

Spatiotemporal Analysis of COVID-19 Tweet Trends in Subnational Areas of the United States

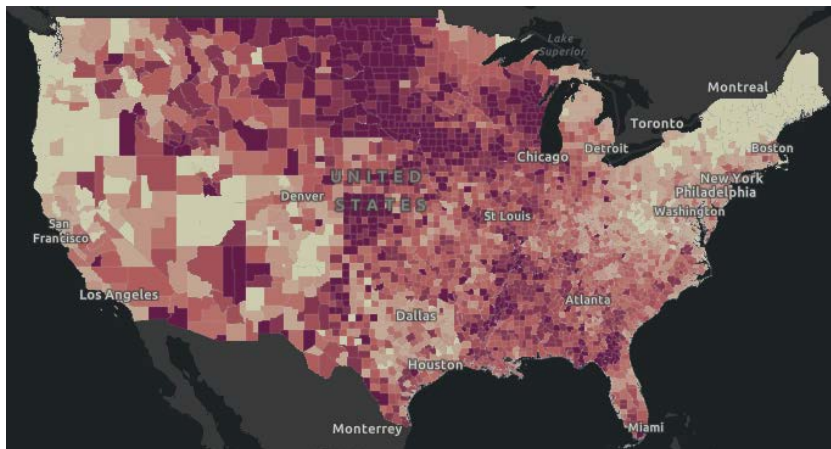
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Background

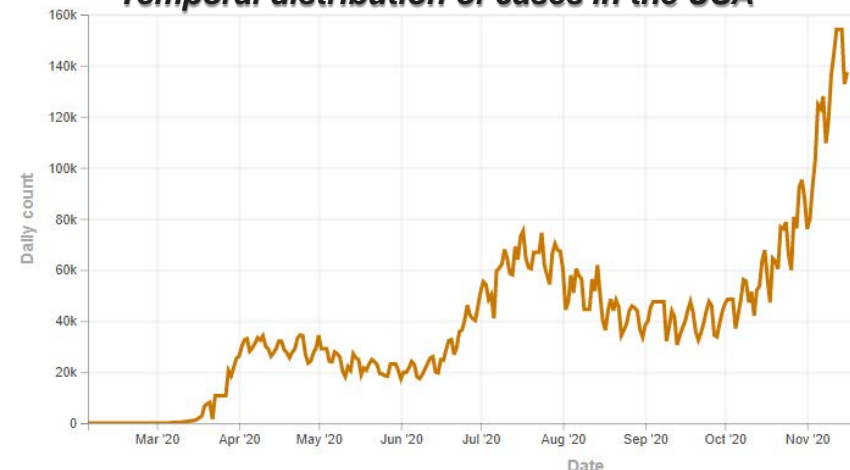
- COVID-19 infection is not evenly distributed across time and space
- At the population level, areas/times with high infection rates are likely to be preceded by low levels of preventive behaviors, and low levels of preventive behaviors are likely to be preceded by low concern relating to COVID-19
- The objective of this study was to describe the spatiotemporal distribution of COVID-19 tweets in the United States as a proxy for COVID-19 concern

Spatial distribution of cases in the USA, Nov 25th



From Johns Hopkins University

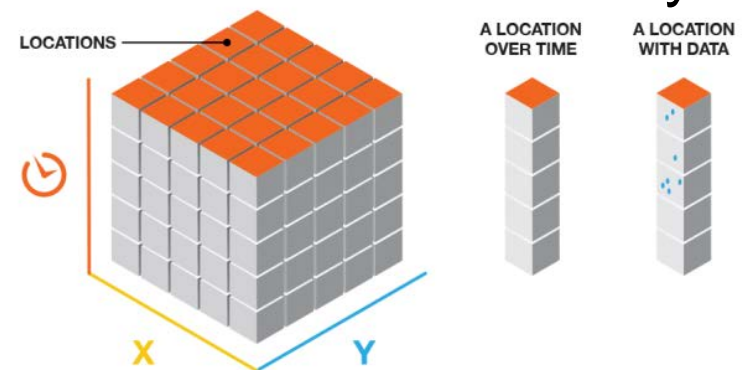
Temporal distribution of cases in the USA



From University of Washington

Methods

- Tweets with COVID-19 keywords and spatial coordinates from March 3rd to April 13th were collected using the Twitter API
 - corona outbreak, corona, anticorona, coronavirus, Wuhan virus, COVID, Wuhan pneumonia, and pneumonia of unknown cause
- A subset of tweets in a separate study manually coded for first-hand experience with COVID-19 was used to train a machine learning classifier (SVM), which was used to remove less relevant tweets
- The C3 algorithm of the Early Aberration Reporting System was used to detect statistically significant aberrations in tweets by state
- We created choropleth map of COVID-19 tweets in the study timeframe
- A space-time cube was computed to relay concurrent spatiotemporal distribution via Emerging Hot Spot Analysis



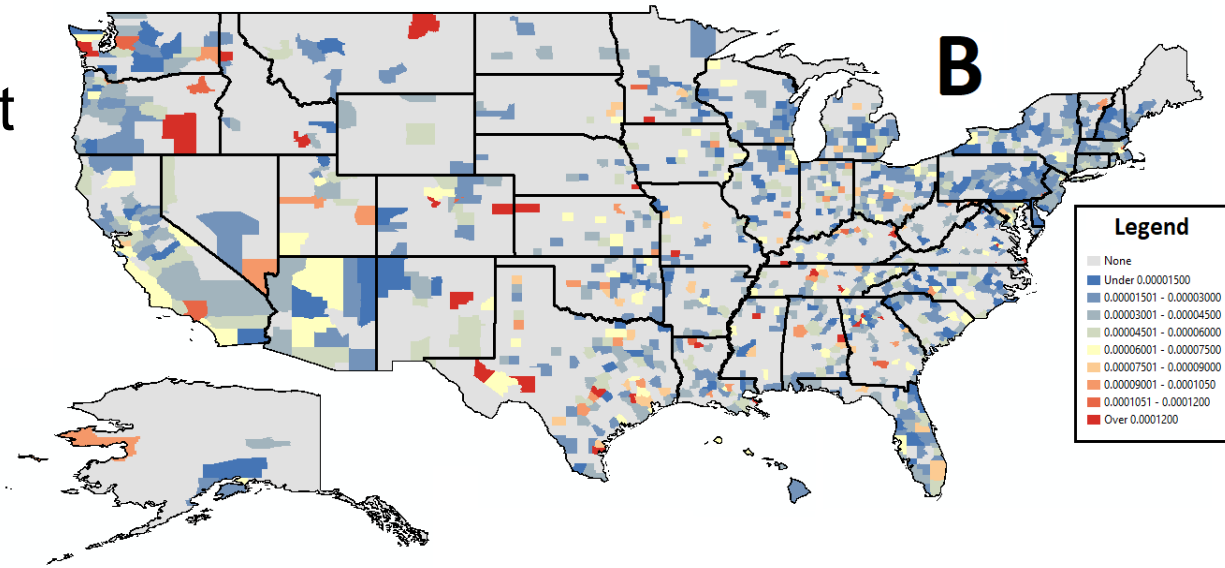
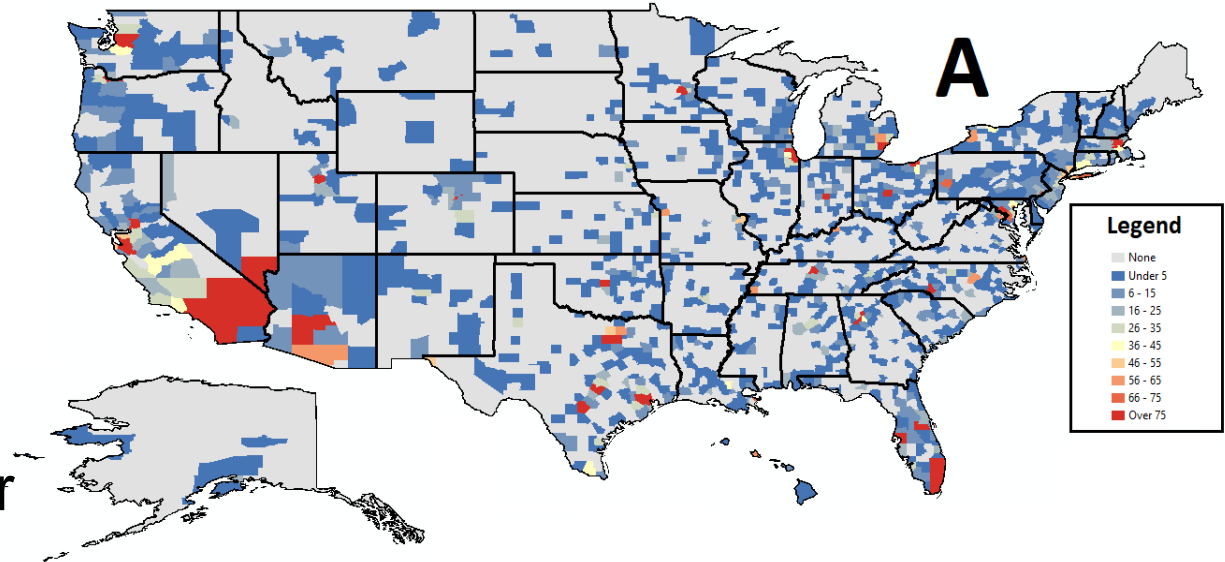
From ESRI

Results

State	Tweets per Day	Aberrant Dates						
Alabama	147			27-Mar	28-Mar			
Alaska	31							
Arizona	357							
Arkansas	49			28-Mar	29-Mar	30-Mar	31-Mar	
California	2346							
Colorado	196							
Connecticut	140							
Delaware	47							
Florida	1101							
Georgia	515					30-Mar		
Hawaii	69							
Idaho	49				29-Mar		1-Apr	2-Apr
Illinois	474							
Indiana	226							
Iowa	93							3-Apr 4-Apr
Kansas	98							
Kentucky	173							
Louisiana	215							
Maine	42							
Maryland	336							
Massachusetts	334							
Michigan	314							
Minnesota	177					31-Mar	1-Apr	
Mississippi	72				29-Mar	30-Mar		
Missouri	215				29-Mar	30-Mar		
Montana	24	19-Mar		23-Mar				
Nebraska	70							7-Apr
Nevada	214							
New Hampshire	49							
New Jersey	351							
New Mexico	72				28-Mar			
New York	1264							7-Apr
North Carolina	368							
North Dakota	15							
Ohio	450						1-Apr	2-Apr 3-Apr 4-Apr
Oklahoma	106			25-Mar				
Oregon	183							
Pennsylvania	513							
Rhode Island	47							3-Apr 4-Apr
South Carolina	169							
South Dakota	17							
Tennessee	294							
Texas	1495							
Utah	106							
Vermont	19							
Virginia	399	19-Mar	20-Mar		23-Mar			
Washington	380							
West Virginia	42						2-Apr	
Wisconsin	146							
Wyoming	8							

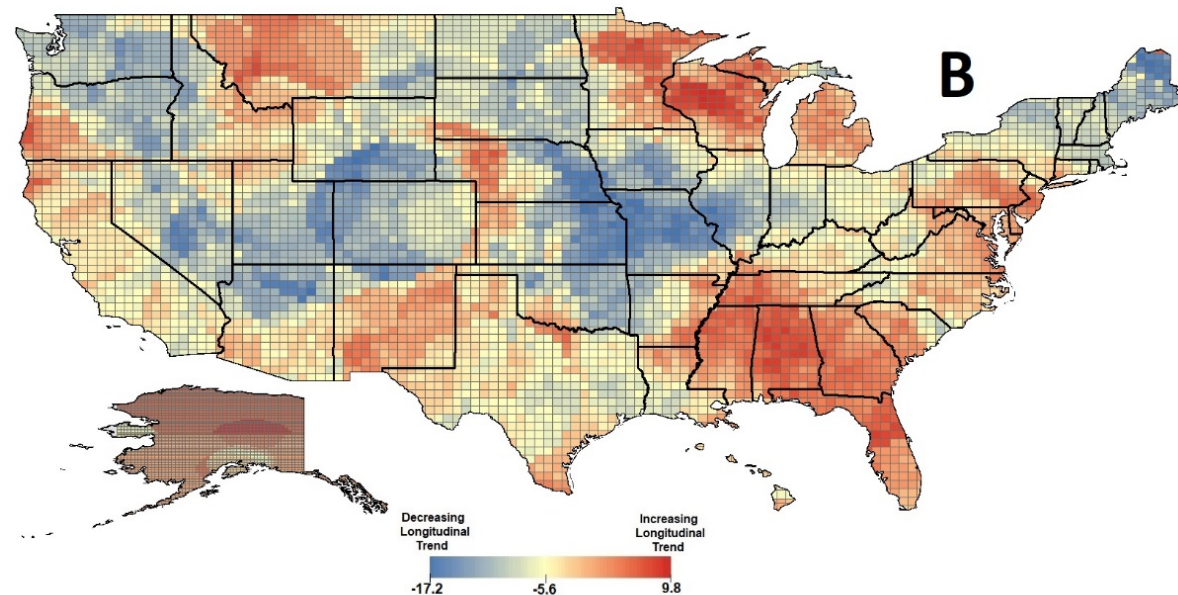
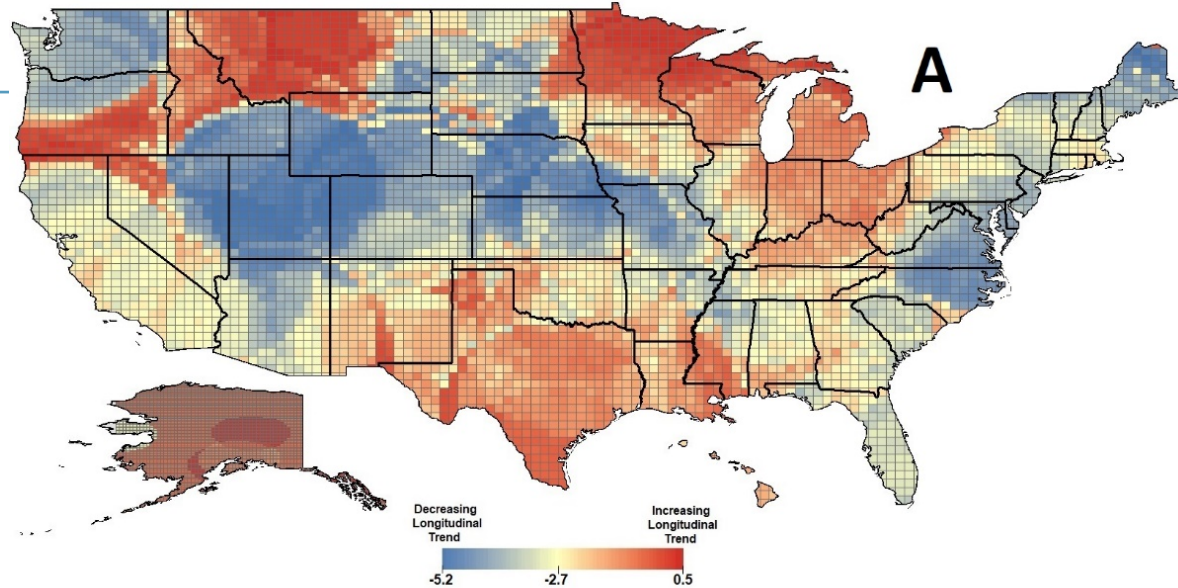
Results (2/3)

- This figure shows, at the county-level, the total number of tweets (**A**) and the population-normalized number of tweets (**B**)
- After population normalization, spatial clustering at the county level is unclear



Results (3/3)

- This figure shows, at 2500 square-kilometer intervals, z scores for the trend in hot/cold spot of total tweets **(A)** and z scores after population normalization **(B)**
- These figures suggest relatively consistency in tweets about COVID-19 from most major metropolitan areas



Discussion

- Tweet amounts:
 - 173,847,058 tweets with COVID-19 keywords globally
 - 1,244,478 of these had geospatial information
 - 698,794 were from the United States
 - 17,841 were chosen by machine learning classifier
- Longitudinal analysis uncovered a relative spike in tweets about COVID-19 around March 29th for predominantly rural areas within the United States.
- Normalized space-time cubes suggest that areas in the southeastern US had increasing trends, likely due to lower levels of engagement with the COVID-19 topic earlier in the study time period

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Conflict of Interest

The authors declare no conflicts of interest.