of Infection ?

Bangalore as outbreak location



If β is small, then infection would have spread to all the places by the time $R \to 0$.

$$S_n + I_n \approx N_n$$

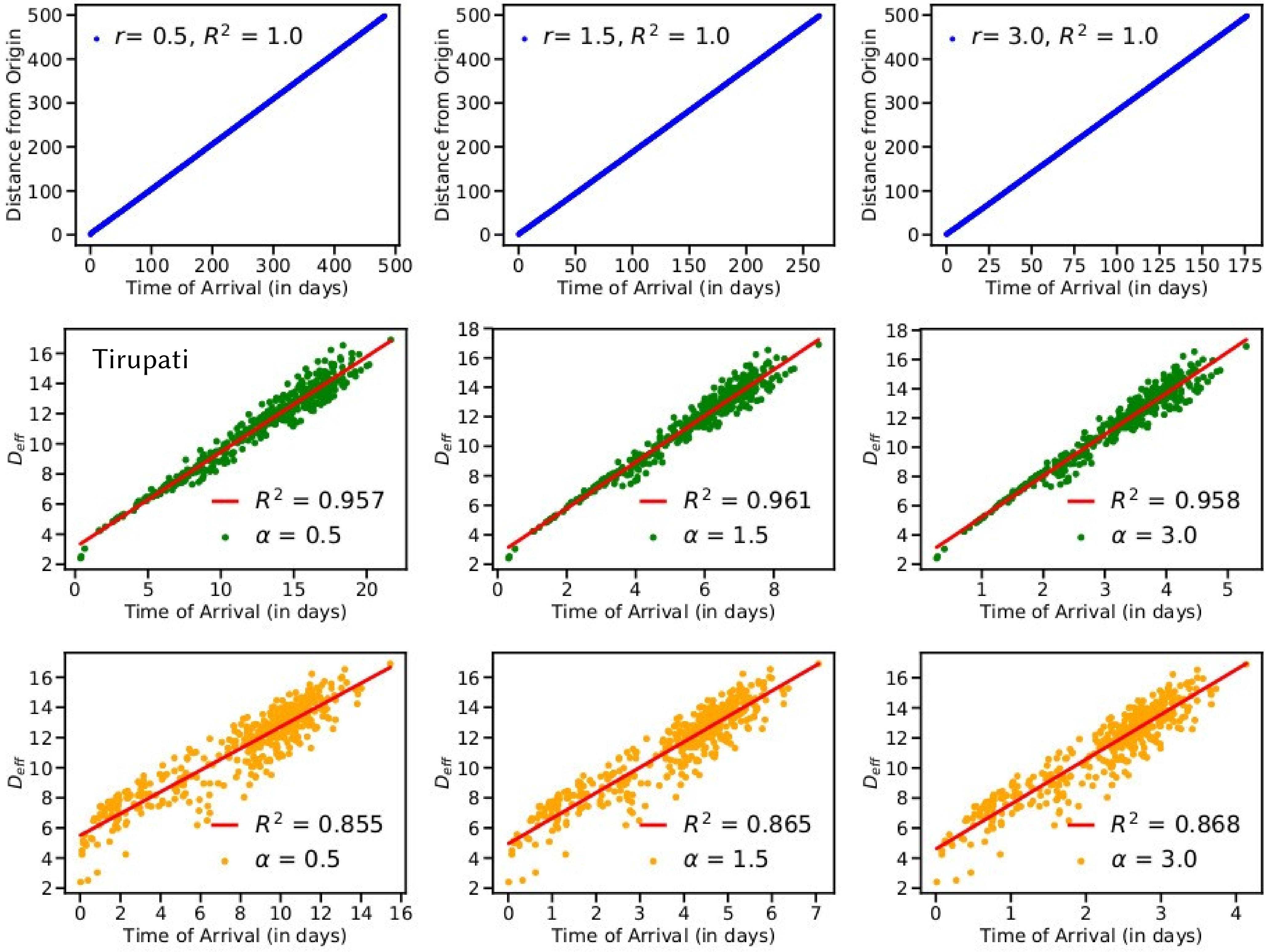
Since city population is a constant, only one variable is involved in the equations.

$$\frac{\partial I_n}{\partial t} = \alpha I_n \left(1 - \frac{I_n}{N_n}\right) - \gamma_n I_n + \sum_m \frac{F_m^n}{N_m} I_m, \quad n,\ m = 1,\ 2,\ \ldots,\ M. \qquad \text{(SI model)}$$

$$\frac{\partial i_n}{\partial t} = \alpha i_n (1 - i_n) + \frac{1}{N_n} \sum_m \left[\gamma_m P_m^n N_m i_m - \gamma_n P_n^m N_n i_n\right], \quad n,\ m = 1,\ 2,\ \ldots,\ M.$$

$$\frac{\partial u}{\partial t} = ru(1-u) + D\frac{\partial^2 u}{\partial x^2}$$

$$\frac{\partial u_n}{\partial t} = ru_n(1-u_n) + D\sum_m \left[\mathscr{P}^n_m u_m - \mathscr{P}^m_n u_n\right], \quad n,\ m = 1,\ 2,\ \ldots,\ M,$$



r= 0.5, R^2 = 1.0
r= 1.5, R^2 = 1.0
r= 3.0, R^2 = 1.0
Distance from Origin
Time of Arrival (in days)
Tirupati
D_{eff}
R^2 = 0.957
α = 0.5
R^2 = 0.961
α = 1.5
R^2 = 0.958
α = 3.0
R^2 = 0.855
α = 0.5
R^2 = 0.865
α = 1.5
R^2 = 0.868
α = 3.0

hazard map . . . .

- Effective distance is a useful metric in the context of spreading processes on complex networks.
- A framework created for a hazard map based on mobility data in India.

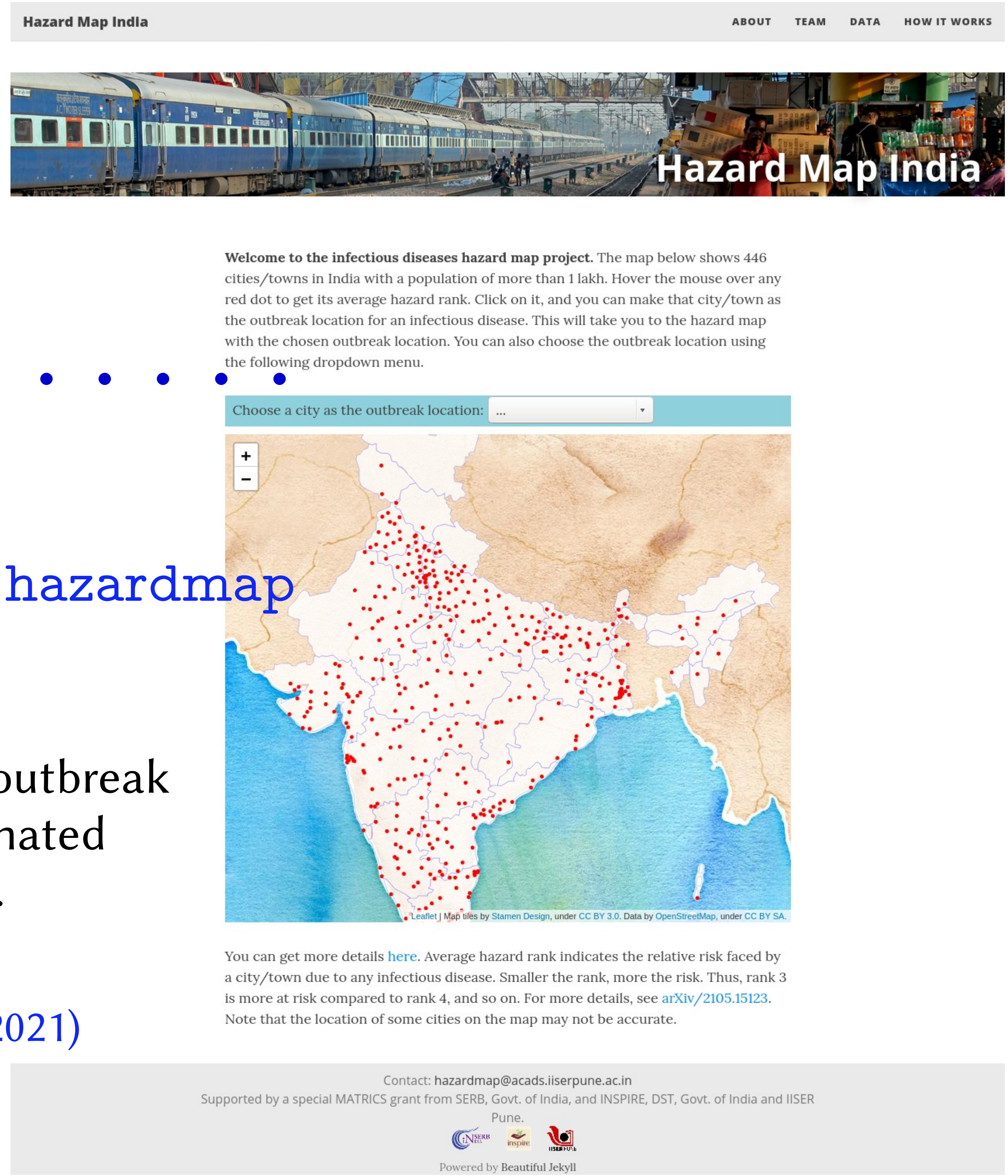
. . . . and future extensions

- Improve mobility data used in the model. More data from Indian Railways, NHAI, DGCA is needed. Reduce estimates as much as possible.
- This system works for multiple outbreak locations.
- This framework is not specific to COVID-19. It is a useful resource for other infectious diseases as well.

THANK YOU . . . . .

sites.iiserpune.ac.in/~hazardmap

- Choose any city/town as outbreak Location and see the estimated hazard for your city/town.
- *Current Science* **121**, 1208 (2021)



mathematical framework

Movement kinetics :

$$\frac{\partial N_n(t)}{\partial t} = \sum_{m=1}^{M} \Big[W_m^n N_m(t) - W_n^m N_n(t) \Big], \quad n, m = 1, 2, \cdots M,$$

Rate of people going from *i*-th to *j*-th city

Population in *n*-th city at time *t*

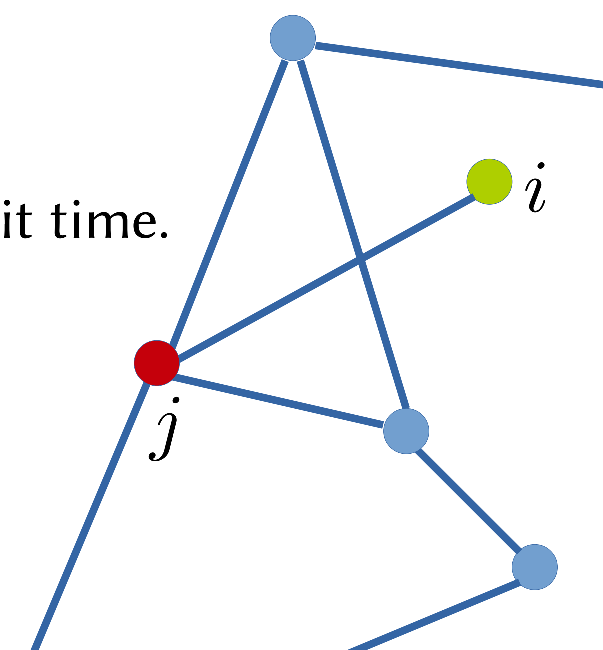
Total number of cities/towns.

- Mobility is accounted through traffic matrix **F**

F_i^j : number of people going from *i*-th to *j*-th city/town.

$F_i = \sum_j F_i^j$: total number of people leaving *i*-th city per unit time.

$$\frac{\partial N_n(t)}{\partial t} = \sum_m [F_m^n - F_n^m]$$



Random matrix theory related work :

- Symmetry deduction from spectral fluctuations in complex quantum systems
  S. Harshini Tekur and M. S. Santhanam
  Physical Review Research (Rapid Communications) **2**, 032063 (2020)

- Scaling in the eigenvalue fluctuations of the empirical correlation matrices
  Udaysinh T. Bhosale, S. Harshini Tekur and M. S. Santhanam
  Phys. Rev. E **98**, 052133 (2018).

- Higher order spacing ratios in random matrix theory and complex quantum systems
  S. Harshini Tekur, Udaysinh T. Bhosale and M. S. Santhanam
  Phys. Rev. B. **98**, 104305 (2018).