Geospatial Software Institute (GSI)

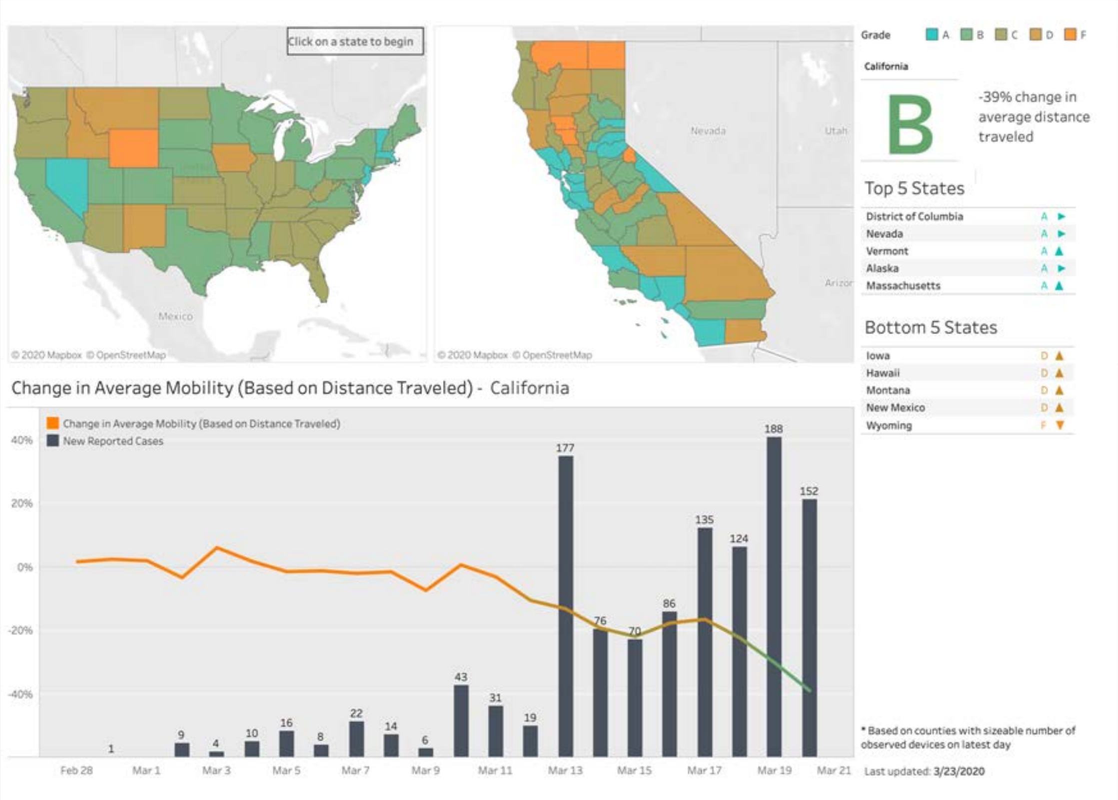
Towards a National Geospatial Software Ecosystem

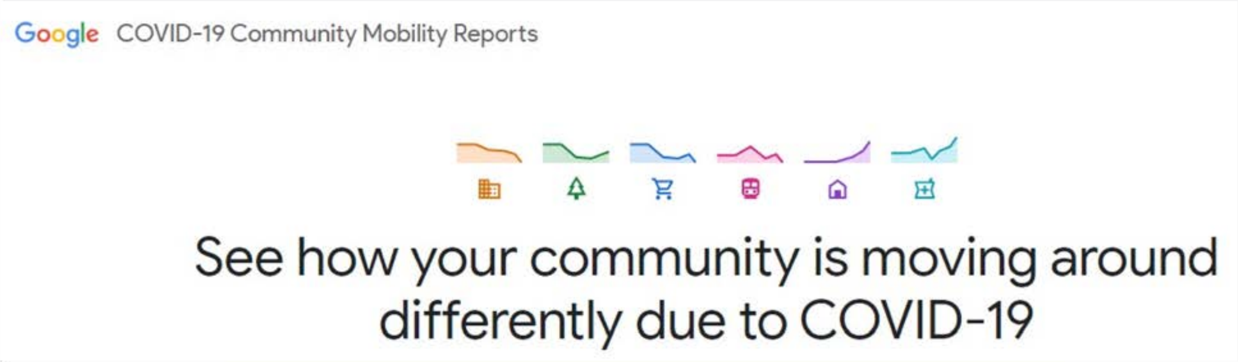
Mapping Multiscale Human Mobility Changes and Geospatial Modeling of COVID-19 Spread

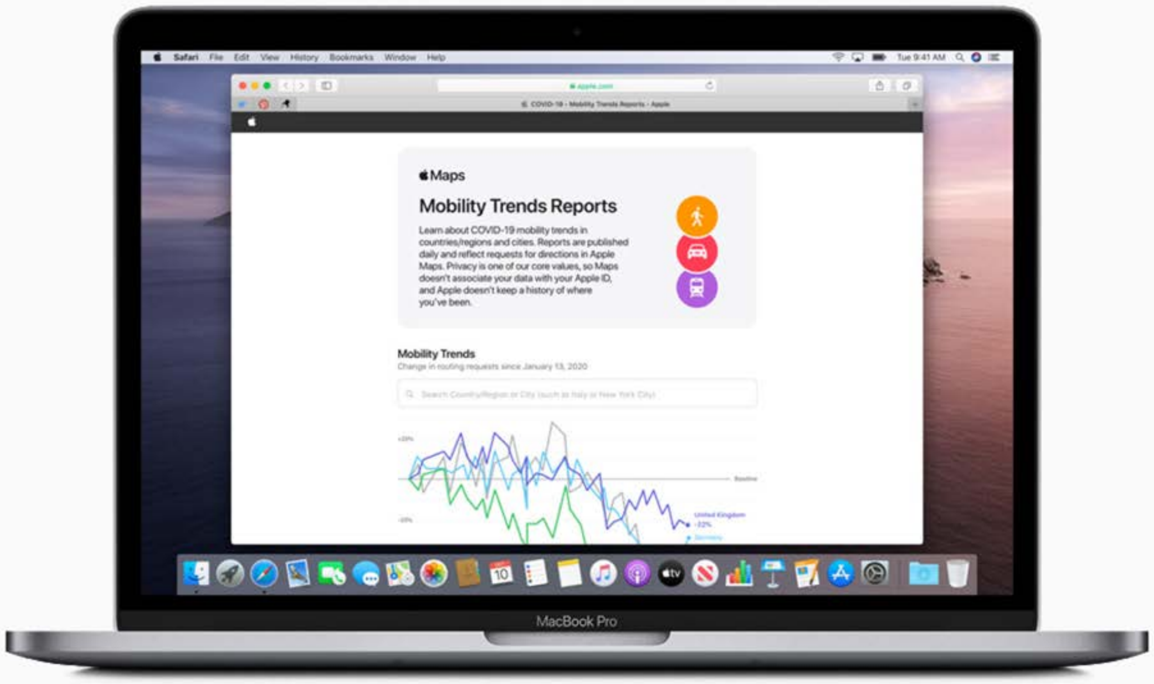
Song Gao
Geospatial Data Science Lab
University of Wisconsin–Madison

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

Human Mobility Open Data Spring Up during COVID-19



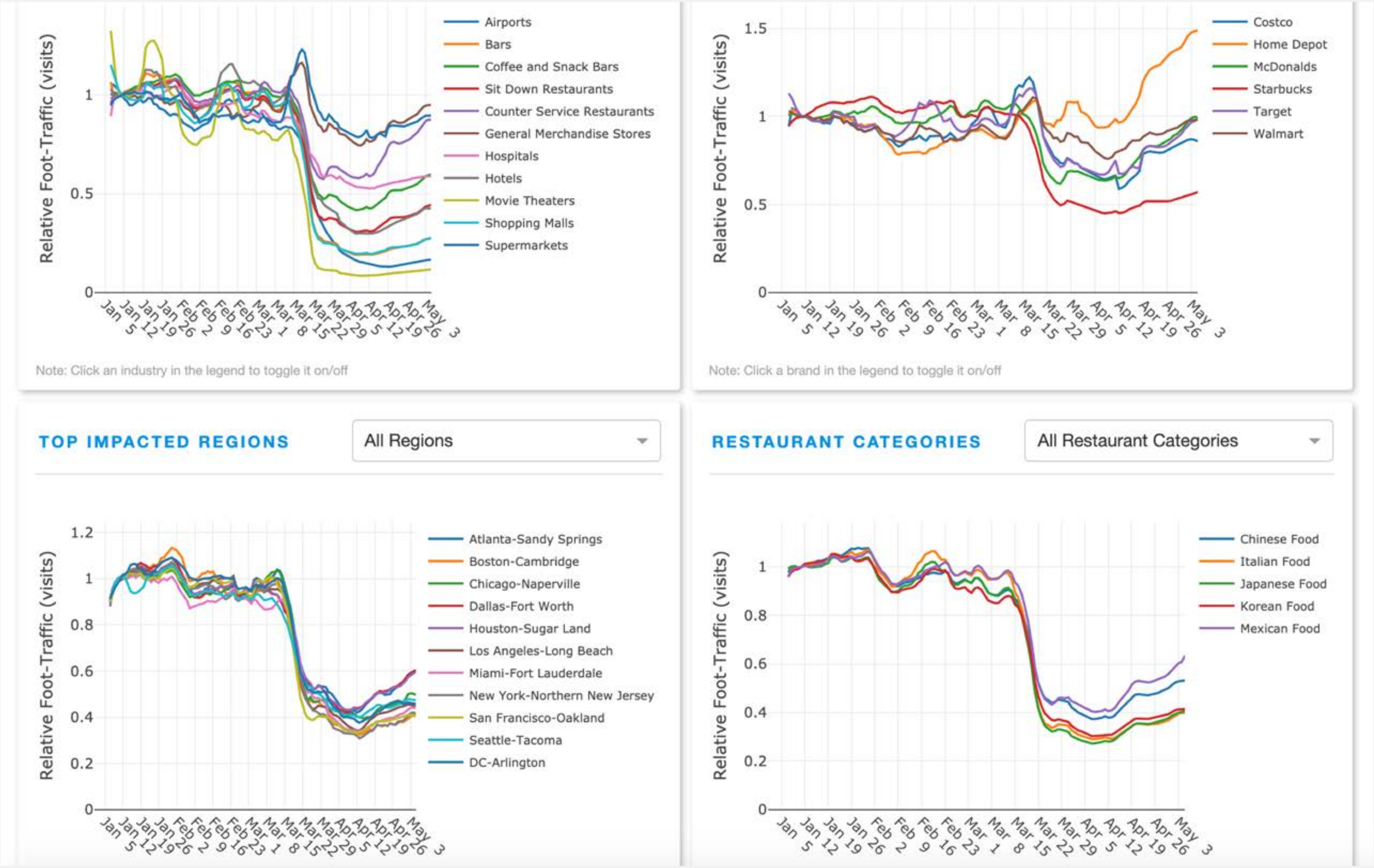




Unacast Social Distancing Scoreboard
Google and **Apple** Mobility Reports
Cuebiq, X-Mode, **Descartes Lab**, and **SafeGraph**

Human Mobility Open Data Spring Up during COVID-19

SafeGraph
POI-type
Foot-Traffic Changes



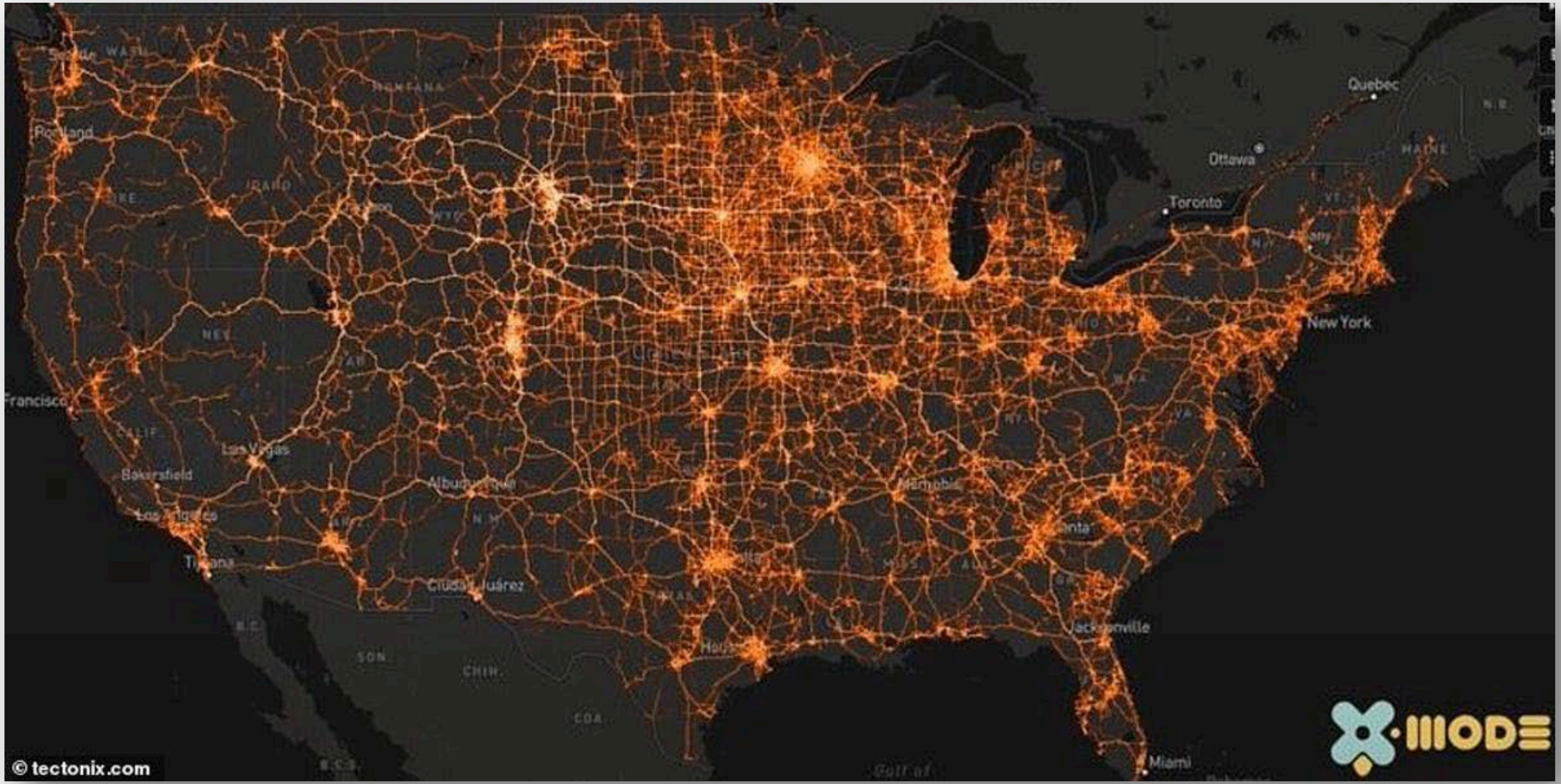
https://www.safegraph.com/dashboard/covid19-commerce-patterns

Human Mobility Open Data Spring Up during COVID-19

Individual-level trajectory tracking
The Sturgis motorcycle Rally in South Dakota

~ 160 GB daily stream

Amazon S3



http://www.citypages.com/news/minnesotas-sturgis-related-coronavirus-cases-are-here-expect-more/572209941

Human Mobility Data from Anonymous Mobile Phone Devices

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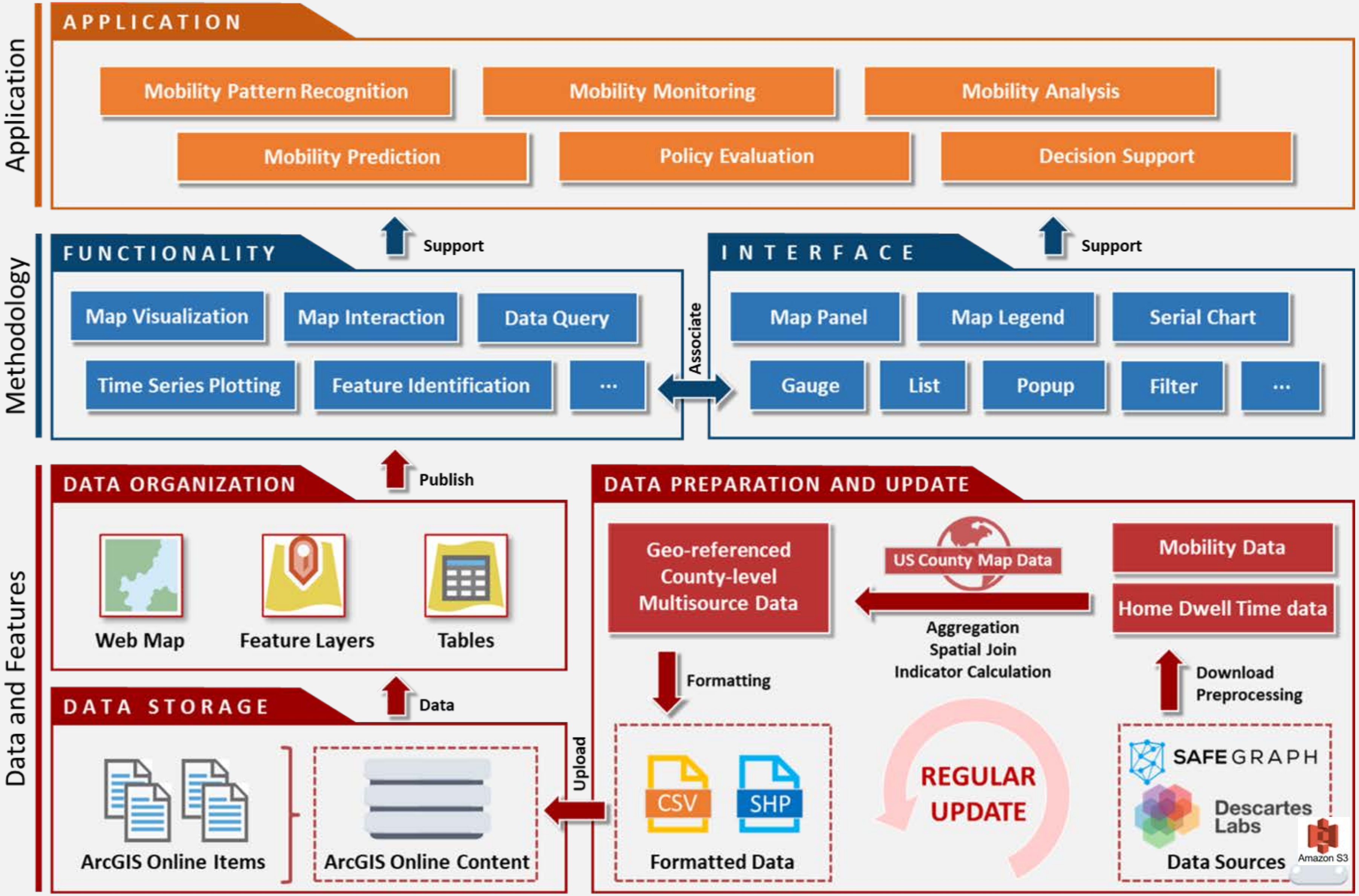

Gao, S., Rao, J., Kang, Y., Liang, Y., & Kruse, J. (2020). Mapping county-level mobility pattern changes in the United States in response to COVID-19. *SIGSPATIAL Special*, *12*(1), 16-26.

Mapping Human Mobility Changes in the US

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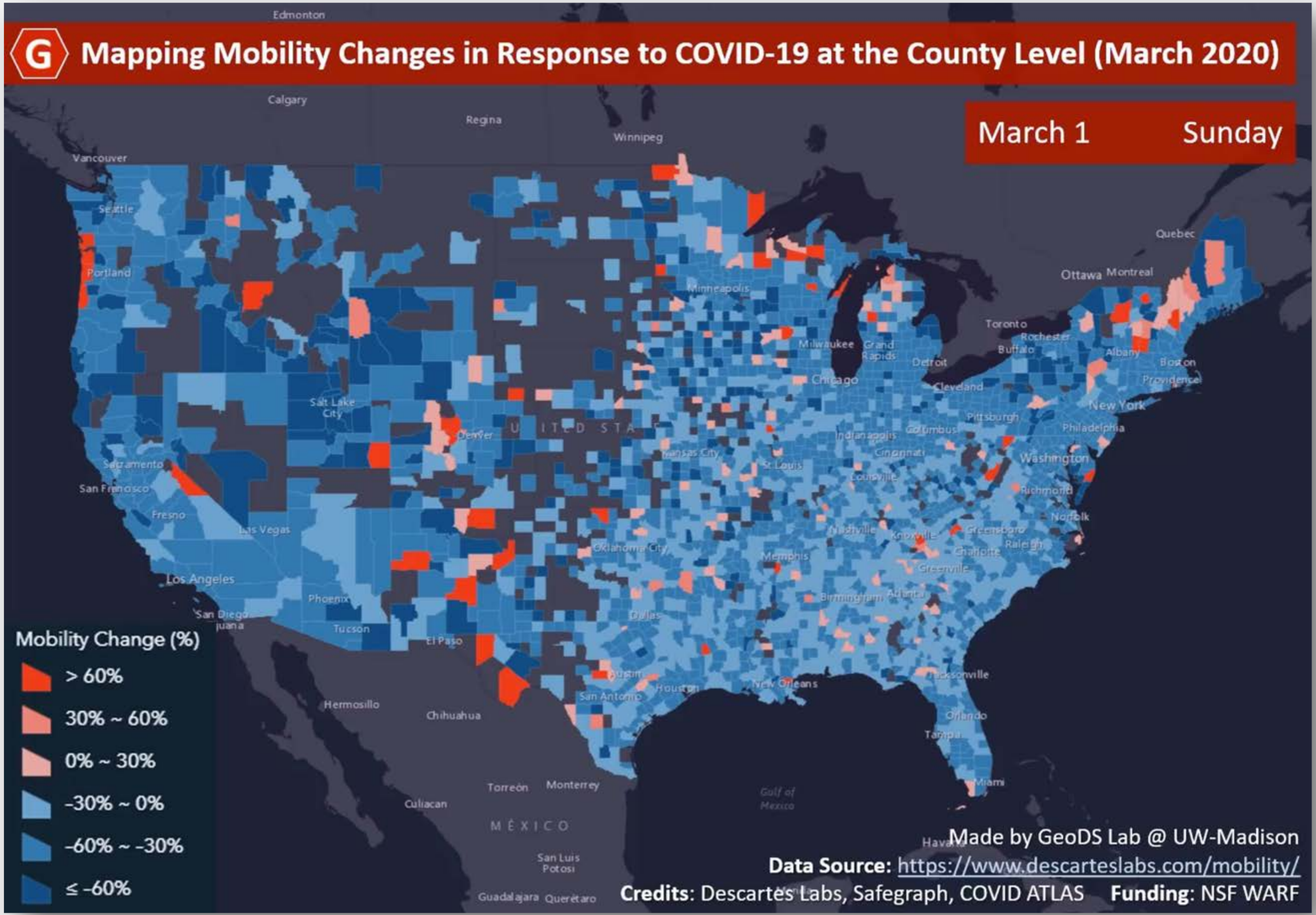
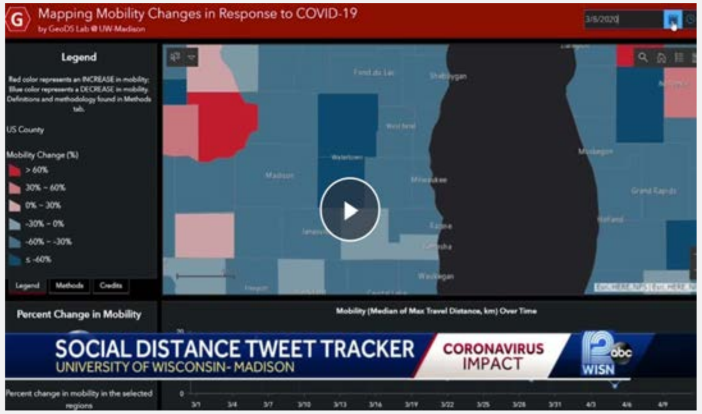
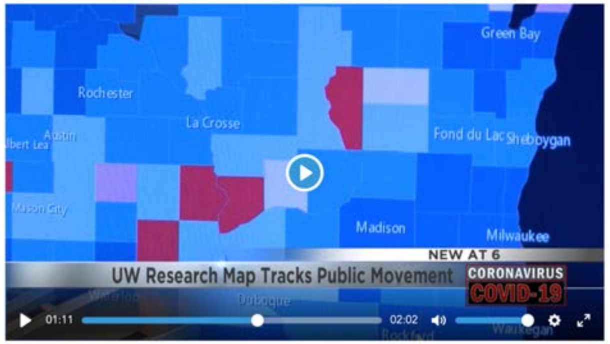




UW research project tracking public movement sees recent spike in travel



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

Association of Mobility Changes with Rate of COVID-19 Cases

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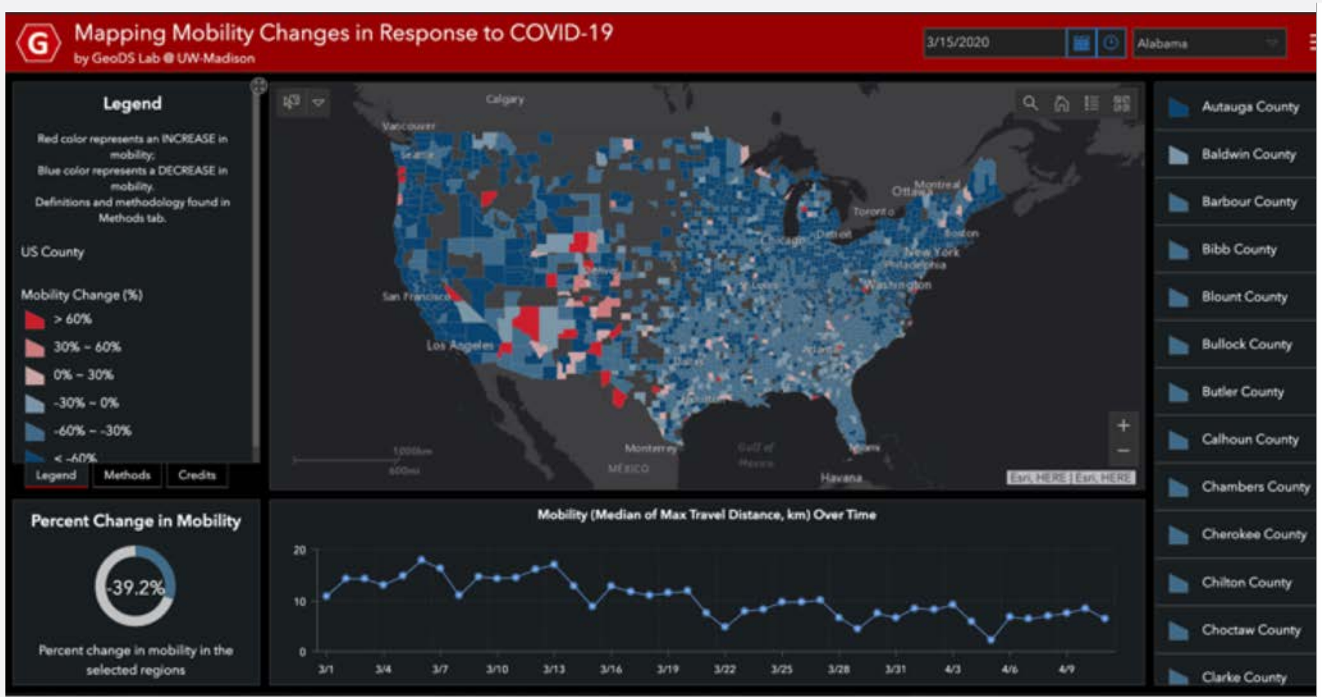
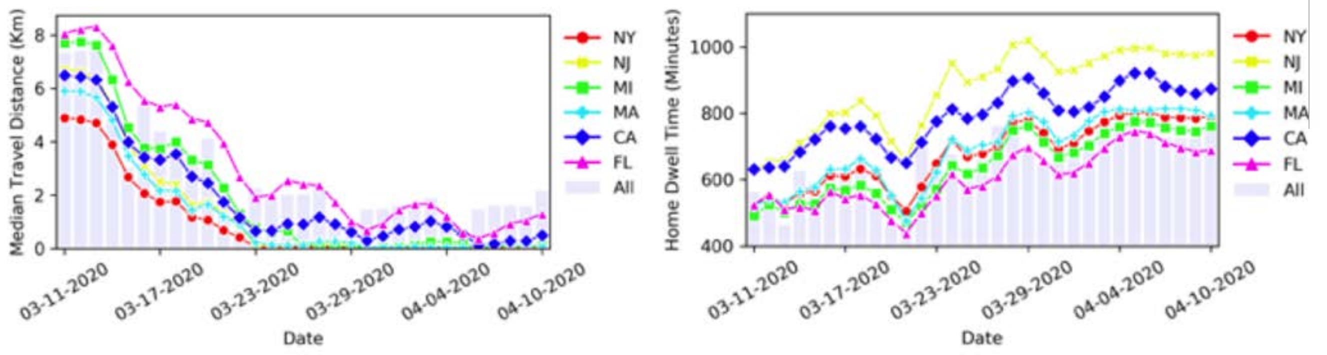
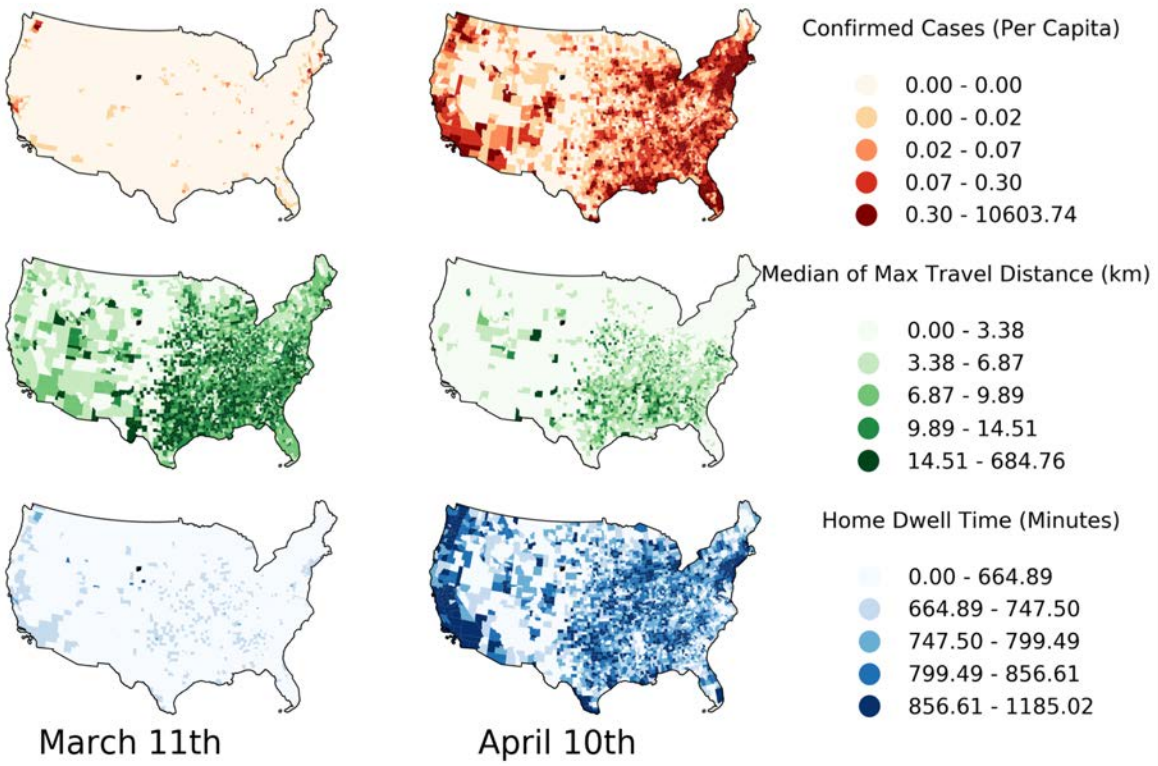




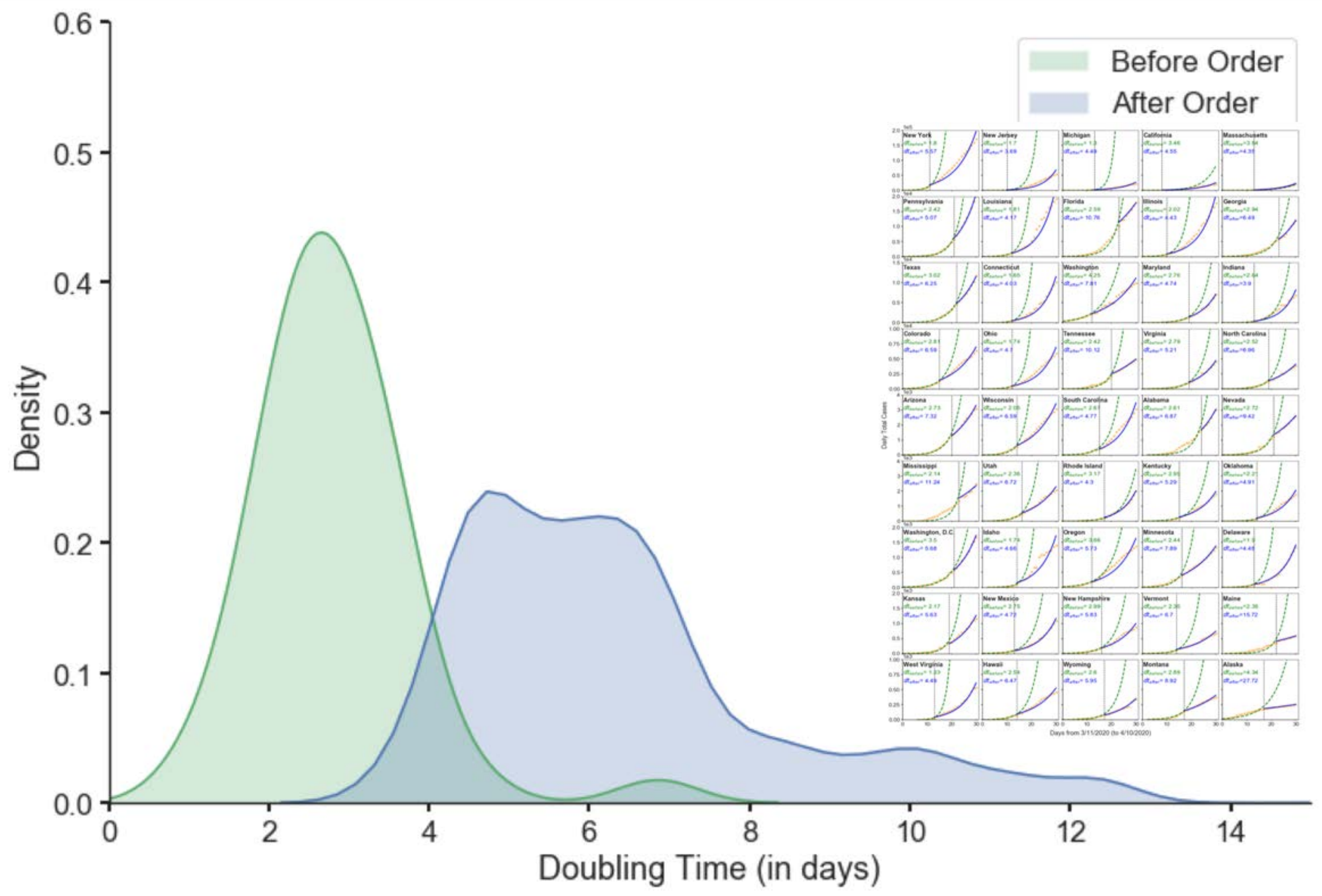


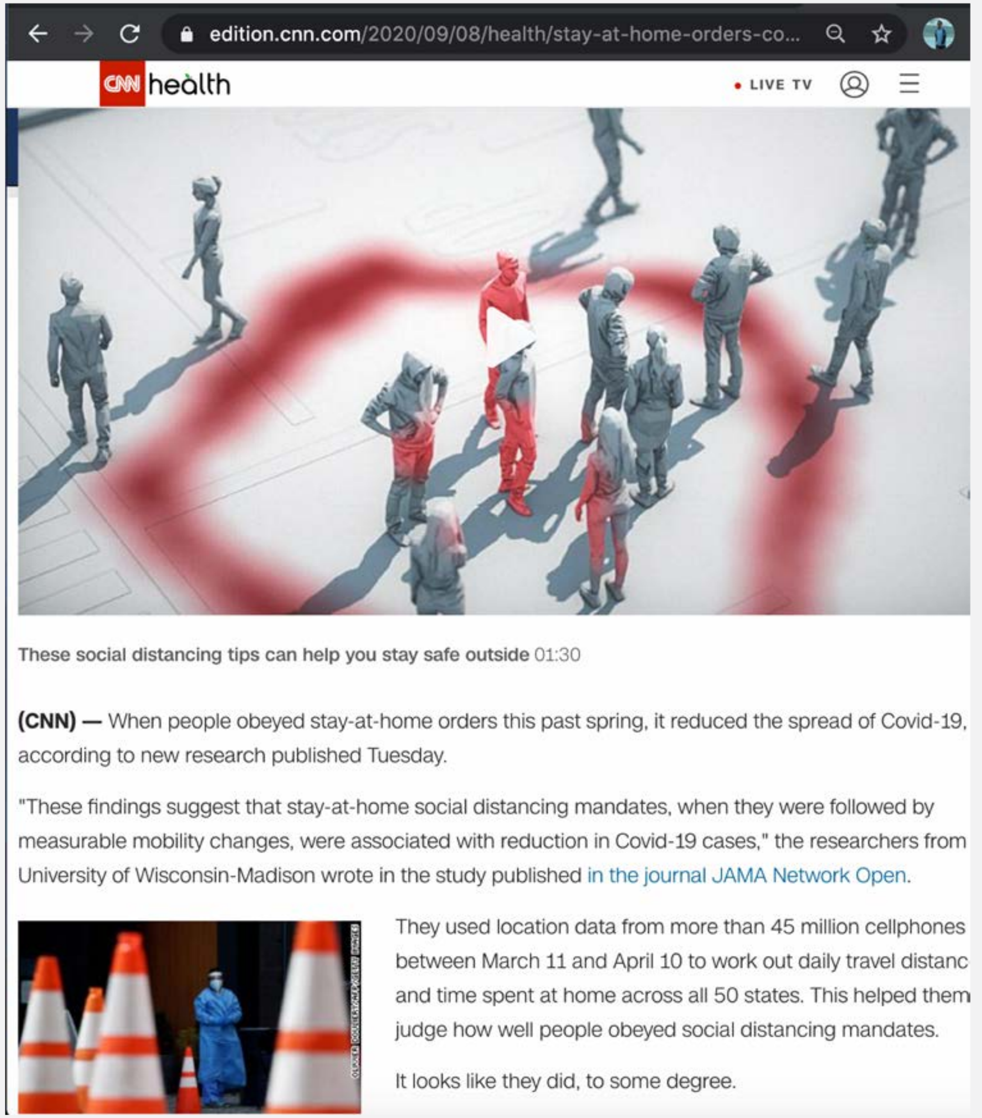
The Pearson’s correlation between the COVID-19 increase rate and **travel distance change rate** and **home dwell time change rate** was **-0.586** (95% CI: -0.742 ~ -0.370) and **0.526** (95% CI: 0.293 ~ 0.700).

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

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

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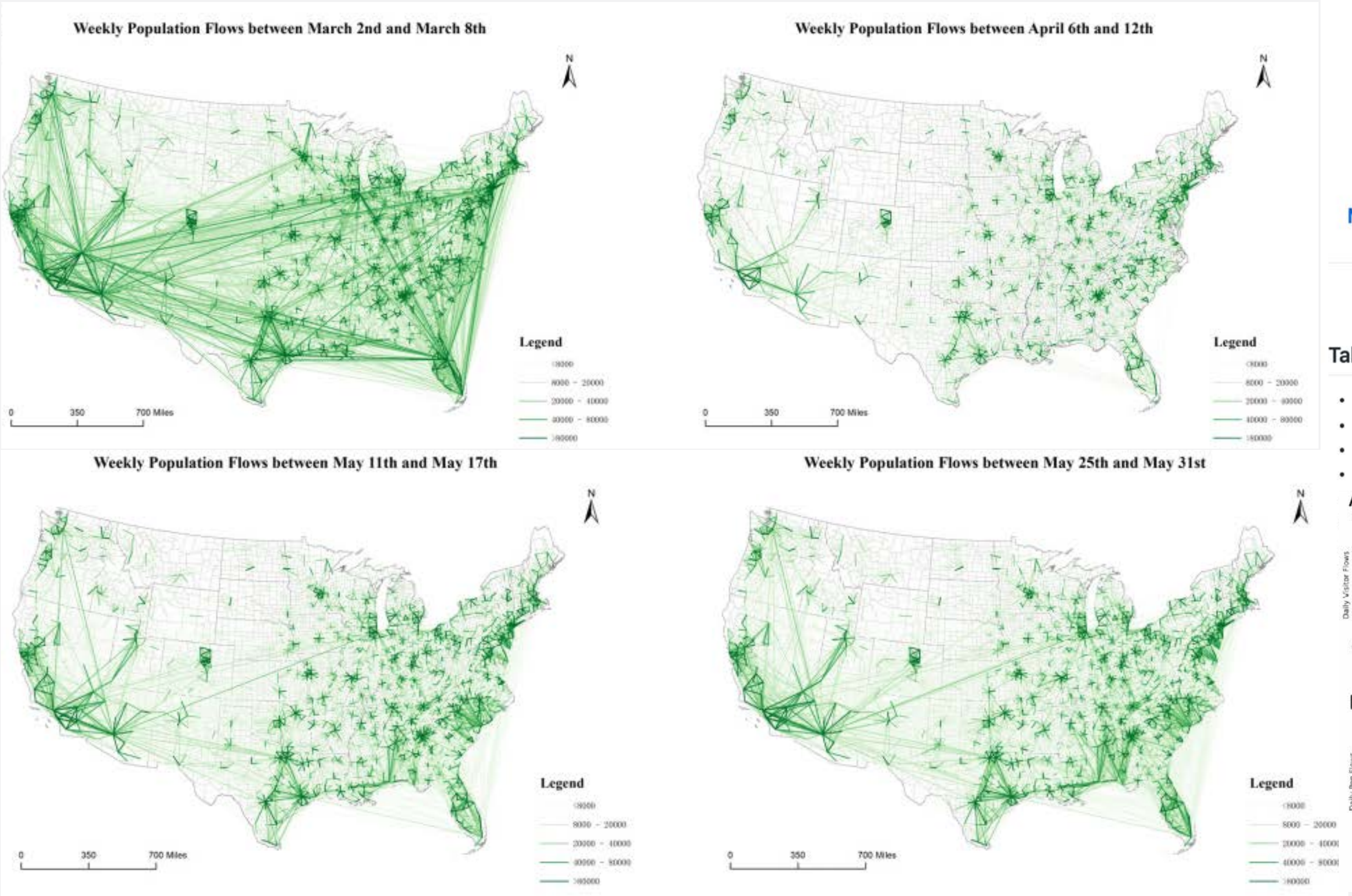
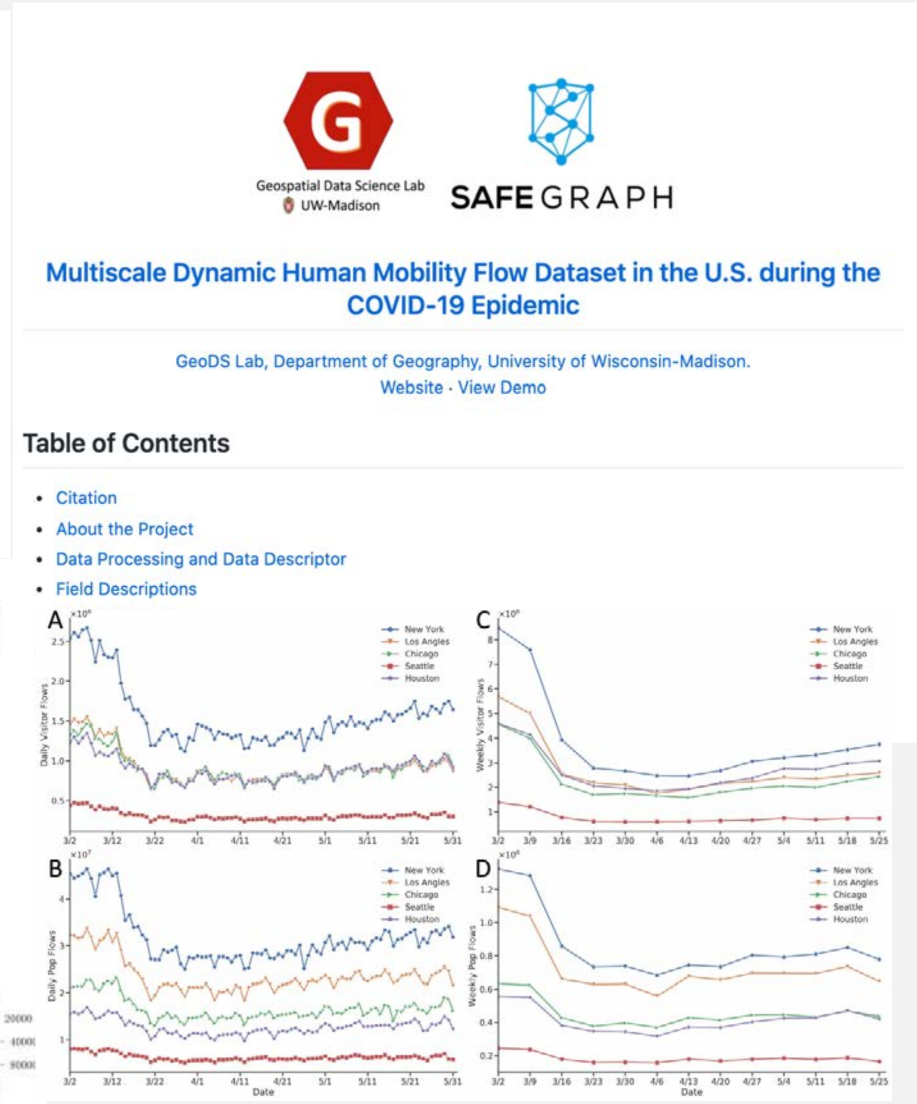


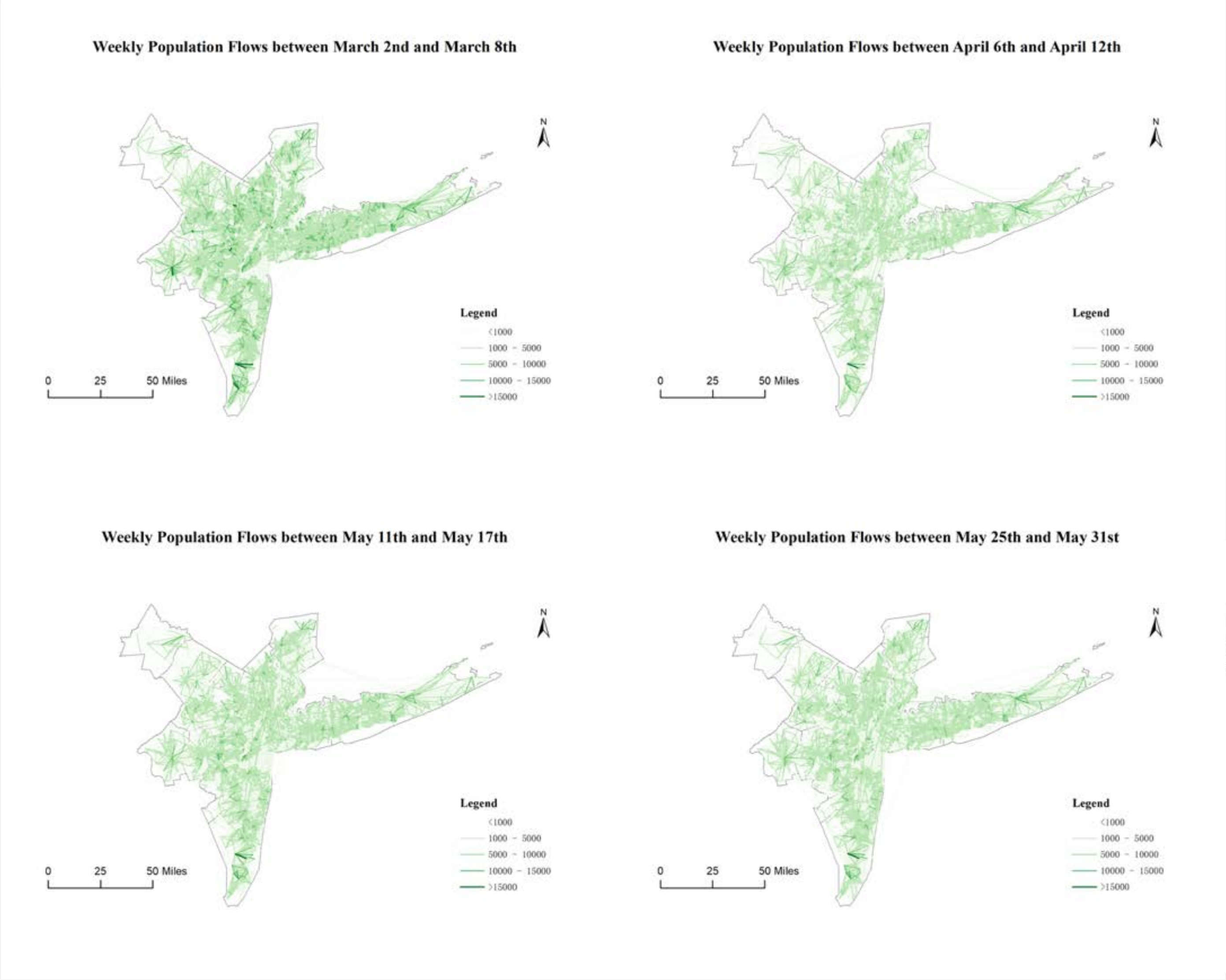


Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale Dynamic Human Mobility Flow Dataset in the US during the COVID-19 Epidemic. preprint arXiv:2008.12238.

https://github.com/GeoDS/COVID19USFlows

Multiscale Dynamic Human Mobility O-D Flow Open Data

Tract to Tract



Geospatial Data Science Lab UW-Madison

SAFEGRAPH

Multiscale Dynamic Human Mobility Flow Dataset in the U.S. during the COVID-19 Epidemic

GeoDS Lab, Department of Geography, University of Wisconsin-Madison.
Website · View Demo

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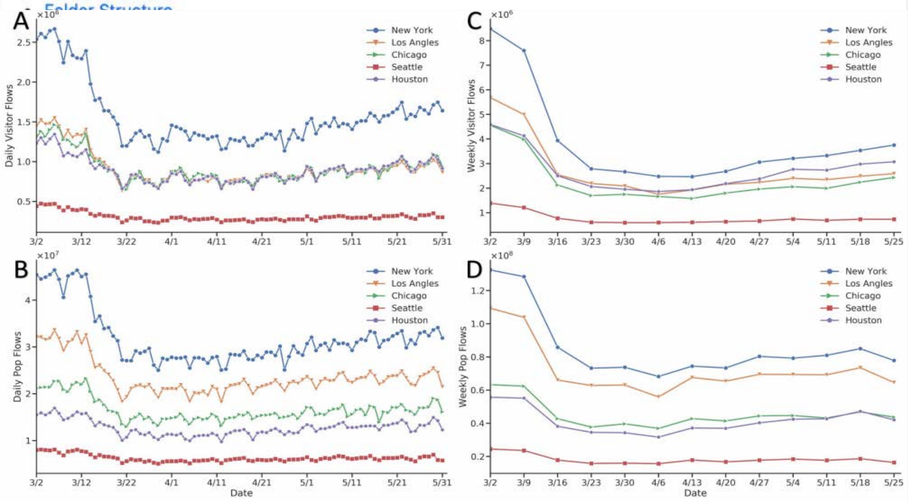
- Field Descriptions



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. preprint arXiv:2008.12238.

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:

$$pop\_flows(o,d) = visitor\_flows(o,d) \times \frac{pop(o)}{num\_devices(o)}$$

- *pop_flows(o, d)* – the estimated dynamic population flows from *o* to *d*
- *visitor_flows(o, d)* – the computed mobile phone-based visitor flow from *o* to *d*
- *pop(o)* - the population at the geographic unit *o*
- *num_devices(o)* - the number of unique mobile devices residing in *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

In addition, we also compare the estimation results with a **gravity** model and a **radiation** model.

Gravity Model and Radiation Model Estimates

Gravity Model

$$F_{i,j} = \frac{k * P_i * P_j}{d_{i,j}^{\beta}}$$

Radiation Model

$$T_i = m_i \frac{N_c}{N}$$

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

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

State-Specific Geospatial Modeling of COVID-19 Spread

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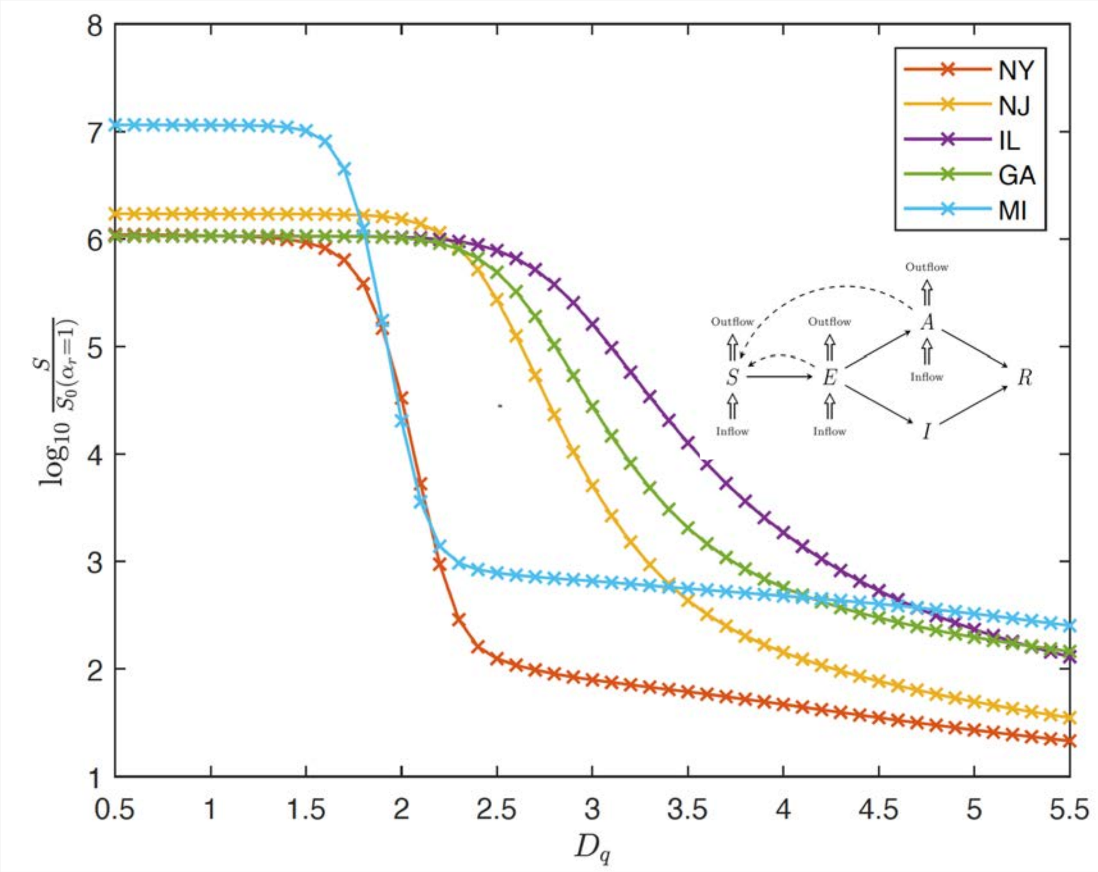

Quantifying the effect of timely quarantine and social distancing mandates.

- 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. medRxiv. https://doi.org/10.1101/2020.04.03.20052720

Intra-County Geospatial Modeling of COVID-19 Spread

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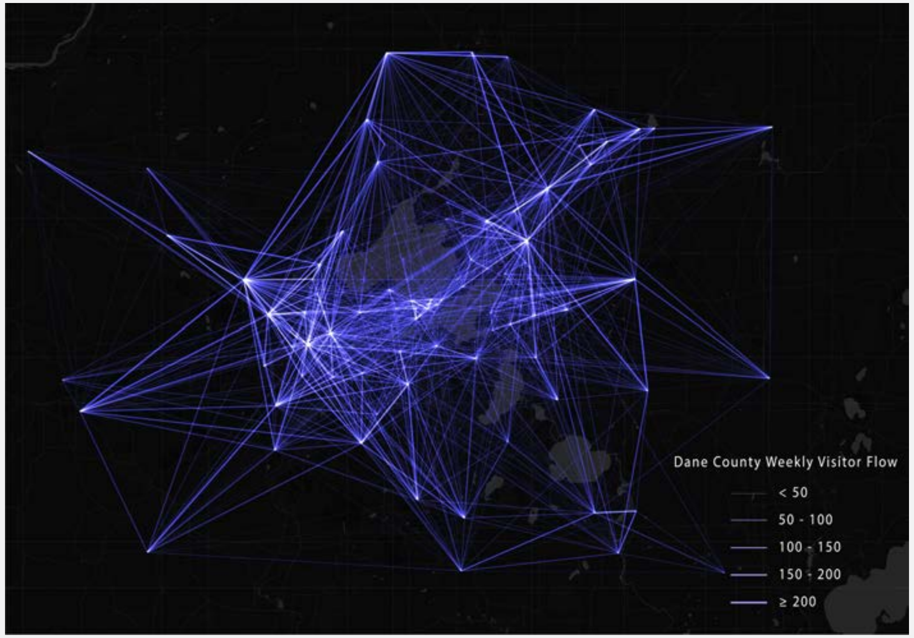
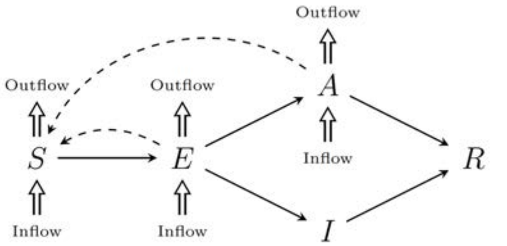
Modeling

O-D Flow



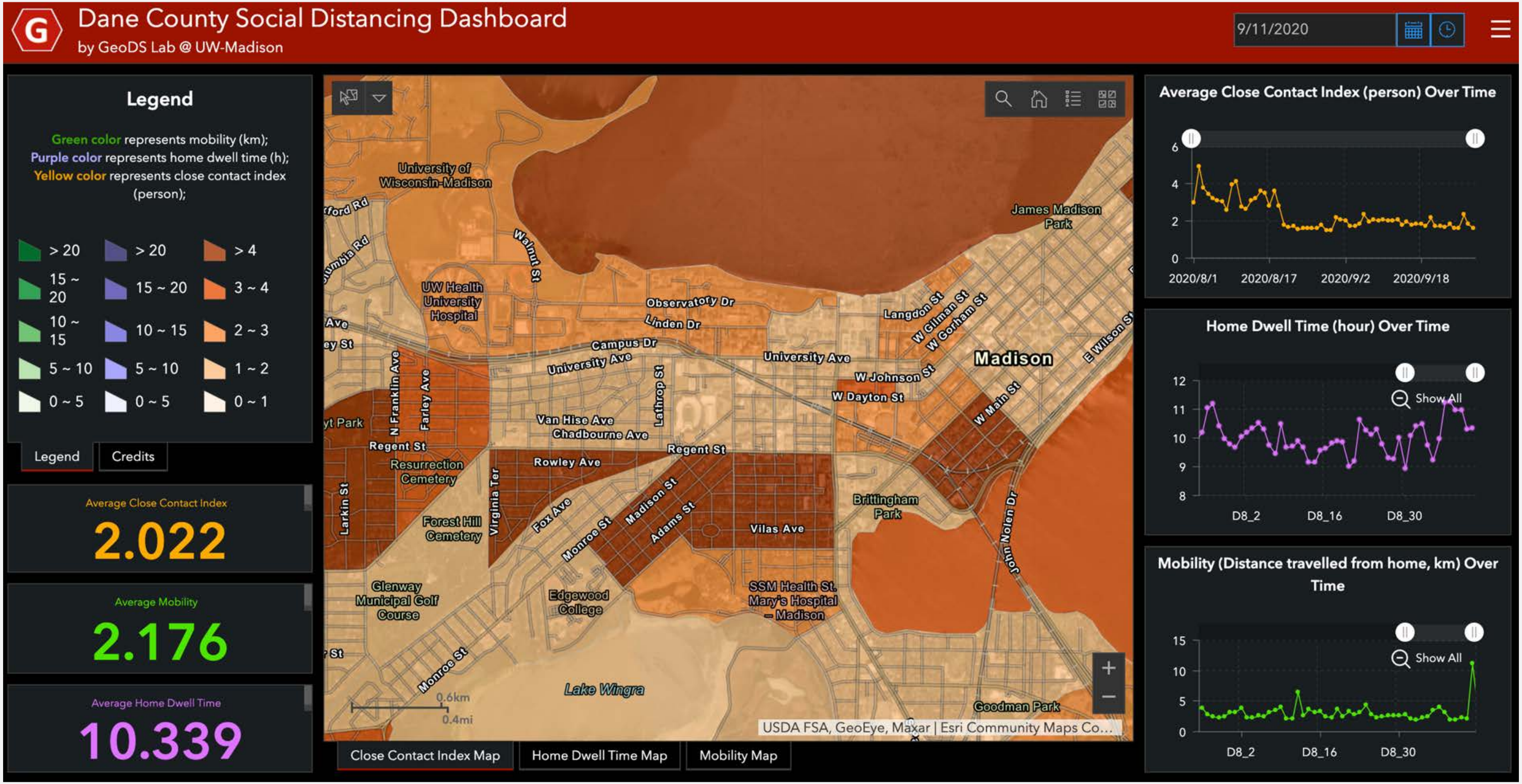
Mobility-Augmented SEIR model

$$
\begin{cases}
\dfrac{dS_i}{dt} = -\dfrac{b_i(S_i - \sum n_{ji}\frac{S_i}{P_i} + \sum n_{ij}\frac{S_j}{P_j})(E_i - \sum n_{ji}\frac{E_i}{P_i} + \sum n_{ij}\frac{E_i}{P_j})}{P_i - \sum n_{ji} + \sum n_{ij}} \\
\dfrac{dE_i}{dt} = \dfrac{b_i(S_i - \sum n_{ji}\frac{S_i}{P_i} + \sum n_{ij}\frac{S_j}{P_j})(E_i - \sum n_{ji}\frac{E_i}{P_i} + \sum n_{ij}\frac{E_i}{P_j})}{P_i - \sum n_{ji} + \sum n_{ij}} - \dfrac{E_i}{D_e} \\
\dfrac{dI_i}{dt} = \dfrac{E_i}{D_e} - c_I\dfrac{I_i}{D_c} - (1 - c_I)\dfrac{I_i}{D_l} \\
\dfrac{dR_i}{dt} = c_I\dfrac{I_i}{D_c} + (1 - c_I)\dfrac{I_i}{D_l} \\
\dfrac{db_i}{dt} = -d_{b,i}(b_i - \hat{b}_i) + \sigma_b\dot{W}\,.
\end{cases}
$$



- Hou, X., Gao, S., Li, Q., Kang, Y., Chen, N., Chen, K. Rao, J., Ellenberga, J., & Patz, J. (2020). Intra-county modeling of COVID-19 infection with human mobility: assessing spatial heterogeneity with business traffic, age and race. medRxiv. https://doi.org/10.1101/2020.10.04.20206763

Dane County Social Distancing Dashboard



Summary Notes

- Mobile phone data can help track the mobility patterns and digital contact tracing
- Mobile phone sensors have different positioning accuracy; it also needs privacy considerations
- Health and social disparities require more attention; Fighting against COVID-19 requires coordination efforts and multidisciplinary collaboration

Thank you!

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UW-Madison

https://geods.geography.wisc.edu