Tribal Mobility and COVID-19: An Urban-Rural Analysis in New Mexico

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ABSTRACT

Tribal communities have experienced disproportionately high infection and death rates during the COVID-19 pandemic [1, 8, 31]. In this work, we examine COVID-19 case growth in proximity to significant tribal presence by providing a novel quantification of human mobility patterns across tribal boundaries and between urban and rural regions at the geographical resolution of census block groups. We use New Mexico as a case study due to its severe case infection rates; however, our methodologies generalize to other states. Results show that tribal mobility is uniquely high relative to baseline in counties with significant case counts. Furthermore, mobility patterns in tribal regions correlate more highly than any other region with case growth patterns in the surrounding county 13–16 days later. Our initial results present a quantification scheme for the underlying differences in human mobility between tribal/non-tribal and rural/urban regions with the goal of informing public health policy that meets the differing needs of these communities.

CCS CONCEPTS

• Networks → Location based services; **Mobile networks**; **• Human-centered computing → Mobile devices**; **• Social and professional topics → Race and ethnicity**; **• General and reference →** *Measurement*.

KEYWORDS

mobility, COVID-19, mobile device location, crowdsourced datasets, rural urban disparity

ACM Reference Format:
Esther Showalter, Morgan Vigil-Hayes, Ellen Zegura, Rich Sutton, and Elizabeth Belding. 2021. Tribal Mobility and COVID-19: An Urban-Rural Analysis in New Mexico. In *The 22nd International Workshop on Mobile Computing Systems and Applications (HotMobile '21), February 24–26, 2021, Virtual, United Kingdom.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3446382.3448654

HotMobile '21, February 24–26, 2021, Virtual, United Kingdom

ACM ISBN 978-1-4503-8323-3/21/02.
https://doi.org/10.1145/3446382.3448654

1 INTRODUCTION

From the start of the COVID-19 pandemic in the United States (US), case counts have shown that the virus impacts Native Americans and other ethnic minorities much more severely than White populations [1, 21]. Many tribes responded to the pandemic by closing tribal borders and imposing strict curfews on tribal lands in addition to other prevention methods [23]. While recent research has investigated the effectiveness of social COVID-19 prevention methods, including physical distancing, curfews, masking, shelter-in-place orders, tribal boundary restrictions, and community testing in tribal and rural communities [8, 23], limited research has assessed the relationship between human mobility in urban/rural and tribal/non-tribal regions and COVID-19 case counts [3]. Given the critical relationship between mobility and resource access in rural and tribal communities, it is important to understand the potential effectiveness of mobility restriction as a means for mitigating a public health crisis. *The goal of this paper is twofold: first, to quantitatively characterize the relationship between urban, rural, and tribal mobility and the growth of COVID-19 cases; and second, to accomplish this characterization by analyzing mobility information derived from crowdsourced mobile devices.*

We focus our analysis in New Mexico (NM) due to the state's representative blend of tribal and non-tribal communities spread across rural and urban areas. NM county case infection rates range from zero cases in some counties to some of the highest case counts in the nation in others. To our knowledge this is the first analysis that considers tribal, urban, and rural mobility at a resolution finer than county-level to assess mobile device movement during COVID-19. Importantly, our methodology generalizes to the greater US.

Our mobility dataset is collected by Skyhook, an opt-in location service company that offers device geo-positioning through wireless sensing [30]. COVID-19 case data is sourced by the NM Department of Health public dashboard [26]. We compare mobility and COVID-19 case growth rate before and after the March 23 stay-at-home (SAH) order for NM [27] against a mobility median established in January–February.

Our novel approach overlays U.S. Census Bureau rural and urban labels and tribal boundary files to assign two labels to census block groups (CBGs) within each county: either *urban* or *rural*, and either *tribal* or *non-tribal* [34, 35]. Our crowdsourced dataset is aggregated at the CBG level, facilitating a more fine-grained analysis than is currently possible with publicly available mobility datasets aggregated by county. Our key findings are the following:

- After the SAH order, tribal mobility on average dropped less than half as far as non-tribal: -6.27 vs. -17.18%, relative to their respective pre-COVID-19 medians. In two counties with the most cases, tribal mobility increased more than 4% above baseline, contrary to expectations that the SAH order would reduce mobility. Non-tribal mobility reduced to -5.05% less than its pre-COVID-19 median.
- Rural mobility dropped less than half as far as urban overall: -8.36% vs. -19.30%; however, within tribal areas the rural drop is less than a third of urban: -3.54% vs. -12.48%.
- Pearson correlation analysis reveals that tribal mobility consistently correlates more strongly with case growth than non-tribal mobility in counties with higher case numbers.

Our findings show the need for more granular case reporting to allow public health interventions that impact mobility to consider factors such as rurality and tribal jurisdiction.

Privacy Acknowledgement: Our dataset has been collected by Skyhook with the consent of the individual device users. Privacy of device users has been ensured by aggregating user data over census block groups. We base our analysis on this level of aggregation and do not disaggregate or identify movement of individuals.

2 RELATED WORK

"Mobility" Interpretations and Datasets: A number of organizations have published mobility datasets based on device movement, but the exact metric that defines "mobility" varies [2, 5, 7, 10, 12, 13, 29, 32]. Both Google and SafeGraph identify *mobility* as the number of visits within a day to certain types of locations, instead of a device-centric mobility metric such as distance traveled in a day [14, 29]. Unacast offers both a social distancing dataset and a dashboard showing migration patterns of New York City residents leaving the city as the pandemic grew [32]. Each of these datasets only represents mobility at the county level and fails to reveal finer differences that may arise from a division of tribal, rural, and urban populations. Google's Community Mobility reports explicitly state the reports are not intended for characterizing regional differences such as urban and rural mobility variations.

Mobility and COVID-19 Case Growth: Mobility has been shown to strongly correlate with COVID-19 case growth, and some studies call for more granular mobility data to help build the science around mapping human movement to understand how better to prevent pandemic spread [20, 25]. Device-based mobility tracking has applications in estimating, predicting, and preventing the propagation of COVID-19 in communities around the world [15, 19, 24, 28]. A number of researchers are currently discovering mobility patterns that lead to increased pandemic spread [22, 28]. Since publicly available datasets of COVID-19 case counts are most commonly presented at the county level [9, 26], prior attempts to categorize case data differences between urban and rural areas rely on county-level classifications [11, 25, 36] rather than smaller regional differences.

3 DATASETS

Our analysis is based on two datasets, as described below.

Mobile Device Mobility Index: To obtain mobility data we partnered with Skyhook, a geo-positioning service provider that logs anonymized records of users' mobile device location [30]. Skyhook collects device locations by providing a software geolocation service to third parties distributing commercial applications. Skyhook estimates the percentage of U.S. residents contributing to their database is typically between 1% and 5% of the population. Users install a third-party app and may consent to data collection by the third party and thus by Skyhook. Each time the app makes a new location request (prompted by app-specific needs such as advertising services, geo-fencing triggers, or navigation updates up to once per second), Skyhook's location service calculates an updated position for that device. This service uses GPS, cellular, Wi-Fi, Bluetooth, and LP-WAN networks, as available, on a variety of personal mobile devices and is compatible with apps for mobile devices running Android, Windows, and Android operating systems.

Skyhook aggregates location data over CBGs for each day of our analysis and includes a unique metric called *bounding box itinerancy*: the diagonal of the bounding box around the total area traveled by any device that appears within the aggregation and time boundary (i.e., each CBG and day). This metric captures the maximum distance traveled by a device each day, averaged over all devices. Personally identifiable information, such as routes or starting points, is not disclosed.

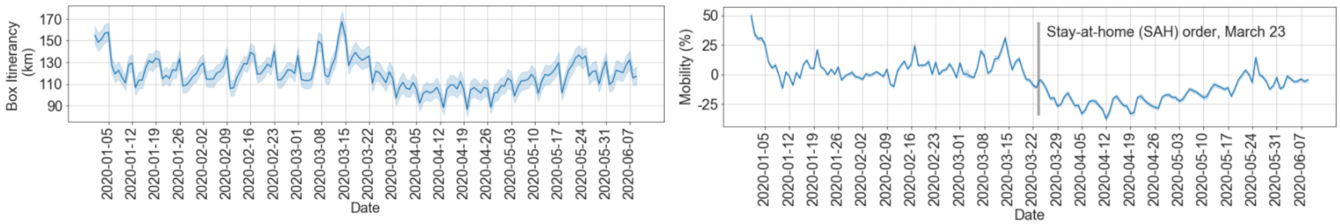
For each of the $1,449$ CBGs in New Mexico and most of the 161 days between January 1 and June 9, 2020, we have a single itinerancy average, for a total of $233,162$ data points[1]. Figure 1a shows the average daily itinerancy over all CBGs over time.

New Mexico COVID-19 Case Infection Counts: The Center for Disease Control releases county-level case infection counts to the public [4] based on daily updates from the New Mexico Department of Health. These numbers represent cases reported on that day; unreported cases are not reflected in the data. We examine case infection counts, not number of deaths, since we seek to understand how mobility correlates with spread of the disease.

4 ANALYSIS

In this section we characterize the relationship between mobility within a county and case growth rate for the entire county. We define "mobility" as used in our study, describe the methodology for regional categorization of mobility, and demonstrate a grouping of counties by case severity that allows for concise reporting of results. We then characterize the relationship between mobility and case growth rate in two ways: first with coarse time-averages of mobility, then with finer correlations that demonstrate the high correspondence of mobility through tribal and rural regional categories with overall case growth rates.

[1] $1,449 \times 161$ is $233,289$. However, on some days either itinerancy failed to be collected for devices appearing in some CBGs, or no devices entered that CBG, resulting in 127 fewer data points.



(a) Raw bounding box itinerancy with a 95% confidence band.

(b) Overall mobility with a (vary narrow) 95% confidence band.

Figure 1: Mobility represented by Skyhook's itinerancy metric and percent change in itinerancy from the pre-COVID-19 median.

4.1 Mobility as Percentage of Itinerancy

We first establish a mobility baseline by taking the median of itinerancy; this is the *pre-COVID-19 median*. This median is calculated starting on January 5, 2020 to avoid New Year holiday travel, and extends through February 6. This time range is similar to the range used in Google's Community Mobility dataset [13], and ends just over two weeks before news of the first virus-related deaths in the U.S. began altering public behavior[2]. This month of "normal" behavior allows us to compare how movement patterns changed as COVID-19 began to affect people's daily travel decisions.

Since "normal" behavior can vary wildly from place to place and by day of the week, we construct custom pre-COVID-19 medians using the same scheme: for each CBG and day in our Skyhook dataset, the itinerancy value is compared to the median itinerancy of all similar days of the week between January 5 and February 6. This matching of days accounts for day-of-week differences and variations particular to each CBG. *Mobility* is then taken as the percent change away from the pre-COVID-19 median itinerancy value of each day. Figure 1b shows the average mobility for the itinerancy metric over all CBGs for each day of January 1–June 9, 2020. Note that the date of the stay-at-home (SAH) order, March 23, 2020, is marked on the graph for reference.

We see rough agreement in the itinerancy change with other public mobility datasets for NM [7, 14]: mobility decreases significantly in late March, maintains its lowest rate through late April, then slowly returns to the pre-COVID-19 median through May and June. We study these trends in urban, rural, and tribal regional categories in the remainder of this analysis.

4.2 Regional Categories: Tribal/Non-tribal and Urban/Rural

We assign two regional category labels to each CBG-day entry: either U (urban) or R (rural), and either T (tribal) or N (non-tribal). These categories are then combined to show: tribal urban (TU), non-tribal urban (NU), tribal rural (TR), and non-tribal rural (NR) categories.

The U.S. Census Bureau publishes urban/rural assignments to individual census blocks using Tiger/Line geographical files [35]. To label an entire CBG, we sum the number of individual blocks within the CBG that are assigned the respective label. If 50% or more blocks within a CBG are labeled rural, then the entire CBG in our dataset is labeled rural. Otherwise the CBG is labeled urban. The effect of this step's over- and underestimation error on final noise in the mobility data is difficult to quantify; however, since neither

[2]Similar results were obtained using baseline end dates of February 16 and March 1.

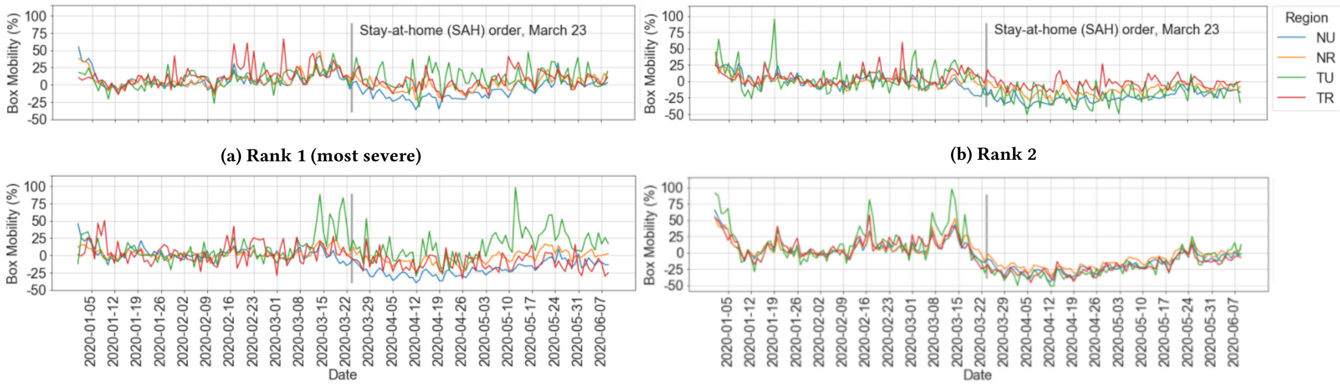
	# CBGs (% dataset)	**Median device (#)**	**% w/ hwys.**	**Med. pop.**	**Median area (km^2)**
Total	1,449 (100%)	624	69%	1241	2
T	113 (8%)	209	88%	1130	123
N	1,336 (92%)	662	67%	1249	2
R	394 (27%)	392	94%	1215	158
U	1,055 (73%)	714	60%	1251	1
TR	84 (6%)	172	85%	1131	205
TU	29 (2%)	345	93%	1195	6
NR	310 (21%)	442	96%	1234	142
NU	1,026 (71%)	729	59%	1253	1

Table 1: Characteristics of CBGs (census block groups) in regional categories (either Tribal/Non-tribal or Rural/Urban, and in combination). Columns show from left to right: number of CBGs that appear in each region (with the corresponding percentage of measurements in the overall dataset); median number of devices that appear in all CBGs of each regional category; percentage of CBGs in each region that contain major highways; median population of CBGs in each region; and median area of CBGs in each region.

mobility nor COVID-19 case data is available at block resolution, some assumption must be made to obtain comparative geometries. Future work to better quantify the noise inherent in this analysis is discussed at the end of Section 4.

Tribal boundaries are released every year by the U.S. government and rarely overlap neatly with census boundaries [34]; both census and county boundaries often shear irregularly through tribal lands. In our analysis, we label all data points within a CBG as tribal if the CBG overlaps tribal lands by 50% or more. However, some CBGs overlap less than 50% with tribal lands but have the majority of device activity falling within the tribal boundary. The Skyhook dataset includes the daily average device location by latitude and longitude of all devices recorded within each CBG each day. If 50% or more of these locations fall within tribal lands, we label that CBG tribal as well.

Table 1 shows defining characteristics of the CBGs in each regional category: total number of CBGs in NM and the equivalent percentage in the dataset; the percentage of CBGs that contain major highways [6] (which may add noise to mobility measurements); the median CBG population drawn from the American Community Survey 5-year estimate [33]; and the median CBG area. The issue of highway noise possibly complicating analysis in tribal and rural areas by contributing pass-through (rather than resident) mobility of devices is discussed in Section 4.4. There we rely on statistical power tests to interpret the significance of our final results.



(a) Rank 1 (most severe)

(b) Rank 2

(c) Rank 3

(d) Rank 4 (least severe)

Figure 2: Mobility as percent deviation in itinerancy from the pre-COVID-19 median grouped in counties of different case severity rank for combined regional categories. The legend in (b) applies to all plots, and the y-axis labels for (a) and (b) are aligned below (c) and (d).

4.3 COVID-19 Cases by County

We next present the concept of *severity ranks*, which are groupings of counties with similar case counts and mobility patterns (as is justified throughout this section). Our goal is to reveal any mobility differences between regional categories that may correlate to greater or lesser virus spread relative to population, and to use rank aggregations to present results for several counties compactly. By comparing the percentage of each county's population that experienced confirmed cases as of June 9, 2020, we find that four ranks of evenly decreasing severity are able to characterize the varying case growth over all of NM and to demonstrate the regional patterns shown next. As Section 4.4 further demonstrates, mobility also naturally falls into these groupings. We include the standard deviation within each rank to demonstrate the consistency of these findings throughout these rankings. The two counties with more than 1% of their populations reporting a positive test for a COVID-19 case as of June 9 (McKinley at 3.8% and San Juan at 1.8%) are assigned the highest severity rank of 1. The next highest county is Cibola at 0.62%, so the COVID-19 case percentage cutoff for rank 1 is set at 0.63%. The remaining three severity ranks are created by evenly splitting the remaining case percentage at 0.42% and 0.21%.

Figure 2 shows these severity rankings used to group mobility in each of the combined regional categories. Several possible trends are immediately obvious in the time after the SAH order was issued: tribal urban (TU) mobility shows the highest peaks in counties of severity ranks 1 and 3 even during the lowest dip in March and April. In rank 2, tribal rural (TR) mobility is the consistently highest category, and tribal urban (TU) mobility follows non-tribal urban (NU) mobility with the lowest values. Rank 4 counties show the most consistency between mobility categories. We further explore these possible trends by looking first at time averages over key mobility periods, then at correlations between mobility and case growth data at a county level.

Table 2 quantifies the overall trends suggested in Figure 2 by showing the average difference from the pre-COVID-19 median in mobility in each combined regional category over all days after the SAH order was issued. The "All regions" row in Table 2 shows that on average, mobility in each category decreased despite the return toward normal operation in May and June. Tribal mobility (T) dropped to -6.27% of its pre-COVID-19 median, whereas non-tribal (N) dropped to -17.18%. Rural mobility (R) dropped almost as little as tribal to -8.36%, and urban mobility (U) dropped the most to -19.30%. These trends are similarly reflected in the combined categories, with CBGs labeled as both tribal and rural (TR) showing mobility dropped the least to -3.54%.

The breakdown by case severity ranks in the rows labeled 1 through 4 shows that tribal mobility in counties of rank 1 actually increased on average over this time to 4.67%, whereas non-tribal remained at -5.04%. Furthermore, TR and TU mobility both increased to 5.02% and 10.30% whereas NR mobility increased only to 0.49% and NU remained subdued at -9.46%. In the lower ranks, we see that tribal mobility typically remained greater than non-tribal mobility in each rank, except for in rank 4, with greater tribal mobility in counties with higher severity rankings[3]. Naturally the choice of end date will strongly affect these averages; however, when comparing averages over just the three lowest weeks (April 6–27) or just the two weeks of return to normalcy (May 24–June 9), we find similar relationships between regional mobility trends.

The results in Table 2 suggest a detectable correlation between tribal mobility–both as a whole and in urban and rural categories–and case growth in counties with a strong tribal presence, despite the minimal representation of tribal mobility measurements within the dataset.

Rural mobility is consistently higher than urban mobility for all time ranges and all severity ranks. It is unclear whether this is due to the considerable coincidence between rural CBGs and highways or the fact that rural areas are often characterized by greater distances from resources and between waypoints [17]. We discuss this in section 4.4.

4.4 Mobility and case growth correlation

We now examine a Pearson correlation between Skyhook itinerancy and COVID-19 case growth rate. We follow the method demonstrated by Freitag et al. [22], who performed a state-level correlation across the U.S. and found that the highest correlation appeared

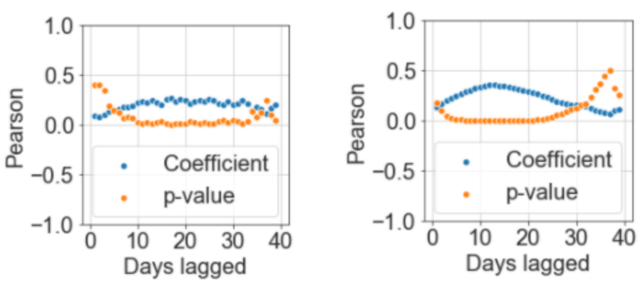
[3]Rank 3 proves an exception to this trend, where the only tribal CBGs are inside Bernalillo county, and three of these four CBGs contain major highways through Albuquerque. When results from the only tribal CBG without highways is considered, this claim holds.

Rank	All regions			T	N	R	U	TR	TU	NR	NU
	Avg.	Med.	St. Dev.	Avg.	Avg.	Avg.	Avg.	Avg.	Avg.	Avg.	Avg.
All	-16.33	-19.15	31.27	-6.27	-17.18	-8.36	-19.30	-3.54	-12.48	-9.65	-19.5
1	-1.74	-2.77	42.07	4.67	-5.04	2.98	-7.43	5.02	10.3	0.49	-9.46
2	-14.36	-16.54	29.83	-8.01	-14.98	-8.51	-16.71	-6.3	-20.18	-9.2	-16.63
3	-20.37	-24.59	28.04	3.82	-20.58	0.08	-21.98	0.48	13.82	0.04	-22.07
4	-17.65	-18.86	29.88	-21.86	-17.37	-14.12	-19.54	-22.11	-21.59	-13.33	-19.45

Table 2: Average mobility changes from pre-COVID-19 median by regional category and rank for March 24–June 9, all dates after the stay-at-home (SAH) order. Median and standard deviation are shown for all regions in each rank to show the range of mobility in each grouping.

when mobility data is lagged by 19 days. This lag time seems reasonable given the following factors: after exposure, symptoms of the virus typically begin to manifest between 5 and 14 days. The additional days up to 19 may represent observing symptom development, decision time to obtain a test, and waiting for test results. We perform a correlation with mobility divided into regional categories to further explore how underlying trends in tribal, rural, or urban regions may affect case growth in their surrounding counties.

The mobility dataset used by [22] is provided by Descartes Labs (DL) and shows the daily county-wide median of the maximum distance in kilometers traveled by devices away from their daily origin point [7]. Skyhook's itinerancy metric, in contrast, shows the diagonal of the bounding box around all movement within a CBG in a day, on average 4–5 times larger than DL's mobility metric.



(a) DL correlation **(b) SK correlation**

Figure 3: Correlations between $\log_{10}$ mobility and growth for Descartes Labs (DL) and Skyhook (SK) from March 1–June 9. *p*-values show likelihood of a false positive and should be <0.05.

Our case dataset begins January 21 and was obtained from the NM Department of Health, which sources the data used in [22]. We calculate the daily change in case counts for each of the 33 counties in NM and the 140 days in January 21–June 9. Daily case growth rate is the natural log of the ratio of each day's case changes to each previous day's. As in [22], we average case growth rate with a 14-day rolling window to smooth weekly trends. Our mobility dataset is created by applying a 14-day rolling average on raw box itinerancy in *km* for each of the 1,449 CBGs in NM and over the same date range, then taking the base-10 log of mobility as in [22].

We first recreate the Pearson correlation shown in [22] with the publicly available DL dataset for NM, over March 1–June 9, the dates available for DL mobility data. A maximum correlation appears at 17 days of lag with a coefficient of 0.27 ($p < 0.01$) (Figure 3a). Repeating the same process with Skyhook's itinerancy shows a maximum correlation of 0.37 ($p < 0.01$) at just 13 days (Figure 3b). This earlier lag time may arise from an important difference between

	Overall		Rank 1		Rank 2		Rank 3		Rank 4	
Cat.	**Co.**	***l***	**Co.**	***l***	**Co.**	***l***	**Co.**	***l***	**Co.**	***l***
All	0.37	13	0.34	12	0.36	23	**0.22**	8	0.34	11
T	0.41	14	0.38	15	0.38	14	0.36	9	0.37	14
N	0.36	13	0.34	13	0.37	22	0.36	22	0.36	22
R	0.37	12	**0.25**	8	**0.23**	4	**0.20**	5	**0.22**	8
U	0.36	13	0.35	8	0.34	13	0.34	11	0.34	10
TR	0.42	14	0.40	15	0.28	14	0.35	9	0.38	14
TU	0.38	12	0.40	33	0.40	13	0.32	13	0.36	22
NR	0.37	12	**0.24**	5	**0.21**	4	**0.19***	5	**0.22**	8
NU	0.36	13	0.34	8	0.34	13	0.34	9	0.34	10

Table 3: Maximum correlation coefficient (Co.) and corresponding lag (*l*) in days between mobility and case growth, grouped by county severity rank and regional categories (Cat.). $p < 0.01$ for all entries except for those marked with bold ($0.01 < p < 0.05$) or an asterisk ($p > 0.05$).

the mobility metrics: greater changes in itinerancy allow greater variety of maximum distance traveled, so that many max distance values would map to the same itinerancy value.

We then divide itinerancy measurements into regional categories by case severity rank, shown in Table 3. We confirm that state-wide, tribal mobility correlates more strongly to case growth than non-tribal. Particularly, TR mobility correlates most strongly at 0.42 ($p < 0.01$). The "Rank" columns show mobility for each region is correlated only to case growth within counties of that rank. Tribal mobility maintains a consistent highest correlation with case growth in each rank, while non-tribal correlation increases slightly in lesser ranks. Tribal presence in lower-ranked counties is lower than in higher-ranked counties, but this does not correspond to a decrease in the correlation between tribal mobility and overall case growth.

5 DISCUSSION

This analysis suggests that mobility through tribal regions is more indicative of case growth in the surrounding county than mobility through non-tribal regions. Furthermore, mobility through tribal and rural regions uniquely increased after social distancing orders went into effect. This trend raises the question of the appropriateness of the SAH order for communities in rural and tribal regions. It is likely that the continued need for basics such as water, medicine, and groceries during March and April contributed to increased mobility by reservation residents. Many of these residents already travel tens of miles for a simple supply run; supply outages would have increased the need to travel longer distances [16, 18]. Finally, tribal land residents, many of whom live paycheck-to-paycheck [23], may not have the option of remaining home from work for even two weeks; as businesses suspended, schools closed, and typical child care services were disrupted, households may have needed to travel further to find work and take children to new day care arrangements. Moving forward, collaboration between healthcare officials and tribal leaders will be critical to studying these patterns further and to adapt preventative measures to meet the mobility needs of residents of sovereign lands.

Imprecision was necessarily introduced to our analysis by requiring aggregation to protect user privacy. Labeling tribal, urban, and rural regions in geometries larger than census blocks intrinsically introduces some amount of error; precise characterization must validate these regional labeling schemes. Additionally, device count is captured for each day and CBG, the number of users of each device cannot be guaranteed. Total distance captured by a single device may represent movement by more than a single person, especially in tribal and rural communities where device sharing is common. Nevertheless, any device movement still represents the mobility of at least one person and corresponds to a greater potential of exposure to the virus.

Finally, the precise amount of noise introduced from non-local highway users, especially in tribal and rural areas, is not captured in this mobility dataset. Highway use increases the daily average distance traversed, but this type of mobility likely does not contribute to more direct personal contact that could spread COVID-19 in the local region. Nevertheless, our observations reflect that total mobility detected through rural tribal lands seems to correspond with an increase in COVID-19 case growth. Currently the only reliable published case data is for county-level totals and not for tribal, urban, or rural regions. Our work explores the possibilities of these limited datasets to delineate recommendations for more precise yet privacy-preserving data collection.

6 CONCLUSION

Although much work remains for the future, our analysis demonstrates that aggregated human movement captured by personal devices reveals different patterns through tribal and non-tribal regions, further delineated between urban and rural lines. Combined with the unusually devastating surges in COVID-19 case growth in counties close to tribal areas in NM, this research could reveal key behaviors captured in personal device mobility data that can help scientists and officials understand and moderate the spread of COVID-19 and future outbreaks. Importantly, our analysis of available information shows a need for consistent case data to be recorded and made publicly available at a finer regional resolution than county-level. We hope future work in this direction will enable public health efforts to better consider the impacts of jurisdictional and regional mobility.

7 ACKNOWLEDGMENTS

This work was funded through the National Science Foundation Smart & Connected Communities award NSF-1831698, and through an NSF Graduate Research Fellowship.

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