Mapping county-level mobility pattern changes in the United States in response to COVID-19

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1 Introduction

To contain the COVID-19 outbreak, one of the non-pharmacological epidemic control measures in response to the COVID-19 outbreak is reducing the transmission rate of SARS-COV-2 in the population through (physical) social distancing. An interactive web-based mapping platform\textsuperscript{1} (as shown in Fig. 1) that provides timely quantitative information on how people in different counties and states reacted to the social distancing guidelines was developed with the support of the National Science Foundation (NSF). It integrates geographic information systems (GIS) and daily updated human mobility statistical patterns derived from large-scale anonymized and aggregated smartphone location big data at the county-level in the United States \textsuperscript{8} \textsuperscript{7} \textsuperscript{4} \textsuperscript{3}, and aims to increase risk awareness of the public, support governmental decision-making, and help enhance community responses to the COVID-19 pandemic.

With the rapid development of information, communication, and technologies, new data acquisition and assessment methods are needed to evaluate the risk awareness of epidemic transmission and geographic spreading from the community perspective. The online mapping platform can help not only effectively monitor the spatiotemporal changes of travel distances of people and the effect of social distancing policies on human movement behavior, but also enhance the understanding of the factors such as social disparities, political and geographic contexts in risk communication and public-health interventions.

We welcome user feedback from different domains for further enhancement.

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\textsuperscript{1}https://geods.geography.wisc.edu/covid19/physical-distancing/
2 Methods

2.1 Data Sources

In response to the rapid spread of the SARS-COV-2 virus, many states in the U.S. have issued the “stay-at-home” or “safer-at-home” orders. People tend to change their travel behavior to slow down the spread of the novel coronavirus but spatial and temporal heterogeneity still exists.

We use the U.S. mobility data released by the Descartes Labs [7] to map the daily human mobility changes. The mobility is represented by the maximum travel distance (km) to a location from the initial location of the day given a unique mobile device (i.e., individual max-distance mobility). To investigate the mobility changes, a baseline was first determined [7], which was defined as the median of the max-distance mobility on the weekdays between 2/17/2020 and 3/7/2020 in the specified region (i.e., by county). By comparing daily mobility with baseline mobility, we can measure how people in each county react to COVID-19 by reducing daily travel distance (i.e., Social Distancing).

**Median Mobility**: The median of the individual daily max-distance for all location samples in the specified region.

**Percent Change in Mobility**: The percentage change in the daily median mobility from the baseline.

In addition, we use the SafeGraph place visit data[^2] to understand place-type specific visit pattern changes over 3.6 million points of interest (POIs) in the U.S. (as shown in Fig. 2). SafeGraph provides unique and valuable insights into the foot-traffic changes to large-scale businesses and consumer POIs [6].

[^2]: <https://www.safegraph.com/dashboard/covid19-commerce-patterns>
2.2 System Design

The interactive web mapping platform was designed and developed using the ArcGIS Operational Dashboards. It integrated maps, time series plots, gauges, and other visual elements to represent the dynamic status of mobility patterns comprehensively. To optimize the mobile user interface and user experience, we employed another design tool – the ArcGIS Experience Builder to construct mapcentric apps and display them on a scrolling and multi-panel screen.

3 Insights and Discussion

On the map, the red color polygons represent an INCREASE in daily mobility compared with the abovementioned baseline statistic, while blue color polygons represent a DECREASE in mobility. The color saturation reflects the degree of changes. The darker the more mobility changes in a county. As March 15, 2020, two days after the U.S. Federal Government announced the national emergency, the people in most states in the Pacific Coast, Midwest, and East Coast had reacted actively to the social distancing guidelines and reduced their daily mobility (in Fig. 1). By zooming into the New York state (in Fig. 3), its median max-distance reduced to less than 0.1 km and decreased about 73% of that compared to the baseline. Despite warnings from health experts that drastic control measures are needed to slow the spread of the virus, people in

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3https://doc.arcgis.com/en/dashboards/
the Franklin County (Florida) and the Monroe County (Florida), and many other counties in Arizona, New Mexico, Colorado, Utah and Wyoming still have increased daily mobility patterns (Fig. 1) since there was no statewide lock-down order yet. As of March 31, 2020, most states in the U.S. had issued fully shelter-in-place or partially safer-at-home and no large-group gatherings orders [1], asking residents to stay at home and go out only for essential services, such as grocery shopping and medical cares. Thus, the spatial distribution of the mobility changes was dominantly in blue (decreased mobility) on that day except for some counties (as shown in Fig. 5), including Sutton County (Texas), Carbon County (Wyoming), Big Horn County (Montana), Millard County (Utah), Yuma, Prowers, and Lincoln counties (Colorado), and Pocahontas and Decatur counties in Iowa. The county/state mobility patterns may change over time if there will be some inevitable gathering events in near future (e.g., in-person voting in presidential primary).

It is worth noting that reduced mobility doesn’t necessarily ensure the (physical) social distancing in practice according to CDC’s definition[4]: ”Stay at least 6 feet (2 meters) from other people”. Due to the mobile phone GPS horizontal error and uncertainty [2], such physical distancing patterns cannot be identified from the used aggregated mobility data; it requires other wearable sensors or trackers. However, it will involve another important issue about personal data privacy and ethical concerns. It is still an ongoing challenge to find a "sweet spot" to use such data to derive effective analyses for saving lives while protecting the individual geoprivacy.

![Figure 3: The mobility change patterns in New York on March 15, 2020.](https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html)
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**References**

[1] About 95% of Americans have been ordered to stay at home. This map shows which cities and states are under lockdown, available at https://www.businessinsider.com/us-map-stay-at-home-orders-lockdowns-2020-3.

[2] S. GAO AND G. MAI, Mobile gis and location-based services, Comprehensive Geographic Information Systems, (2017), pp. 384–397.

[3] Y. LIANG, S. GAO, Y. CAI, N. Z. FOUTZ, AND L. WU, Calibrating the dynamic huff model for business analysis using location big data, Transactions in GIS, (2020).

[4] T. PRESTBY, J. APP, Y. KANG, AND S. GAO, Understanding neighborhood isolation through spatial interaction network analysis using location big data, Environment and Planning A: Economy and Space, (2019), p. 0308518X19891911.

[5] R. ROTH, Cv-13-user interface and user experience (ui/ux) design, University Consortium for Geographic Information Science, (2017).

[6] SAFEGRAPH, The impact of coronavirus (COVID-19) on foot traffic, U.S. Consumer Activity During COVID-19 Pandemic, (2020).

[7] M. S. WARREN AND S. W. SKILLMAN, Mobility changes in response to COVID-19, arXiv preprint arXiv:2003.14228, (2020).

[8] C. ZHOU, F. SU, T. PEI, A. ZHANG, Y. DU, B. LUO, Z. CAO, J. WANG, W. YUAN, Y. ZHU, ET AL., COVID-19: Challenges to GIS with big data, Geography and Sustainability, (2020).