Song Gao, Jinmeng Rao, Yuhao Kang, Yunlei Liang, Jake Kruse
Geospatial Data Science Lab
University of Wisconsin–Madison

Email: song.gao@wisc.edu
https://geods.geography.wisc.edu/

Mapping Multiscale Human Mobility Changes and Geospatial Modeling of COVID-19 Spread

WISCONSIN
UNIVERSITY OF WISCONSIN-MADISON

Song Gao (GIS)

Qin Li (Mathematics)

Kaiping Chen (Science Communication)

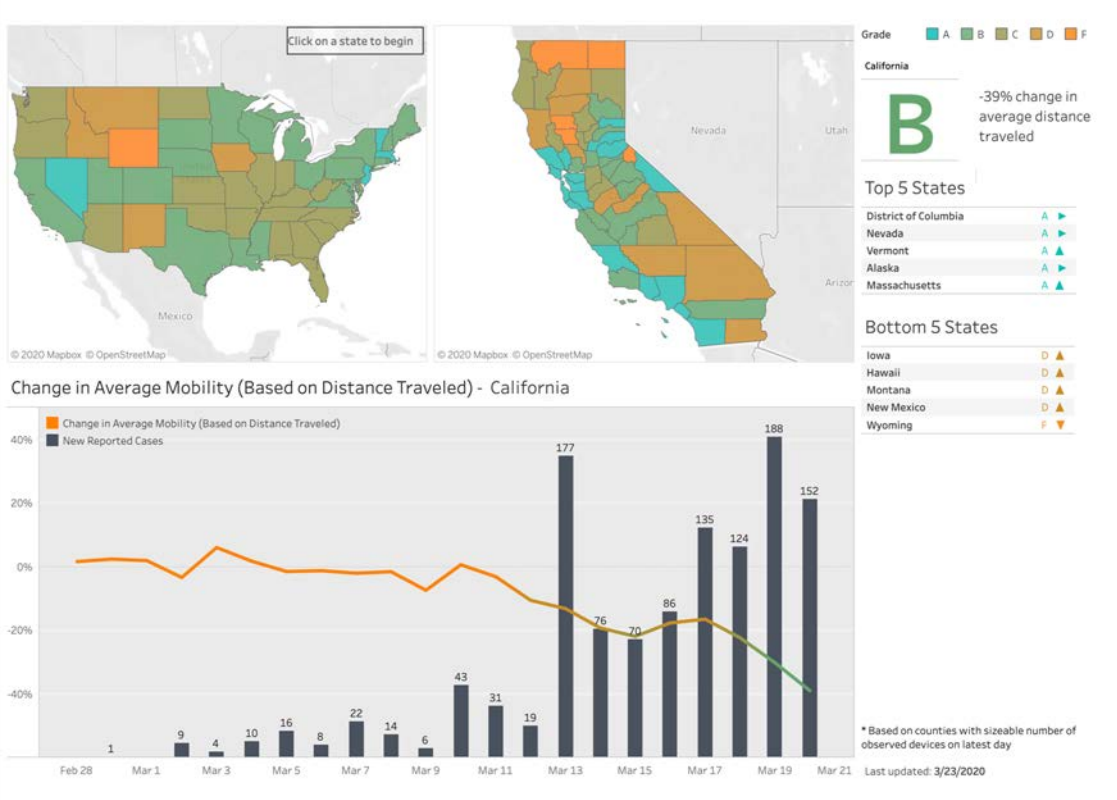
Jonathan Patz (Public Health)

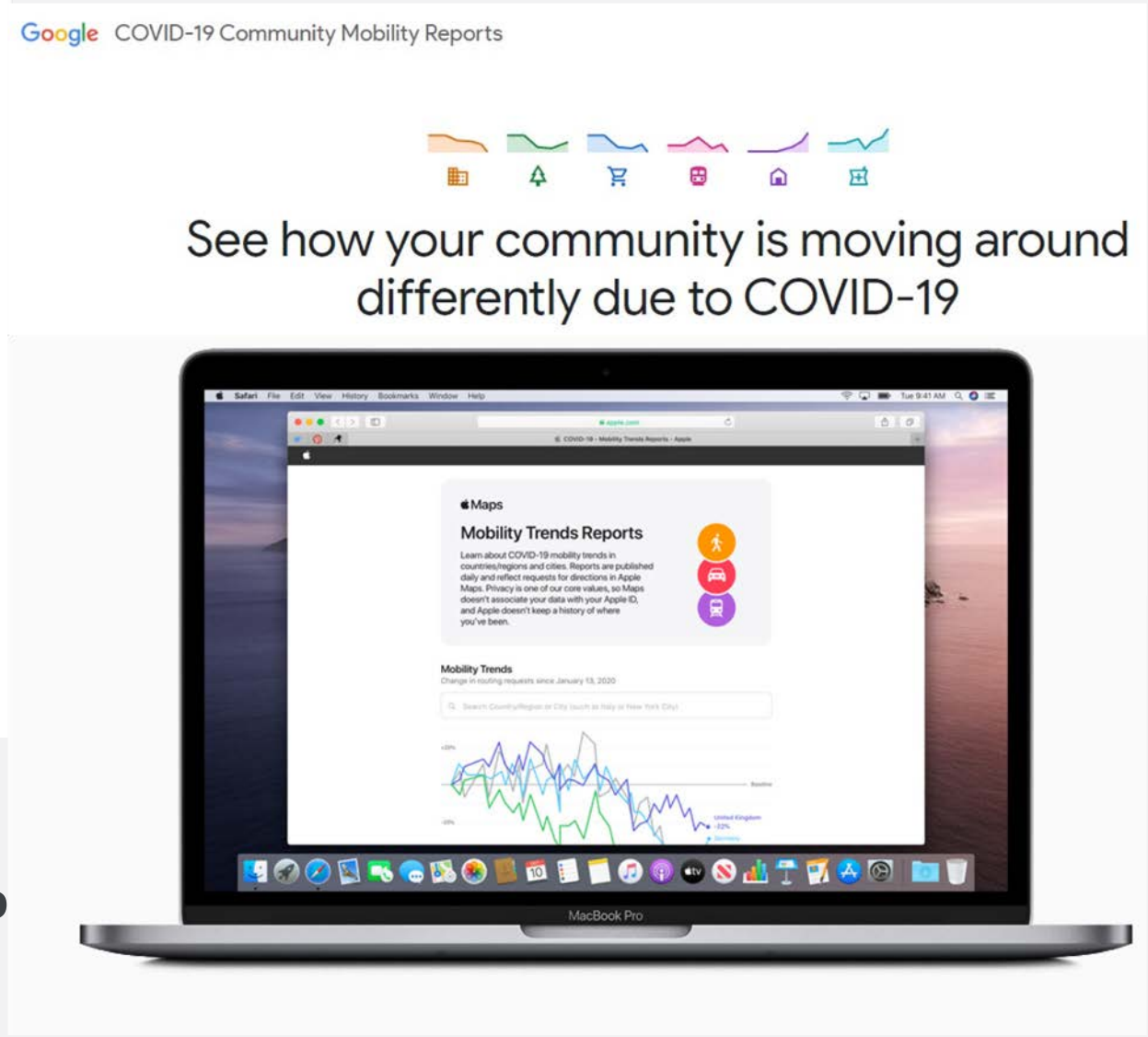
https://geods.geography.wisc.edu

Human Mobility Data Sources

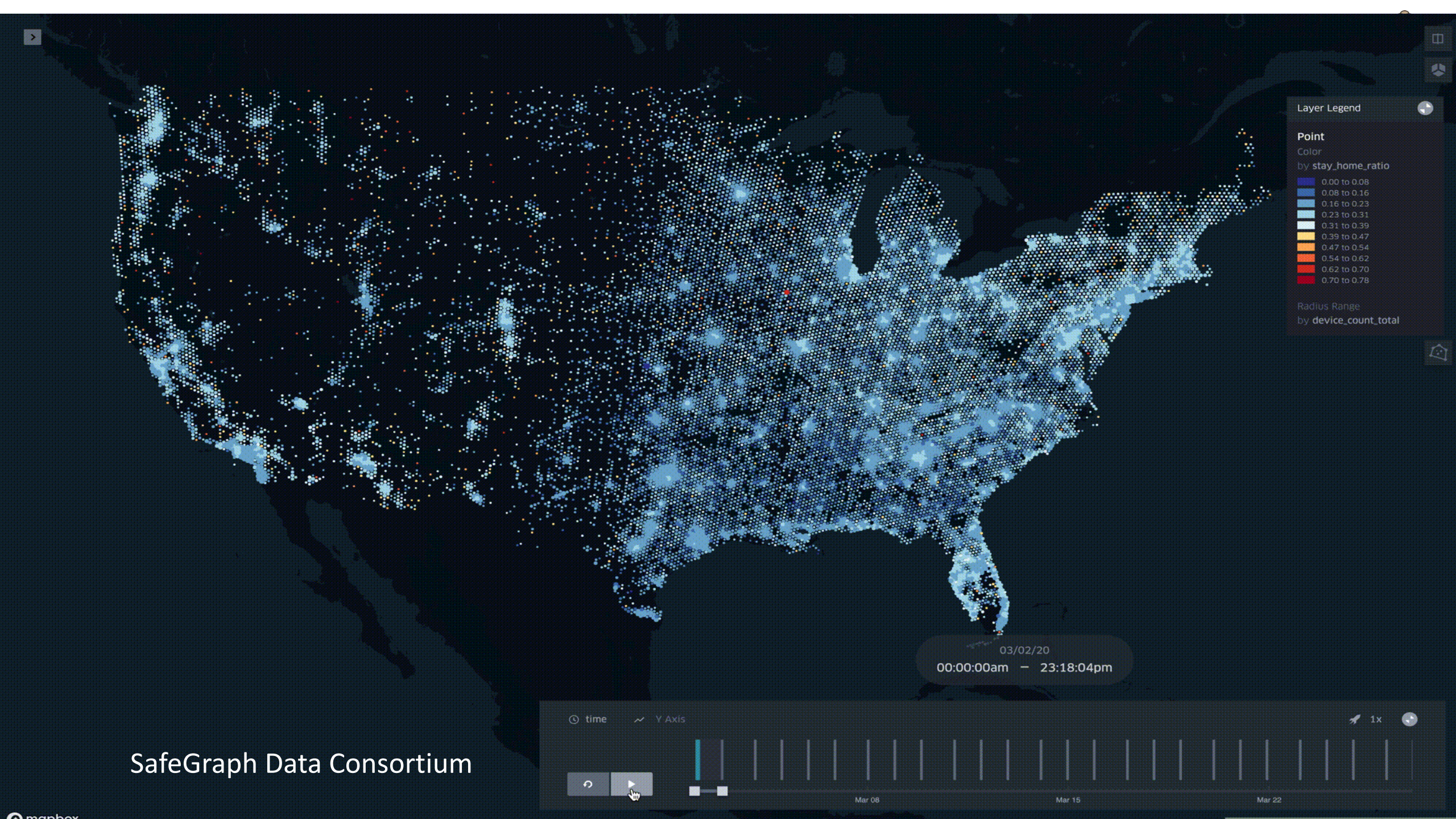
Source	Spatial	Social	Activity	Characteristics
Travel Survey	Yes	Yes	Yes	Small sample rich semantics
Social Media	Maybe	Maybe	Maybe	Large sample sparse
Call Detail Records	Yes	Yes	No	Large sample dense hard access
Location-Based Service	Yes	Maybe	Maybe	Large sample enterprise

Human Mobility Open Data Spring Up during COVID-19





Unacast Social Distancing Scoreboard
Google and **Apple** Mobility Reports
Cuebiq, UberMedia, X-Mode, **Descartes Lab** and **SafeGraph**


Layer Legend
Point
Color
by stay_home_ratio
0.00 to 0.08
0.08 to 0.16
0.16 to 0.23
0.23 to 0.31
0.31 to 0.39
0.39 to 0.47
0.47 to 0.54
0.54 to 0.62
0.62 to 0.70
0.70 to 0.78
Radius Range
by device_count_total
03/02/20
00:00:00am – 23:18:04pm
time
Y Axis
1x
Mar 08
Mar 15
Mar 22
SafeGraph Data Consortium
mapbox

Human Mobility Data from Anonymous Mobile Phone Devices

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Application

APPLICATION

Mobility Pattern Recognition | Mobility Monitoring | Mobility Analysis

Mobility Prediction | Policy Evaluation | Decision Support

Support

Methodology

FUNCTIONALITY

Map Visualization | Map Interaction | Data Query

Time Series Plotting | Feature Identification | ...

Associate

INTERFACE

Map Panel | Map Legend | Serial Chart

Gauge | List | Popup | Filter | ...

Support

Data and Features

Publish

DATA ORGANIZATION

Web Map | Feature Layers | Tables

Data

DATA STORAGE

ArcGIS Online Items | ArcGIS Online Content

Upload

DATA PREPARATION AND UPDATE

Geo-referenced County-level Multisource Data

Formatting

CSV | SHP

Formatted Data

US County Map Data

Aggregation
Spatial Join
Indicator Calculation

REGULAR UPDATE

Mobility Data

Home Dwell Time data

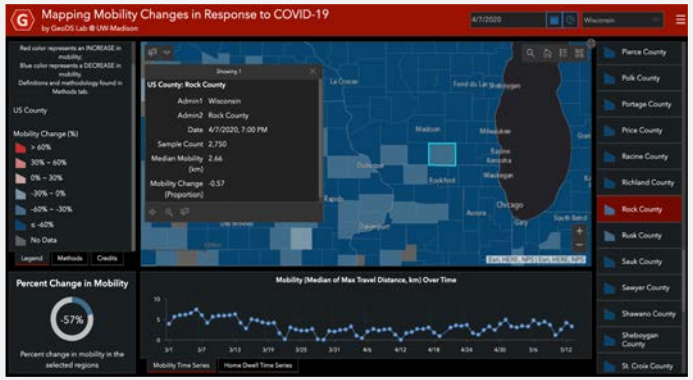
Download
Preprocessing

SAFEGRAPH

Descartes Labs

Amazon S3

Data Sources



Gao, S., Rao, J., Kang, Y., Liang, Y., & Kruse, J. (2020). Mapping county-level mobility pattern changes in the United States in response to COVID-19. *SIGSPATIAL Special*, *12*(1), 16-26.

Mapping Human Mobility Changes in the US

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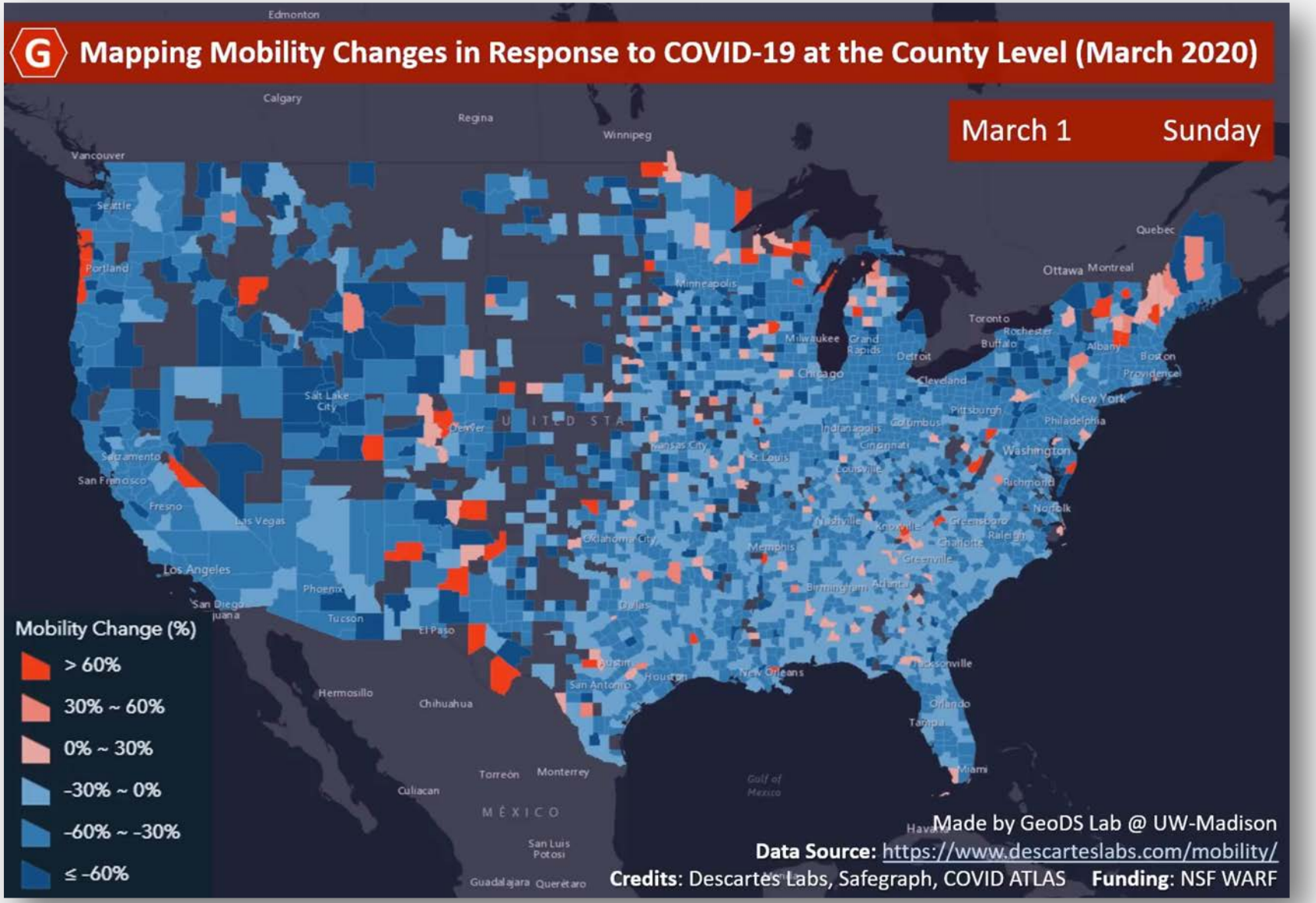
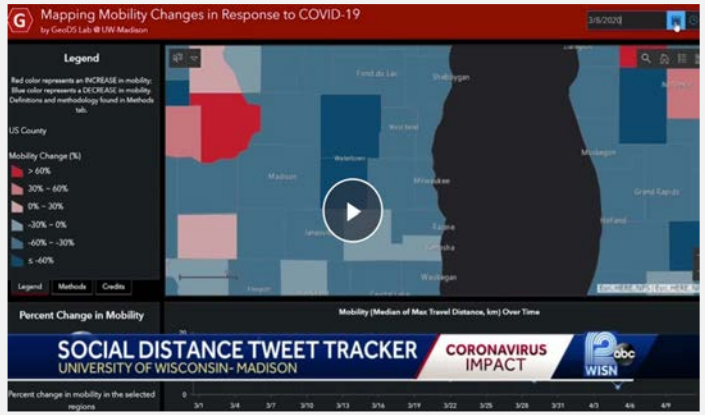
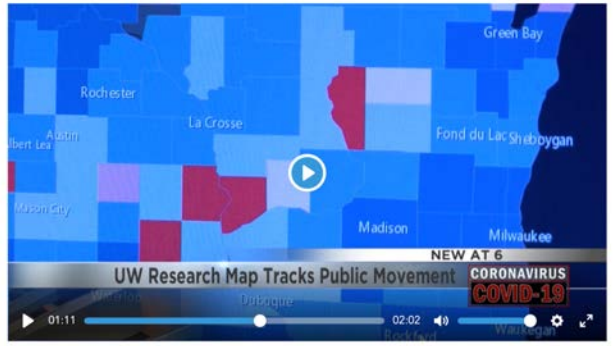


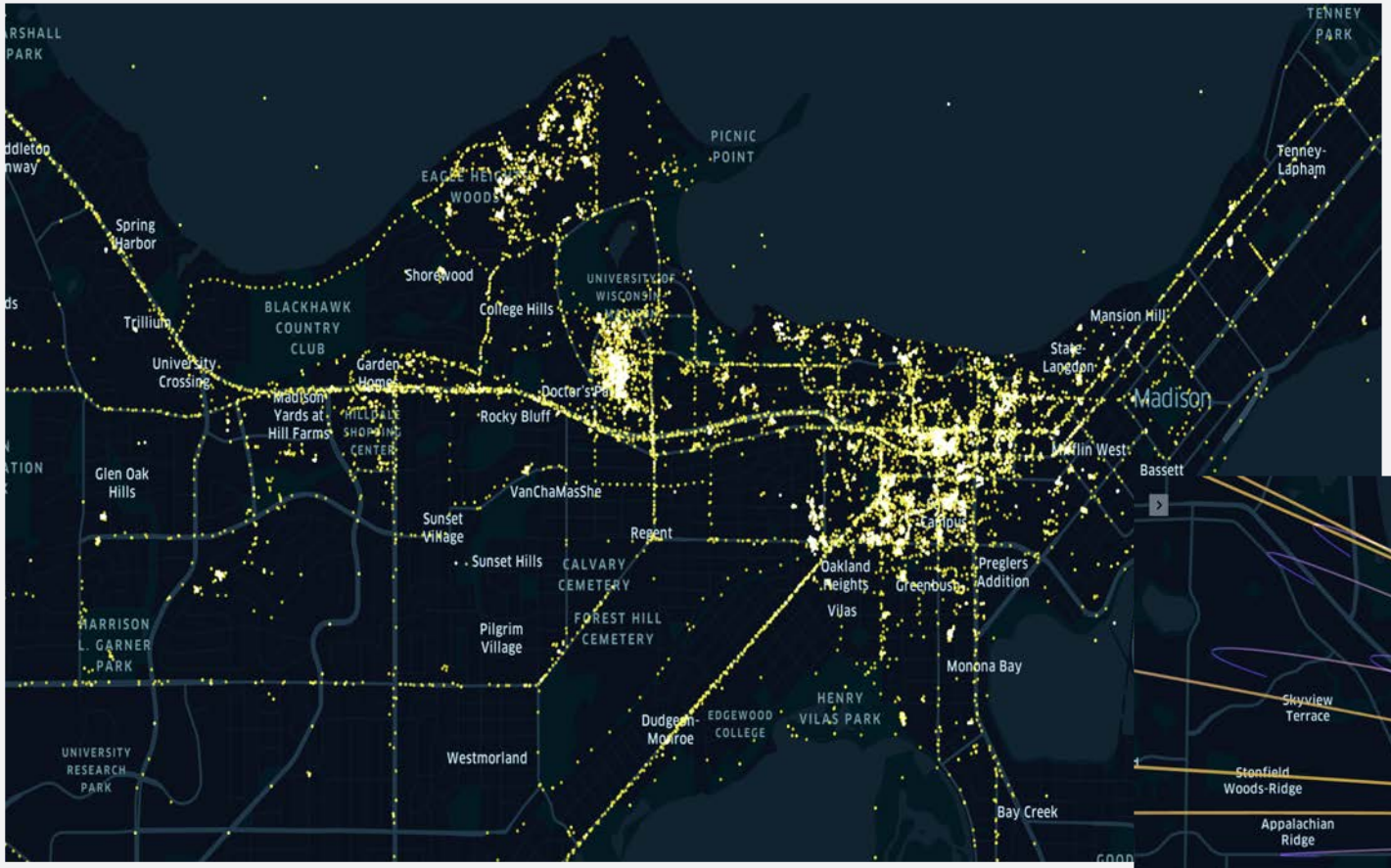


UW research project tracking public movement sees recent spike in travel

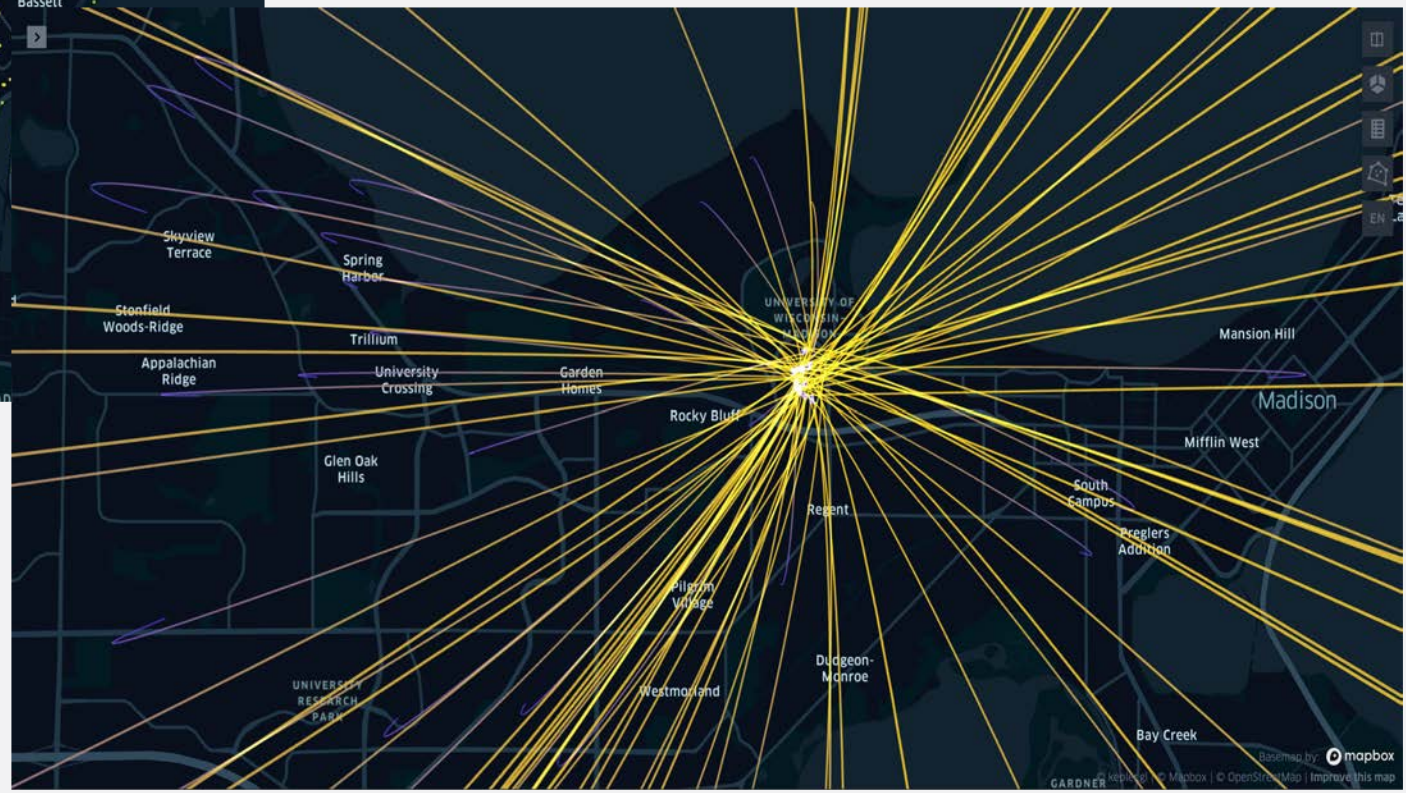


https://geods.geography.wisc.edu/covid19/physical-distancing/

Individual-Level Location Data Tracking



GPS Trajectories



Origin-Destination Flow

Dane County Social Distancing Dashboard

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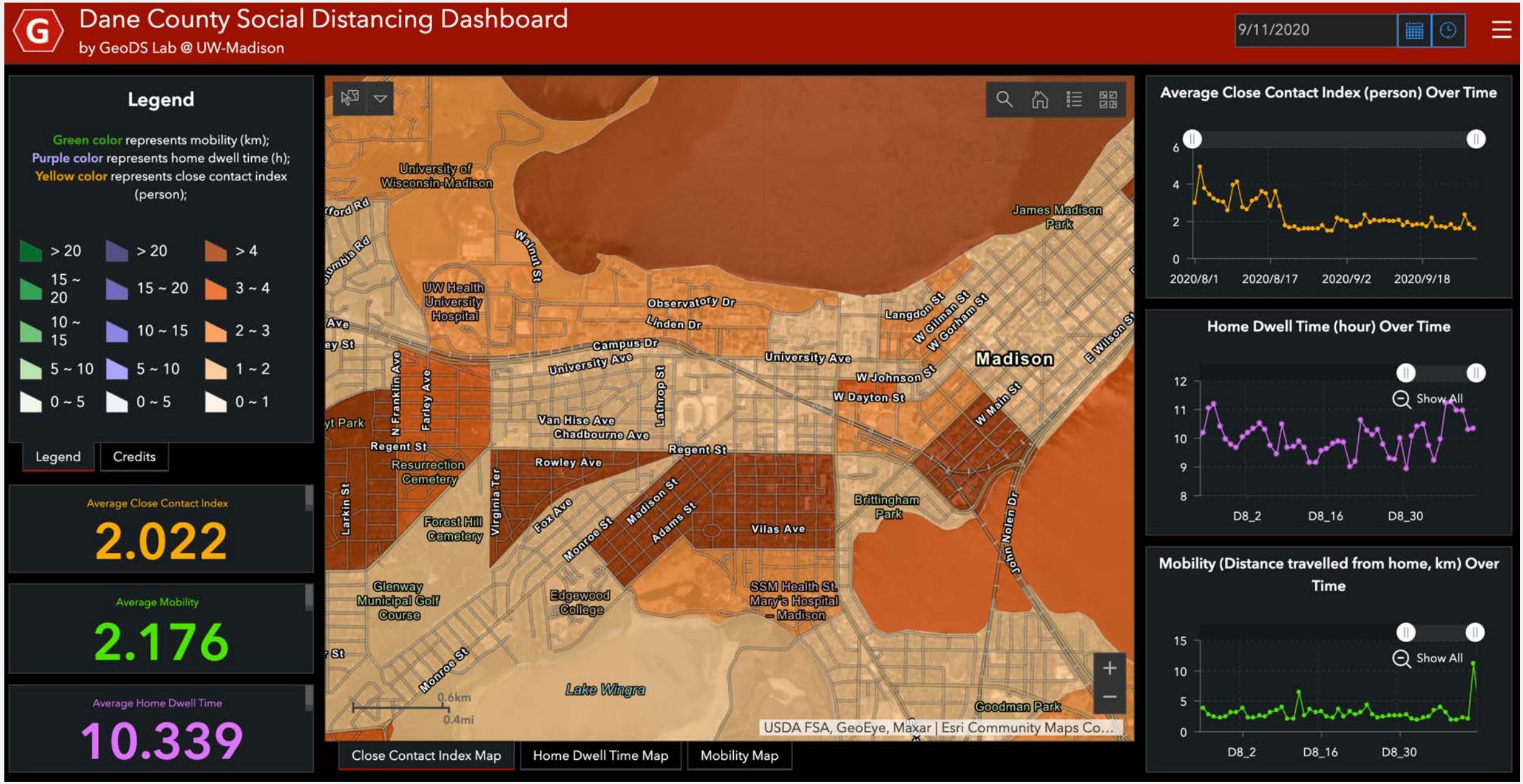

Association of Mobility Changes with Rate of COVID-19 Cases

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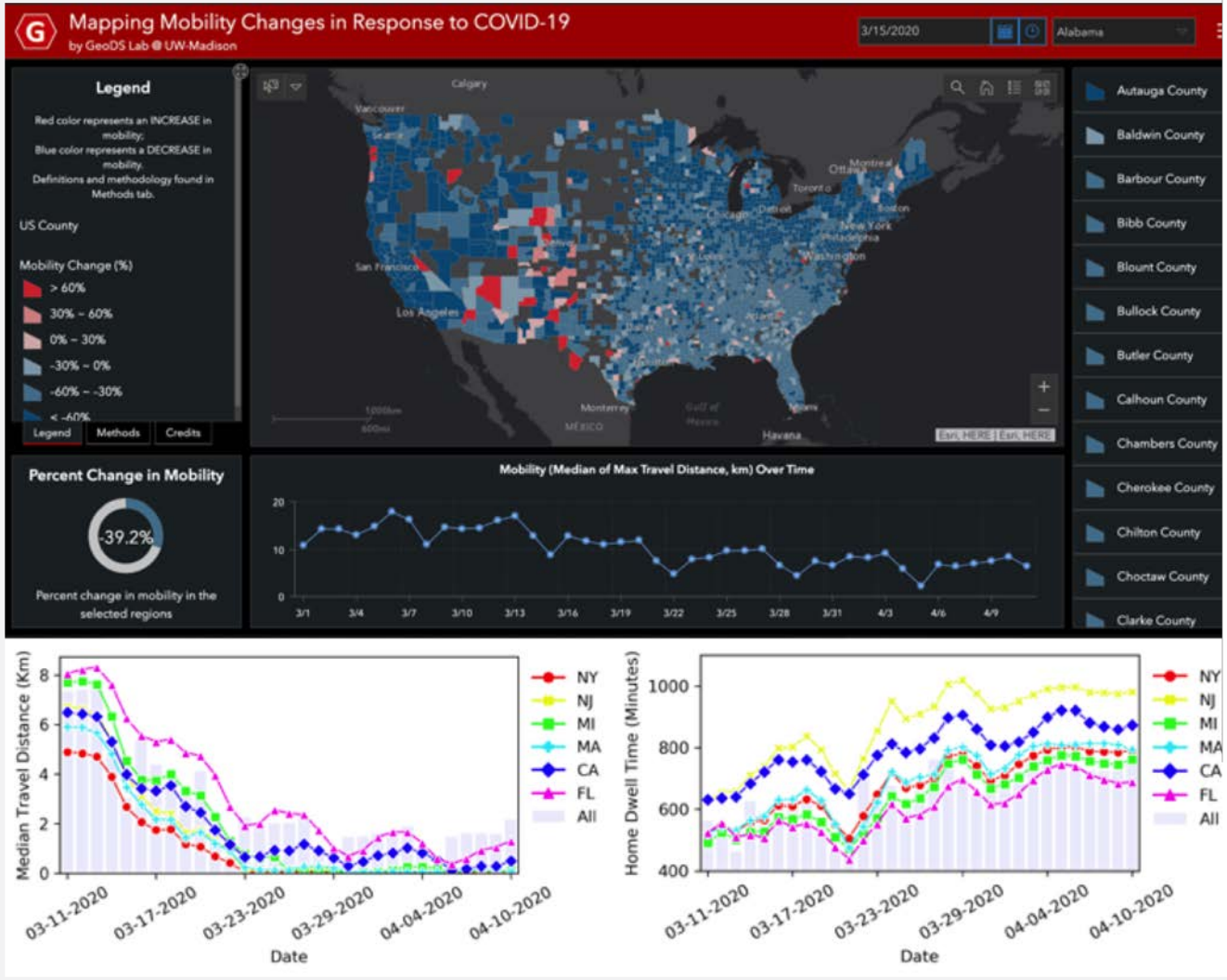
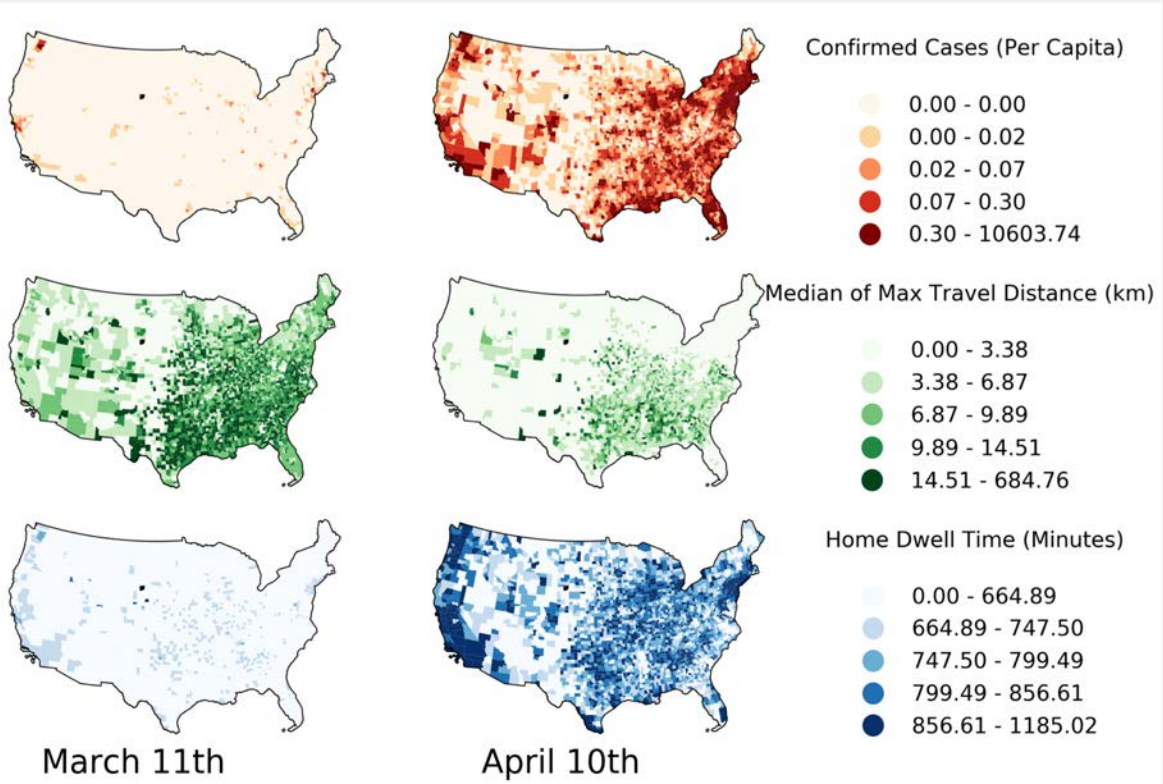




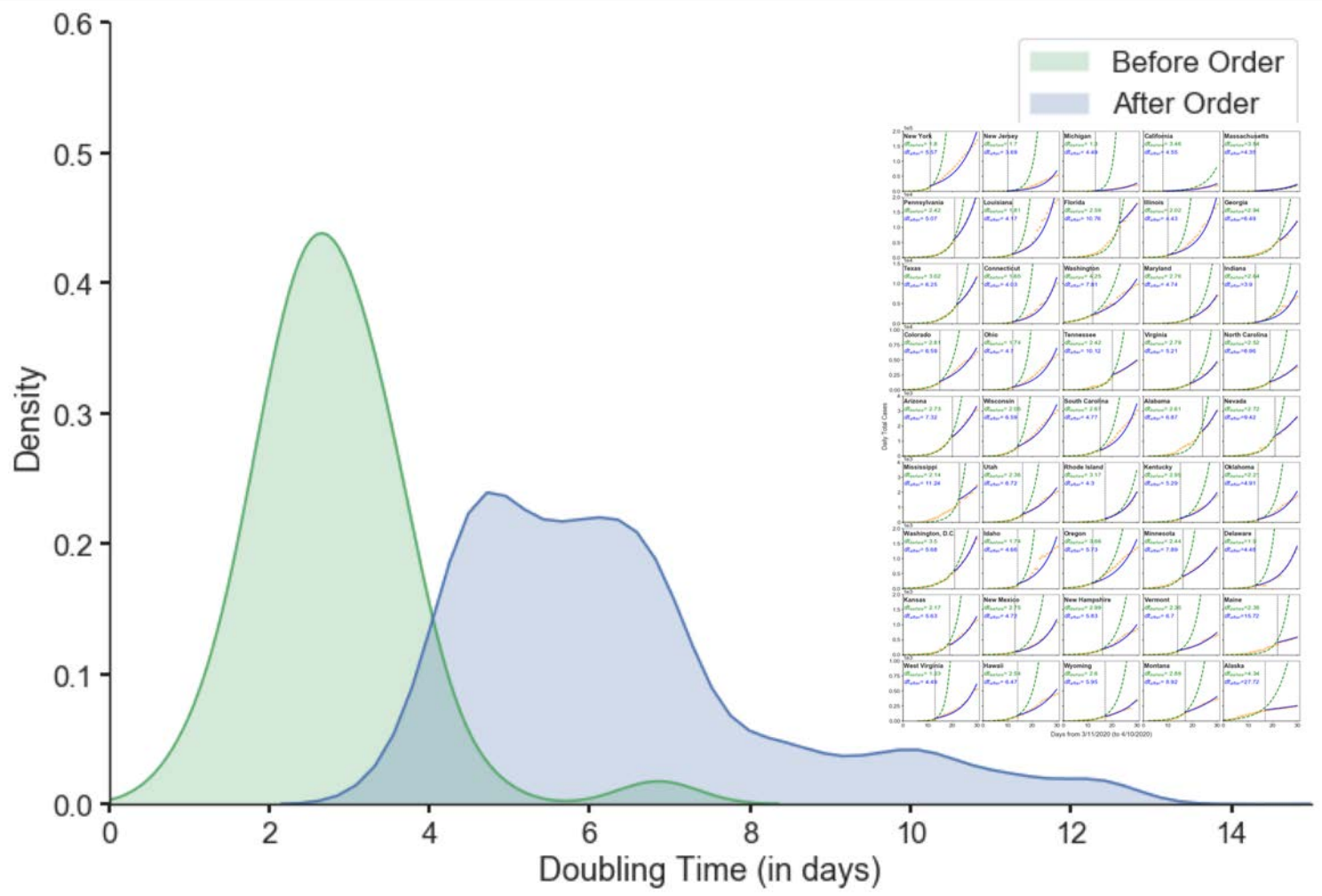
The Pearson's correlation between the COVID-19 increase rate and **travel distance change rate** and **home dwell time change rate** was **-0.586** (95% CI: -0.742 ~ -0.370) and **0.526** (95% CI: 0.293 ~ 0.700).

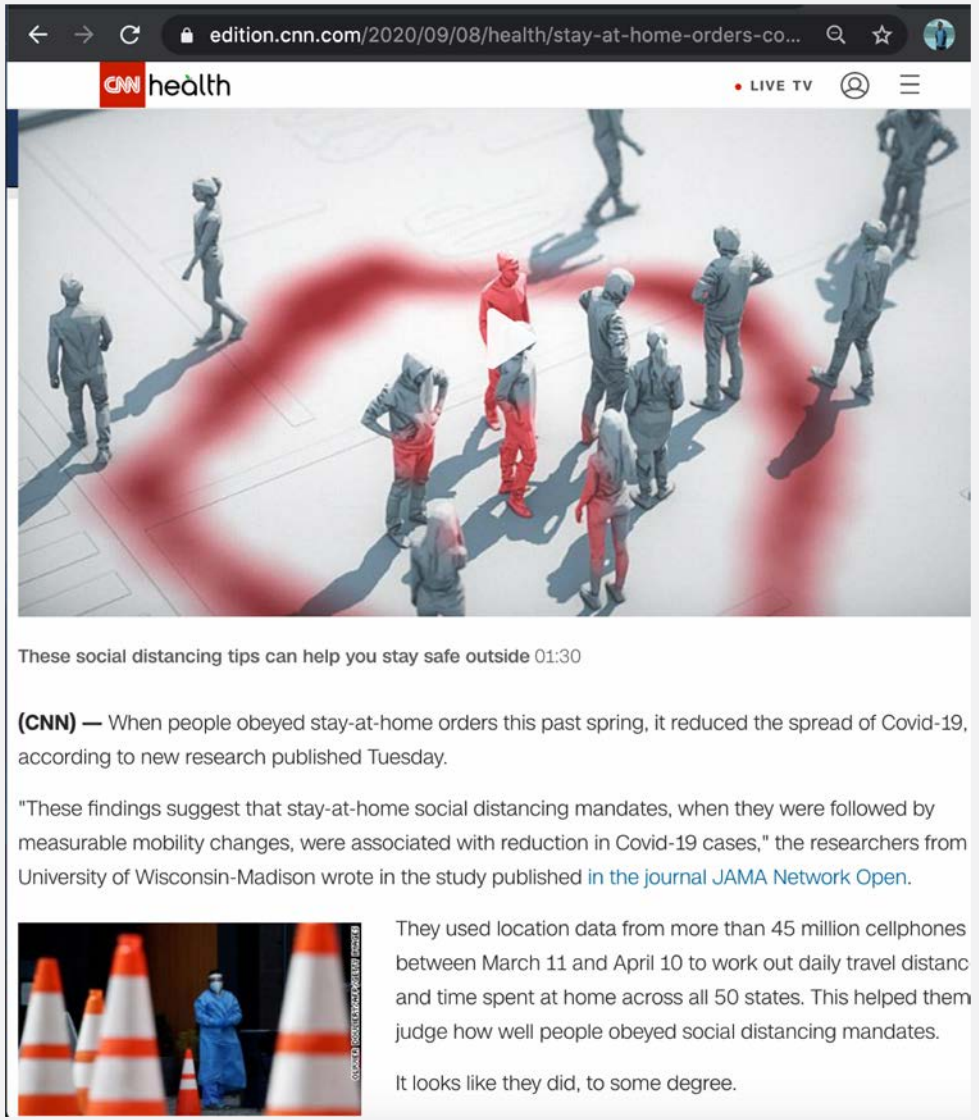
Gao S, Rao J, Kang Y, Liang Y, Kruse J, Dopfer D, Sethi A, Reyes J, Yandell B, and Patz J. (2020) Association of mobile phone location data indications of travel and stay-at-home mandates with COVID-19 infection rates in the US. ***JAMA Network Open***. 2020;3(9):e2020485.

The Effects of Stay-at-Home Mandates

GeoDS Lab @UW-Madison

Increases in state doubling time ranged from 1.04 ~ 6.86 (**median: 2.7**) days to 3.66 ~ 30.29 (**median: 6.0)** days after orders.





edition.cnn.com/2020/09/08/health/stay-at-home-orders-co...

CNN health

LIVE TV

These social distancing tips can help you stay safe outside 01:30

(CNN) — When people obeyed stay-at-home orders this past spring, it reduced the spread of Covid-19, according to new research published Tuesday.

"These findings suggest that stay-at-home social distancing mandates, when they were followed by measurable mobility changes, were associated with reduction in Covid-19 cases," the researchers from University of Wisconsin-Madison wrote in the study published in the journal JAMA Network Open.

They used location data from more than 45 million cellphones between March 11 and April 10 to work out daily travel distanc and time spent at home across all 50 states. This helped them judge how well people obeyed social distancing mandates.

It looks like they did, to some degree.

Gao S, Rao J, Kang Y, Liang Y, Kruse J, Dopfer D, Sethi A, Reyes J, Yandell B, and Patz J. (2020) Association of mobile phone location data indications of travel and stay-at-home mandates with COVID-19 infection rates in the US. ***JAMA Network Open***. 2020;3(9):e2020485.

Multiscale Dynamic Human Mobility O-D Flow Open Data

GeoDS Lab @UW-Madison

TRACK PLACE VISITS

SAFEGRAPH

Mobile Phone Data

User Trajectory

Place Visitors

COMPUTE VISITOR FLOWS

Daily CBG to CBG Visitors

Weekly POI to CBG Visitors

MULTI-SCALE AGGREGATION

Census Tract to Census Tract

County to County

State to State

INFER POPULATION FLOWS

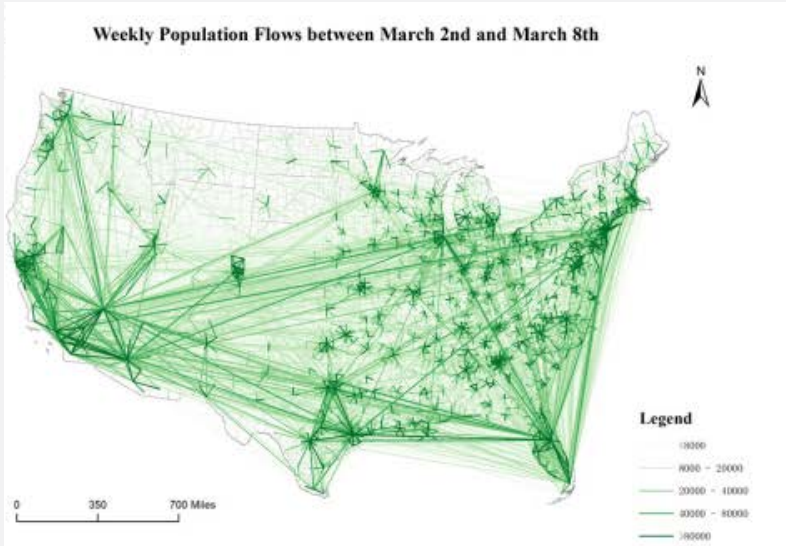
Dynamic Population Flows = SafeGraph Visitor Flows x $\frac{\text{Census Population}}{\text{SafeGraph Devices}}$

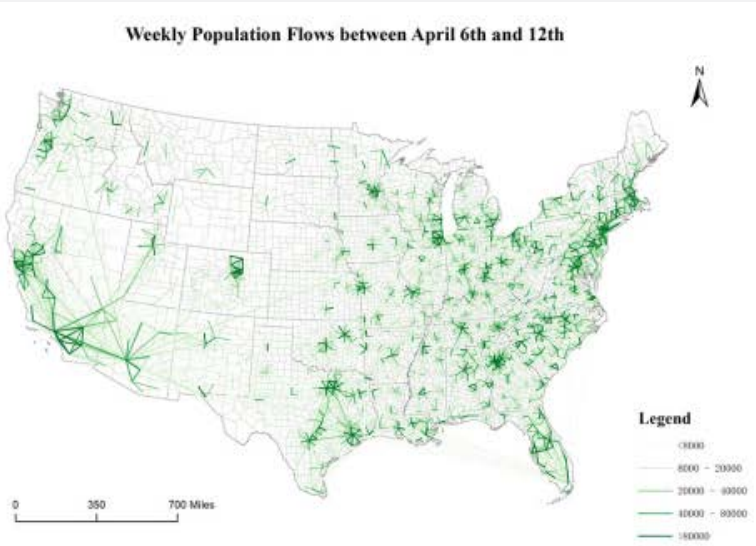
Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale Dynamic Human Mobility Flow Dataset in the US during the COVID-19 Epidemic. ***Scientific Data.*** Preprint at arXiv:2008.12238.

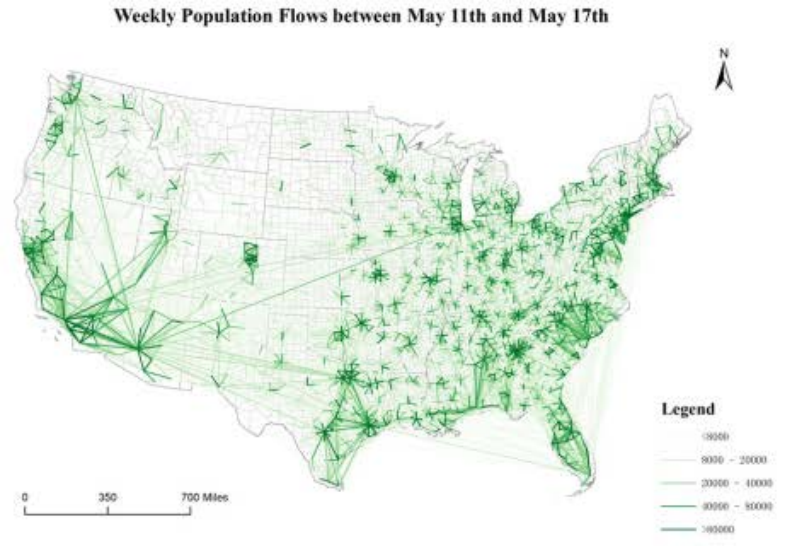
https://github.com/GeoDS/COVID19USFlows

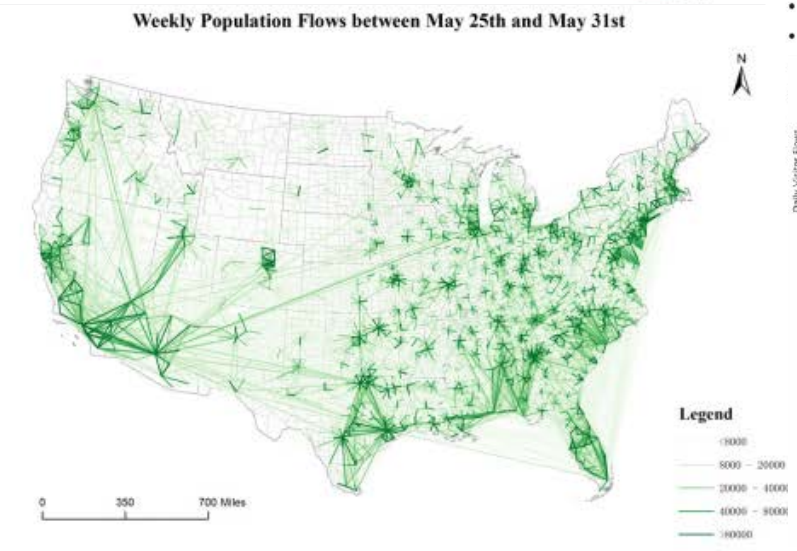
Multiscale Dynamic Human Mobility O-D Flow Open Data

GeoDS Lab @UW-Madison









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GeoDS Lab, Department of Geography, University of Wisconsin-Madison.

Website · View Demo

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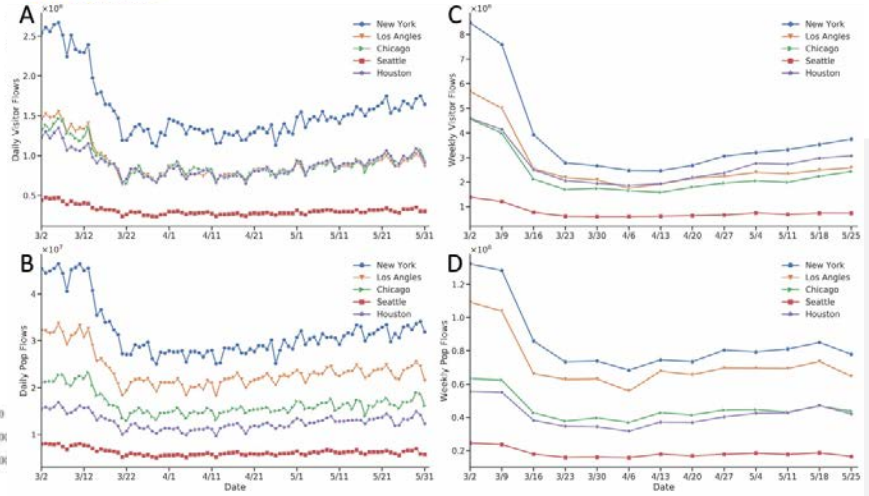
- Field Descriptions



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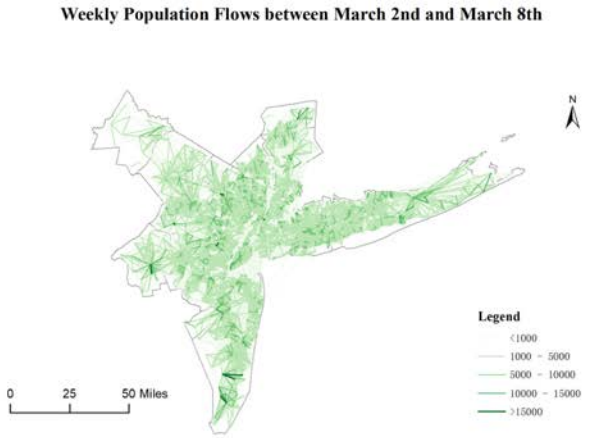
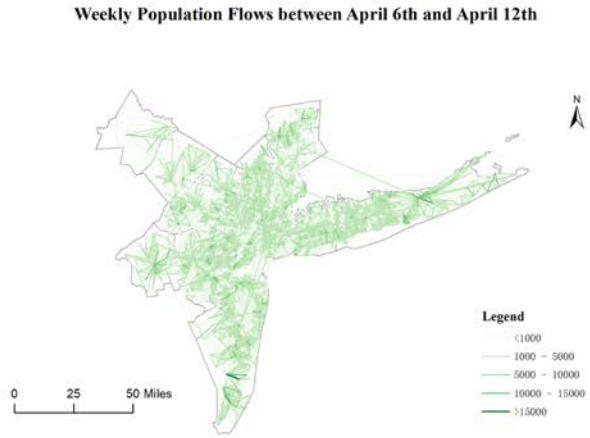
https://github.com/GeoDS/COVID19USFlows

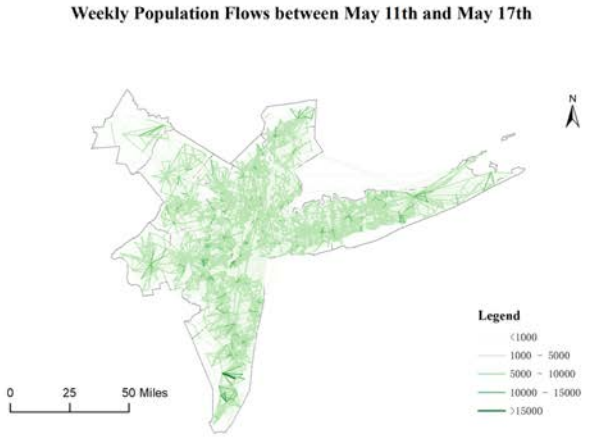
Multiscale Dynamic Human Mobility O-D Flow Open Data

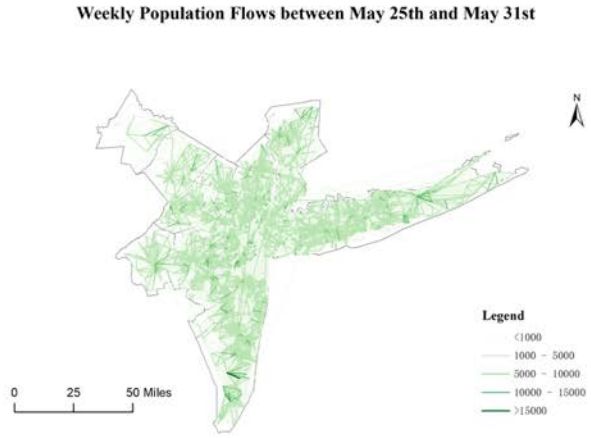
GeoDS Lab @UW-Madison

Tract to Tract









Geospatial Data Science Lab
UW-Madison

SAFEGRAPH

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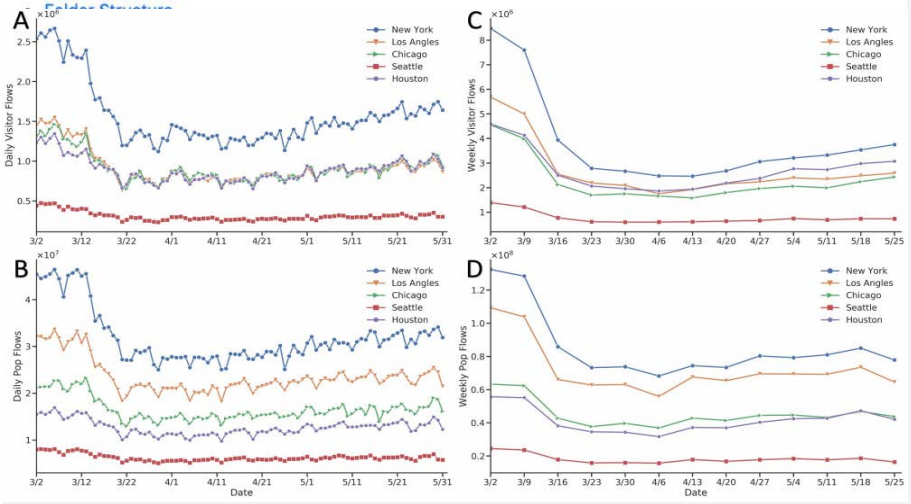

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https://github.com/GeoDS/COVID19USFlows

Infer Dynamic Population Flows

The visitor flows at three spatial scales are based on 10% of the entire population in the US. Using the American Community Survey (ACS) population data with mobile phone visitor patterns, the dynamic population-scale flows are estimated as:

$$pop_flows(o,d) = visitor_flows(o,d) \times \frac{pop(o)}{num_devices(o)}$$

geoid_o	geoid_d	lng_o	lat_o	lng_d	lat_d	date_range	visitor_flows	pop_flows
01	01	-86.8445209956579	32.75687994183124	-86.8445209956579	32.75687994183124	2020-03-01	1074126	10716851.0
01	02	-86.8445209956579	32.75687994183124	-151.25054883603903	63.78846947897309	2020-03-01	50	498.0

We also compare the estimation results with a **gravity** model and a **radiation** model.

Gravity Model and Radiation Model Estimates

Gravity Model **Radiation Model**

$$F_{i,j} = \frac{k * P_i * P_j}{d_{i,j}^{\beta}} \qquad T_i = m_i \frac{N_c}{N}$$

$$T_{i,j} = T_i \frac{m_i * n_j}{(m_i + S_{ij}) * (m_i + n_j + S_{ij})}$$

Date	Gravity Model			Radiation Model	
	k	β	correlation	Nc/N	correlation
03-02	0.000049300	0.8636853	0.6484	0.782	0.755
03-09	0.000062300	0.9010593	0.6301	0.763	0.751
03-16	0.000065800	0.9419980	0.6108	0.654	0.756
03-23	0.000070300	0.9505486	0.5852	0.619	0.753
03-30	0.000078200	1.0023736	0.5698	0.579	0.748
04-06	0.000072100	0.9754115	0.5656	0.572	0.749
04-13	0.000077600	0.9297287	0.5620	0.586	0.747
04-20	0.000090900	1.0044105	0.5602	0.611	0.753
04-27	0.000076800	0.9284104	0.5682	0.627	0.756
05-04	0.000080000	0.9269356	0.5690	0.629	0.757
05-11	0.000061200	0.8748065	0.5721	0.643	0.756
05-18	0.000060800	0.8532109	0.5718	0.660	0.758
05-25	0.000061600	0.9175823	0.5645	0.671	0.756

- Dynamic population flows are inferred based on the parameters.
- The correlation coefficients between the population flows and the flows estimated by gravity model and radiation model are calculated.

https://github.com/GeoDS/COVID19USFlows

Comparison with Other Data Sources

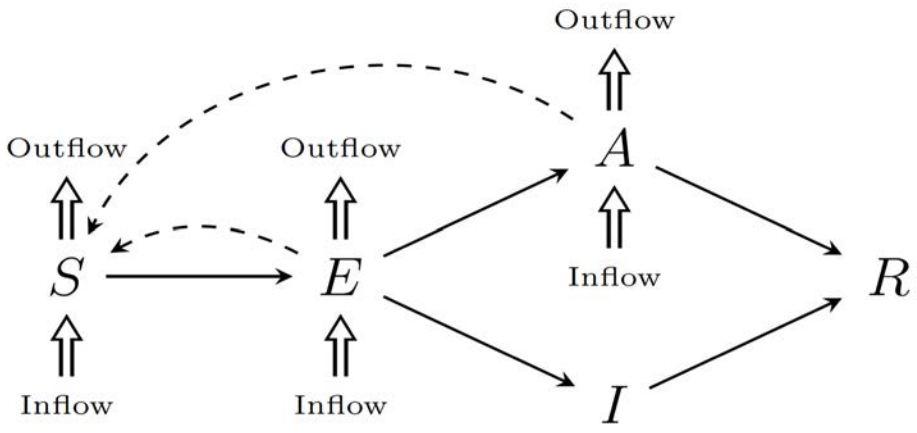
- Comparison of the population flows with Descartes Lab's COVID-19 mobility changes dataset: https://github.com/descarteslabs/DL-COVID-19

Weekly Flow Data				Daily Flow Data			
Date	Type	Matched Records	Pearson Correlation Coefficient	Date	Type	Matched Records	Pearson Correlation Coefficient
3/2/2020	Visitor Flows	102750	0.961	3/2/2020	Visitor Flows	102206	0.953
3/2/2020	Population Flows		0.984	3/2/2020	Population Flows		0.985
4/6/2020	Visitor Flows	78577	0.932	4/6/2020	Visitor Flows	92297	0.935
4/6/2020	Population Flows		0.981	4/6/2020	Population Flows		0.98
5/11/2020	Visitor Flows	91069	0.917	5/11/2020	Visitor Flows	94729	0.934
5/11/2020	Population Flows		0.977	5/11/2020	Population Flows		0.981
5/25/2020	Visitor Flows	95350	0.915	5/25/2020	Visitor Flows	99037	0.934
5/25/2020	Population Flows		0.974	5/25/2020	Population Flows		0.980

- High correlation coefficients (greater than 0.9) show the reliability of the generated mobility flow dataset.

Metropolitan Area	Pearson Correlation Coefficient
New York	0.977
Los Angeles	0.956
Chicago	0.928
Houston	0.92
Seattle	0.951

State-Specific Geospatial Modeling of COVID-19 Spread

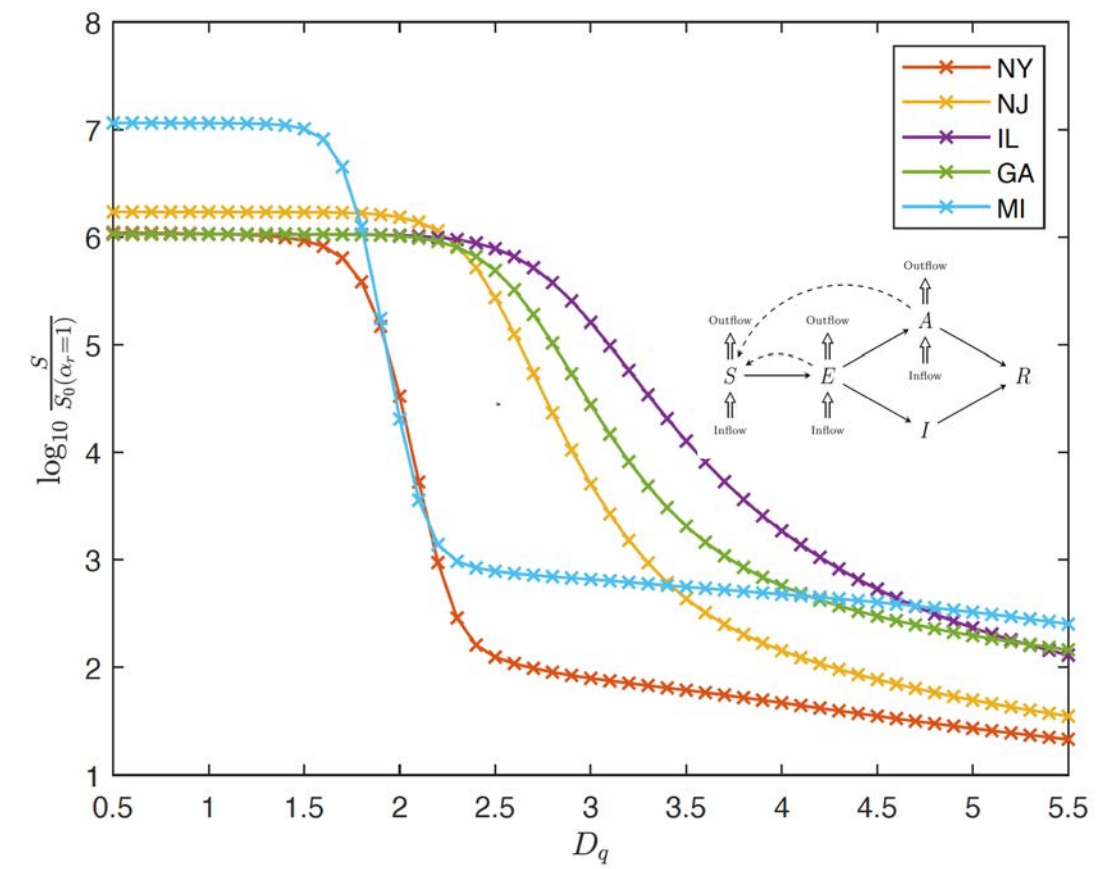


$$
\begin{cases}
\dfrac{\mathrm{d}S_i}{\mathrm{d}t} = -\dfrac{b_i S_i (A_i + \gamma E_i)}{P_i} + \sum_{j \neq i} \alpha_t n_{ij} \dfrac{S_j}{P_j} - \sum_{j \neq i} \alpha_t n_{ji} \dfrac{S_i}{P_i} \\
\dfrac{\mathrm{d}E_i}{\mathrm{d}t} = \dfrac{b_i S_i (A_i + \gamma E_i)}{P_i} - \dfrac{E_i}{D_e} + \sum_{j \neq i} \alpha_t n_{ij} \dfrac{E_j}{P_j} - \sum_{j \neq i} \alpha_t n_{ji} \dfrac{E_i}{P_i} \\
\dfrac{\mathrm{d}I_i}{\mathrm{d}t} = r_i \dfrac{E_i}{D_e} - c_I \dfrac{I_i}{D_c} - (1 - c_I) \dfrac{I_i}{D_l} \\
\dfrac{\mathrm{d}A_i}{\mathrm{d}t} = (1 - r_i) \dfrac{E_i}{D_e} - c_A \dfrac{A_i}{D_c} - (1 - c_A) \dfrac{A_i}{D_l} + \sum_{j \neq i} \alpha_t n_{ij} \dfrac{A_j}{P_j} - \sum_{j \neq i} \alpha_t n_{ji} \dfrac{A_i}{P_i} \\
\dfrac{\mathrm{d}R_i}{\mathrm{d}t} = c_I \dfrac{I_i}{D_c} + (1 - c_I) \dfrac{I_i}{D_l} + c_A \dfrac{A_i}{D_c} + (1 - c_A) \dfrac{A_i}{D_l}
\end{cases}
$$

A new mobility-network-based SEIR compartmental model

- Chen, S., Li, Q., Gao, S., Kang, Y., & Shi, X. (2020). Mitigating COVID-19 outbreak via high testing capacity and strong transmission-intervention in the United States. *Scientific Reports*. Preprint at medRxiv. https://doi.org/10.1101/2020.04.03.20052720

State-Specific Geospatial Modeling of COVID-19 Spread



Quantifying the effect of timely quarantine and social distancing mandates.

- Chen, S., Li, Q., Gao, S., Kang, Y., & Shi, X. (2020). Mitigating COVID-19 outbreak via high testing capacity and strong transmission-intervention in the United States. *Scientific Reports*. Preprint at medRxiv. https://doi.org/10.1101/2020.04.03.20052720

State-Specific Geospatial Modeling of COVID-19 Spread

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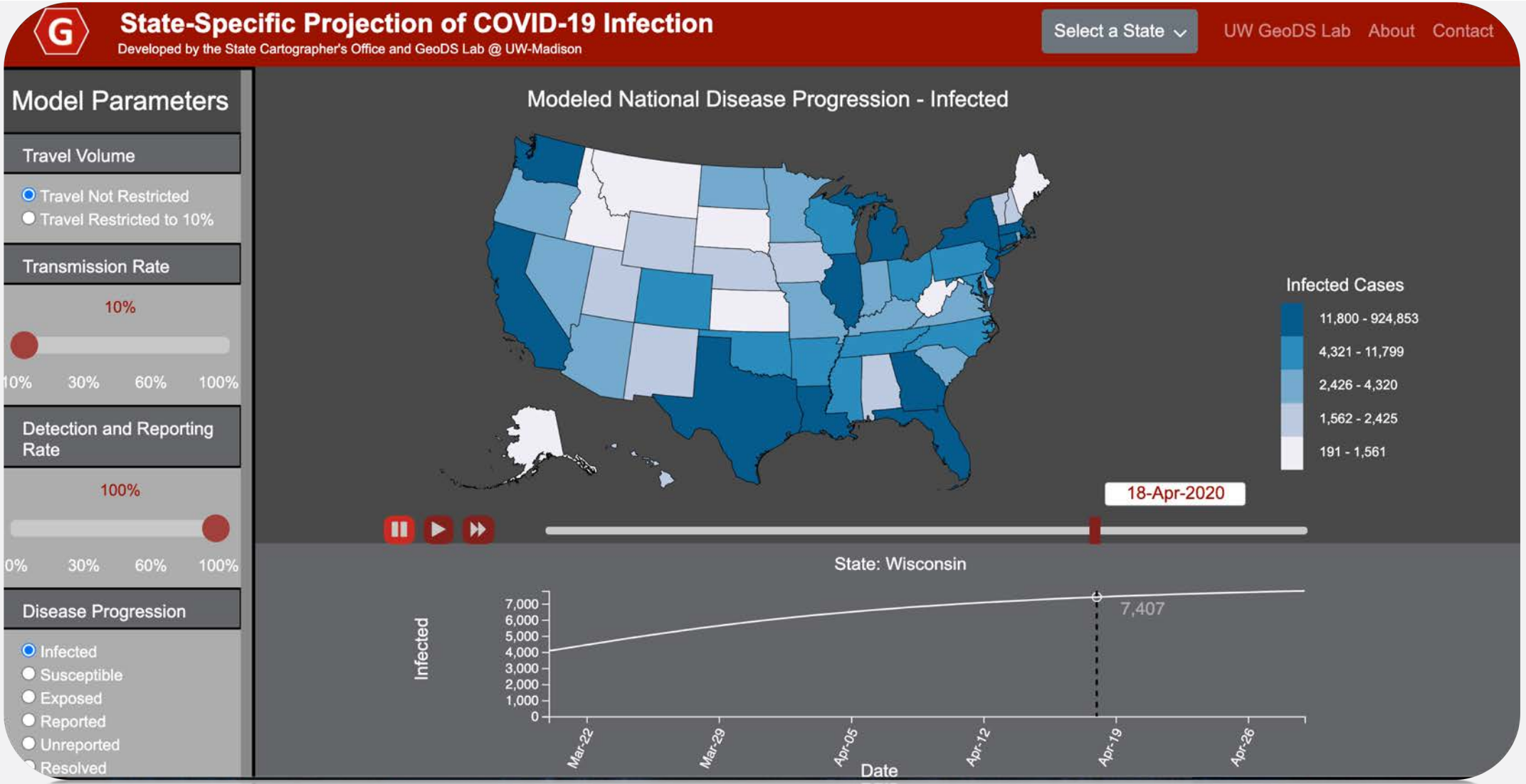

https://geods.geography.wisc.edu/covid19/us_model/

https://github.com/GeoDS/Travel-Network-SEIR

Summary Notes

- Mobile phone data can help track the mobility patterns and digital contact tracing;
- Spatial and temporal heterogeneity of transmission;
- Health and social disparities require more attention;
- Fighting against COVID-19 requires coordination efforts and multidisciplinary collaboration

https://geods.geography.wisc.edu/

Thank you!

https://geods.geography.wisc.edu