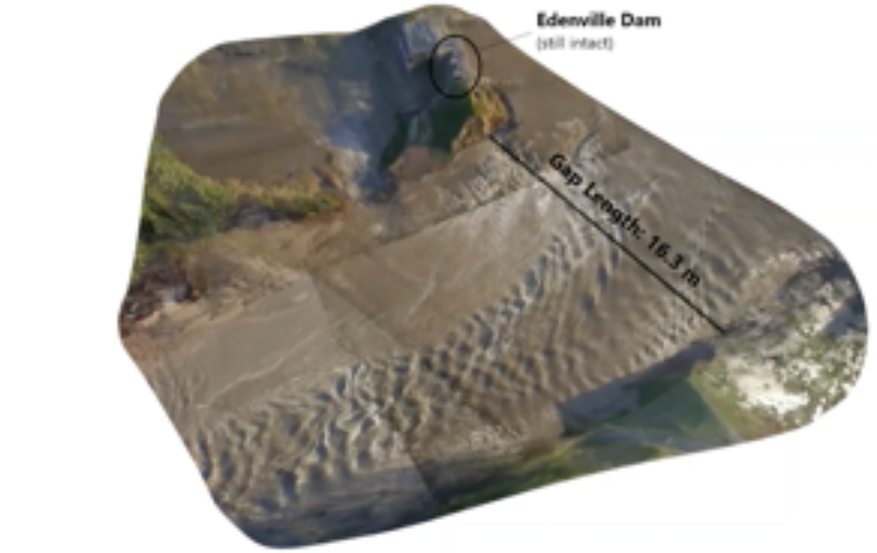
New Opportunities and Challenges for Water Research: AI, Social Media, and Flooding

Ruo-Qian (Roger) Wang

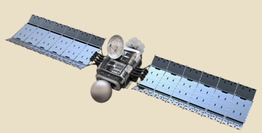
Department of Civil and Environmental Engineering, Rutgers University

1st CAWRA Webinar
July 8, 2020



Hyper-resolution Model and Existing Datasets

Hyper-resolution Urban Flooding Model



Remote Sensing

Low frequency and low resolution

Sensor Network

High cost of complete coverage

Witness Survey

Inaccurate and incomplete

Insurance Reports

Incomplete, delay and inaccesible

Social Media Data

Streamed Twitter Data:

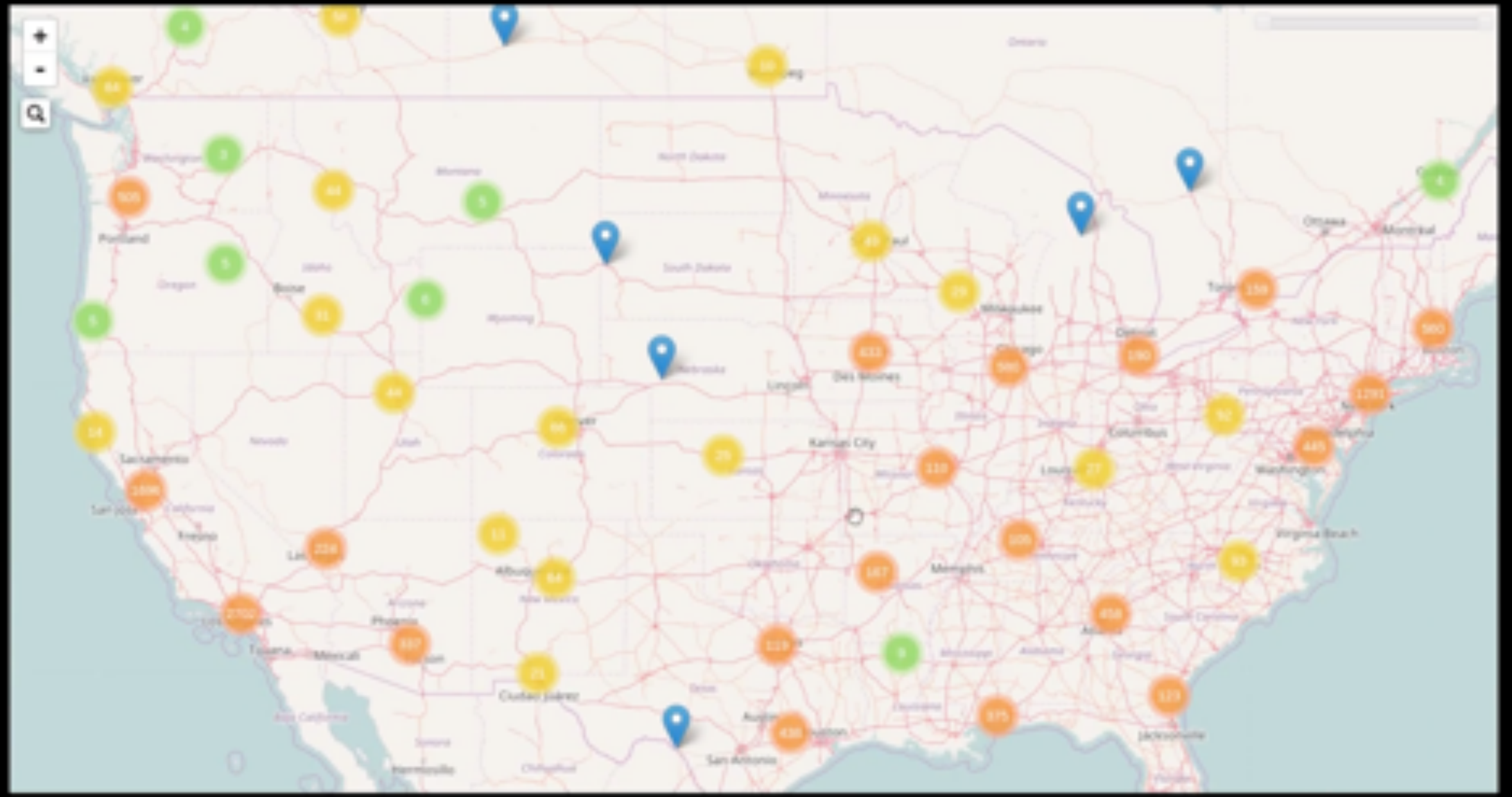
Google Geocode API

Live Map to Monitor Urban Flooding

Wang et al., *Computers and Geoscience, 2018*

START FLOODCHASER

ABOUT FLOODMAP CONTACT



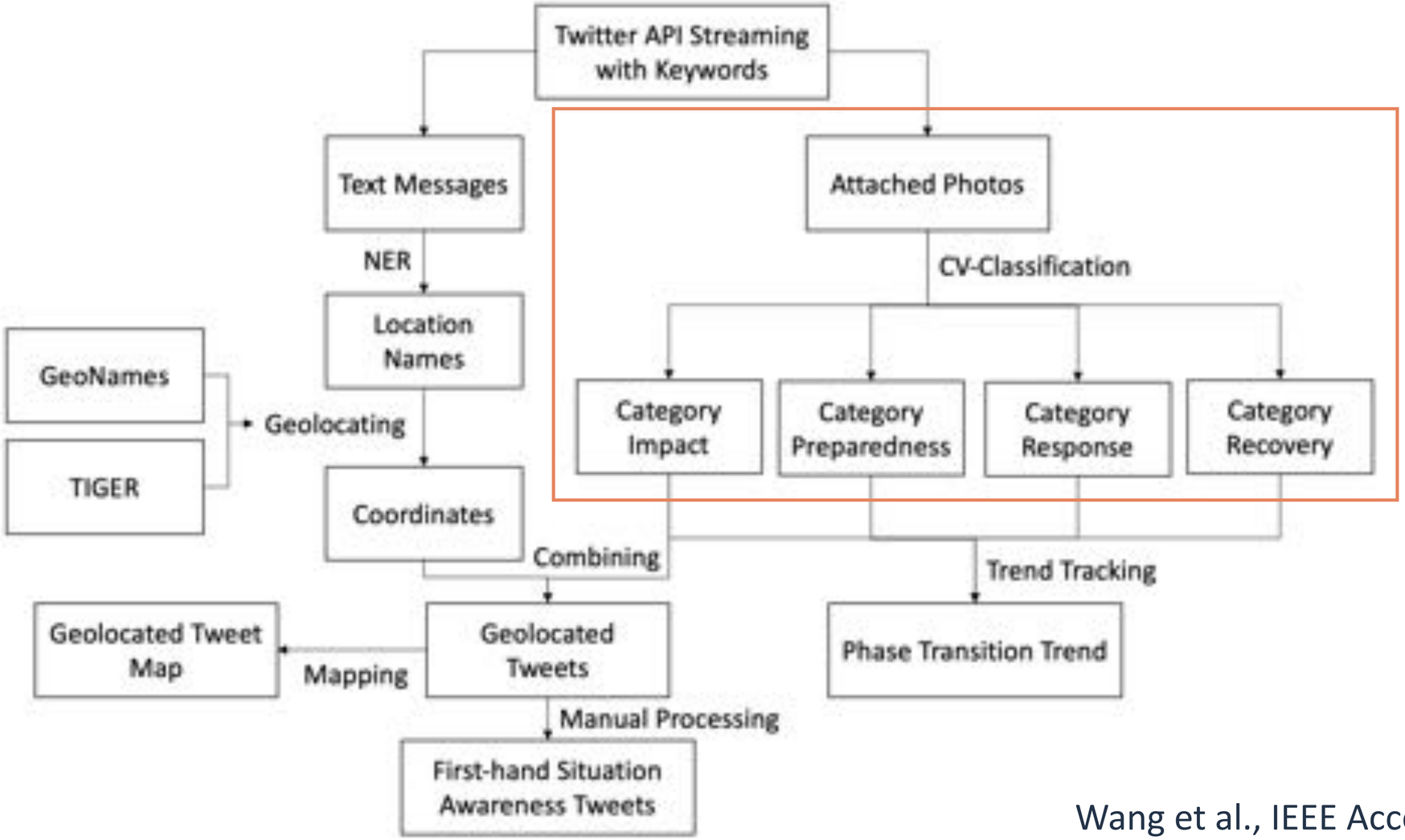
Deep Learning to enhance application of social media data in flooding management

How can we use social media data more effectively?

Hurricane Harvey in 2017

- A Twitter dataset was collected
- August 18, 2017 to September 22, 2017
- 7,041,794 tweets and retweets
- 43.2 GB data in the format of JSON
- 7537 are geo-tagged

Two types of data flow



Wang et al., IEEE Access 2020

Disaster Management Phase is used to categorize social media

- **“Preparedness, Emergency Response, Recovery, Mitigation”**
- “Caution, Advice, Fatality, Injury, Offers of Help, Missing, and General Population Information” (Vieweg, 2012)
- “Caution and Advice, Casualty and Damage, Donation and Offer, and Information Source” (Imran et al., 2013)
- “Preparedness, Emergency Response, and Recovery” (Huang and Xu, 2014)

Categorization with a keyword list

Table 1. Tweet classes and keywords during different disaster phase.

Phase	Category	Keywords	Report Information about
Preparedness	prepare	beprep, gear up, get ready, hurricaneprep, hurricanepreparation, in ready for, prep for, preparation, prepare, prepared, preparedness, preparing, prepping, readiness, ready for, sandyprep, sandypreparation, stormprep	preparation, getting ready, *etc*., without mentioning specific actions(such as heading to a store)
	plans	emergency plan	emergency plans
	shelter in place	snuggled up safely inside, stay home, stay inside, stay safe, staysafe	staying home and keeping safe
	stock up	checklist, fill up tub, frankenstorm supplies, go to *PLACE*, groceries, grocery shopping, head to *PLACE*, hurricane necessities, hurricane shop, hurricane supplies, kits, pick up *PLACE*, prep kit, sandy essentials, sandy necessities, sandy provisions, sandy supplies, sandybags, shopping, stock, stocked, stocking, storm necessities, storm supplies, survival kit, tool kit, trip to *PLACE*	actions in stocking up goods, food, tools, *etc*., in a store
	prepare for outage	candle, candles, charge power, flashlight, flashlights, generator, generators, in case of power outage	charging electrical products (e.g., phones and notebooks), or purchasing generators, candles, flashlights, *etc*., in case of power outage
	evacuation	evacuate, evacuated, evacuating, evacuation, evacuee, head away from, leave home, leaving city, police ask leave, seeking refuge, sleep outside, stay with friends	leaving the home or city, seeking refuge, sleeping outside, or staying with friends or involving police asking citizens to evacuate the potential flooding zone.
	tip	frankenstorm tip, hurricane tips, storm tip	advice for behavior during the disaster
	event tracking	crisis response map, following news, Google's map of resources and information, hurricane sandy live air travel updates, map, service alert, track, tracking, watch nbc, weather channel	monitoring and tracking the status of the disaster event by watching the news from TV or other sources

Image classification

Impact: first-hand onsite witness of flood scenes that can be found in social media only.

Preparedness: flood warnings, preparedness tips, and forwarded weather forecasts.

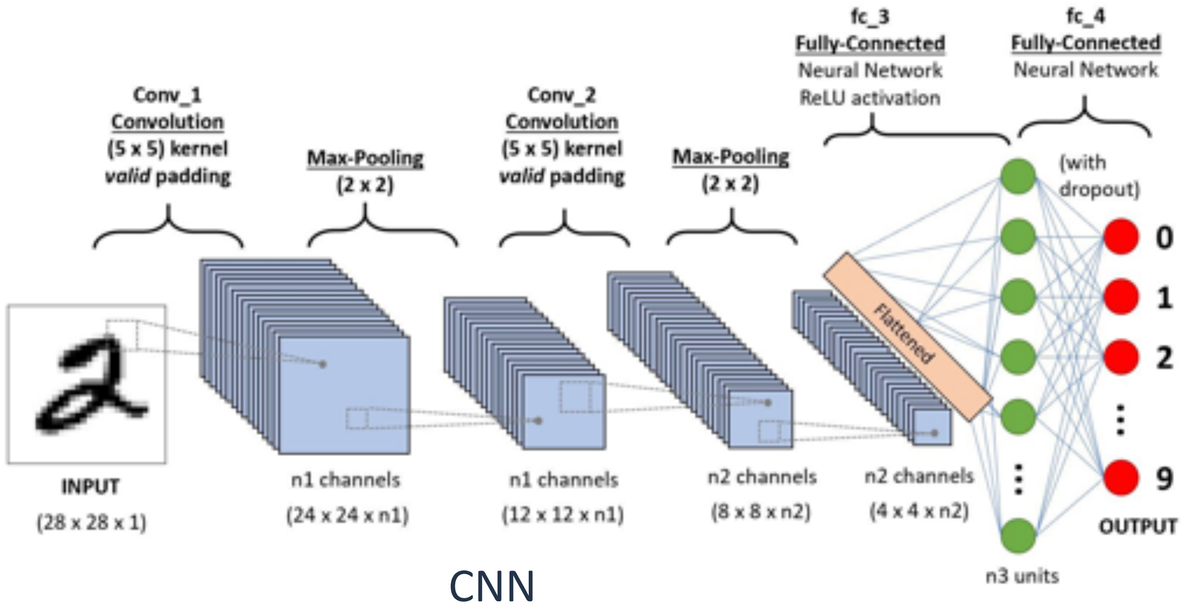
Recovery: activities about community rebuilding and flood cleaning.

Response: forwarded media reports about flood events and rescue activities.

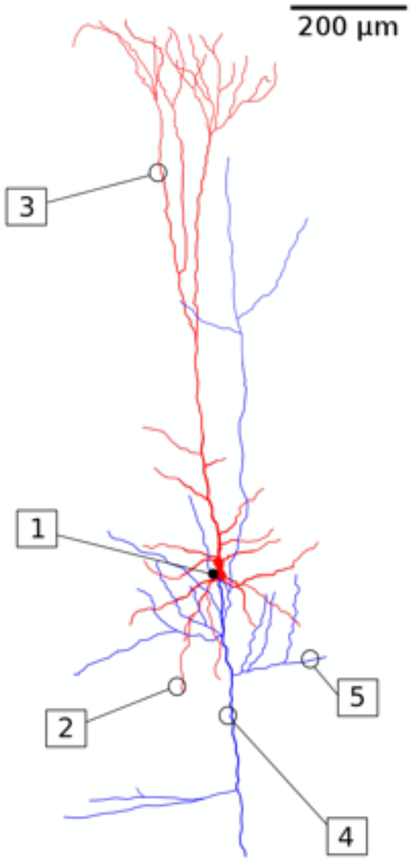
Wang et al., IEEE Access 2020

Computer Vision Schemes: CNN and ResNet

- We randomly selected 6542 images from a Twitter database
  - Impact: 4617
  - Preparedness: 772
  - Recovery: 79
  - Response: 1074



CNN



ResNet

CV performance

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

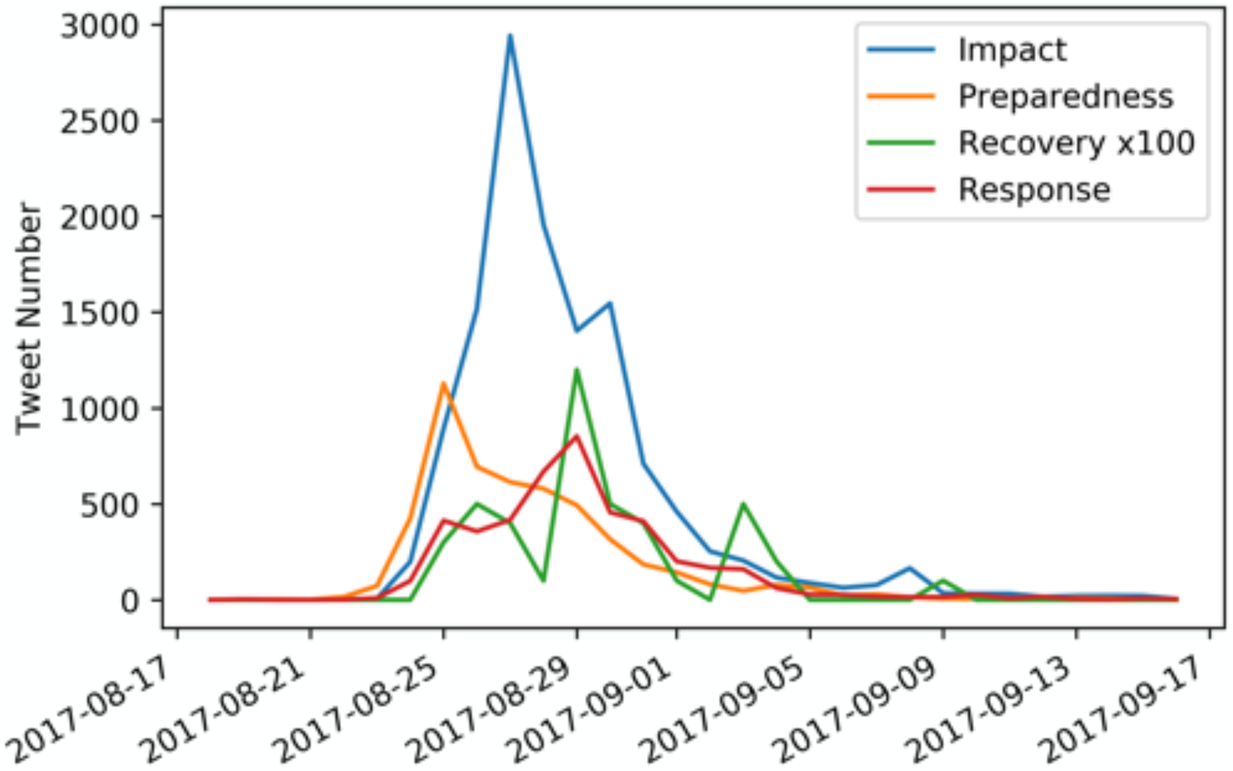
$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

TABLE 1: Computer Vision performance (P: Precision; R: Recall; F: F1-Score).

Category	Resolution 32 × 32						Resolution 256 × 144					
	CNN			ResNet			CNN			ResNet		
	P	R	F	P	R	F	P	R	F	P	R	F
Impact	0.85	0.55	0.67	0.85	0.90	0.88	0.92	0.31	0.46	0.84	0.90	0.87
Preparedness	0.65	0.58	0.62	0.67	0.64	0.65	0.24	0.70	0.36	0.67	0.67	0.67
Recovery	0.01	0.07	0.02	0.03	0.02	0.02	0.00	0.00	0.00	0.14	0.13	0.13
Response	0.28	0.63	0.39	0.53	0.43	0.48	0.24	0.62	0.35	0.56	0.39	0.46

Wang et al., IEEE Access 2020

Daily Volume Time Series

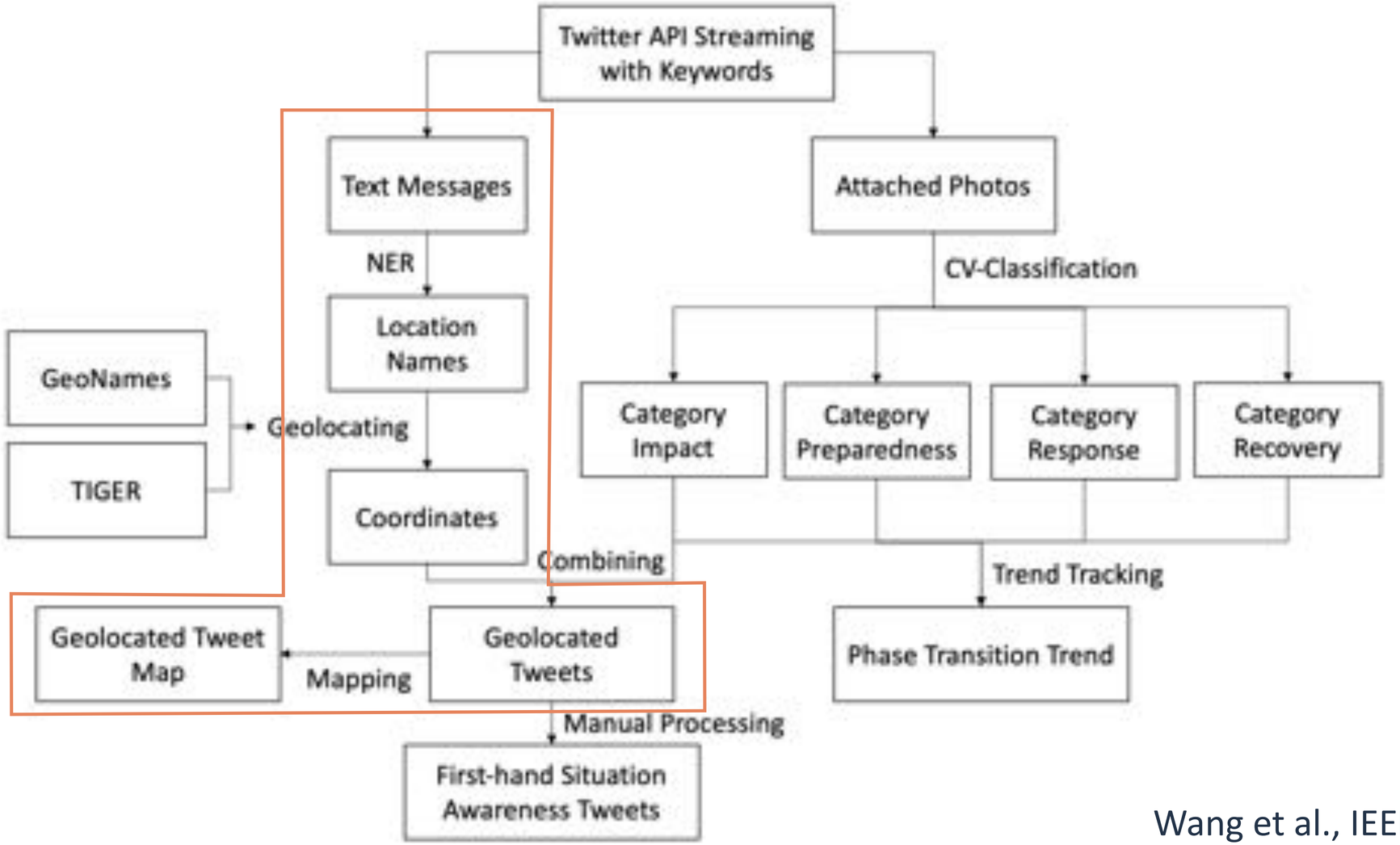


A total number of 22,390 images are classified

- 12,829 to the “Impact” category,
- 5,064 to the “Preparedness” category,
- 43 to the “Recovery” category, and
- 4,454 to the “Response” category.

Wang et al., IEEE Access 2020

Flow chart



Wang et al., IEEE Access 2020

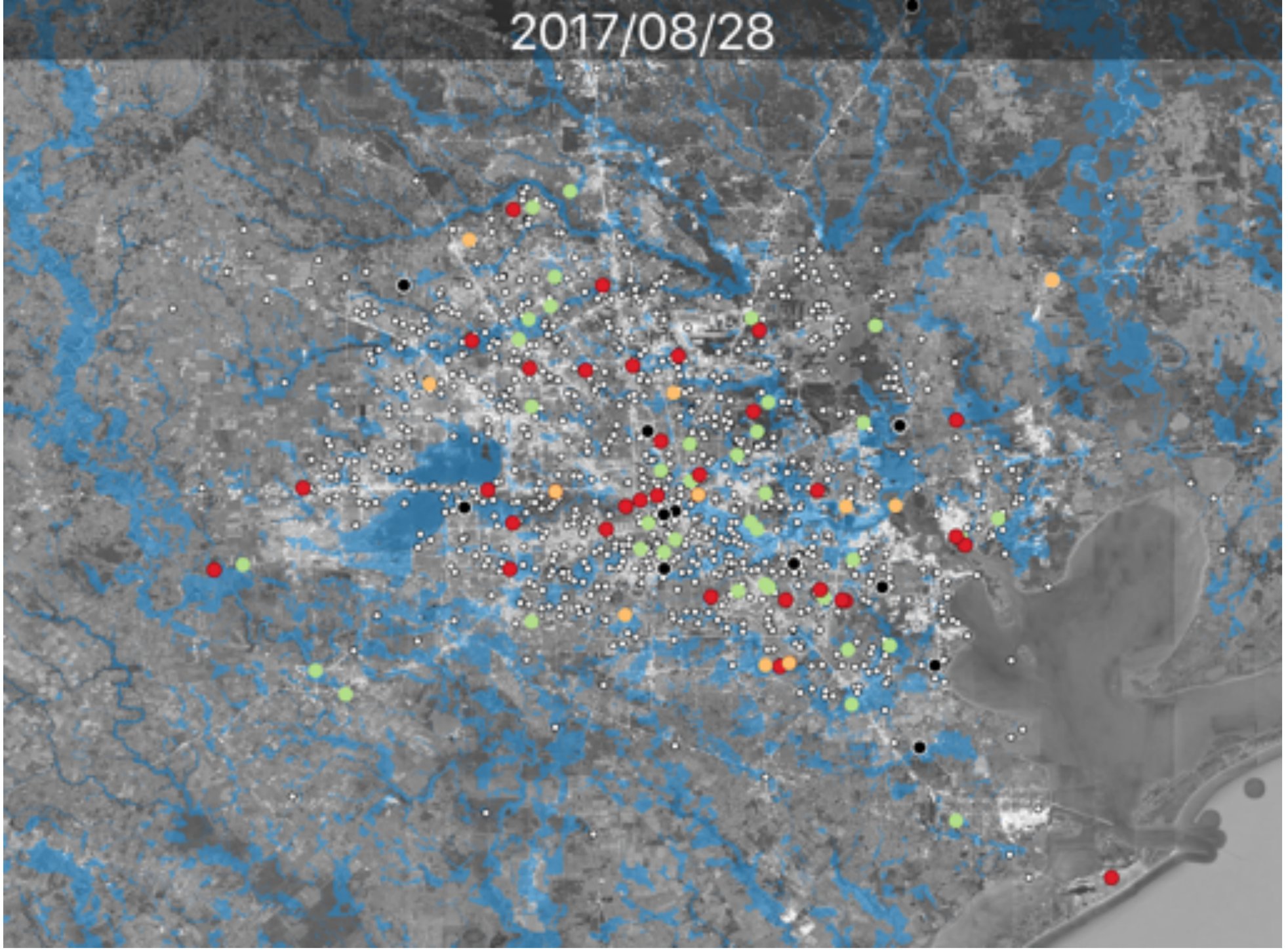
Combination of NLP and Computer Vision

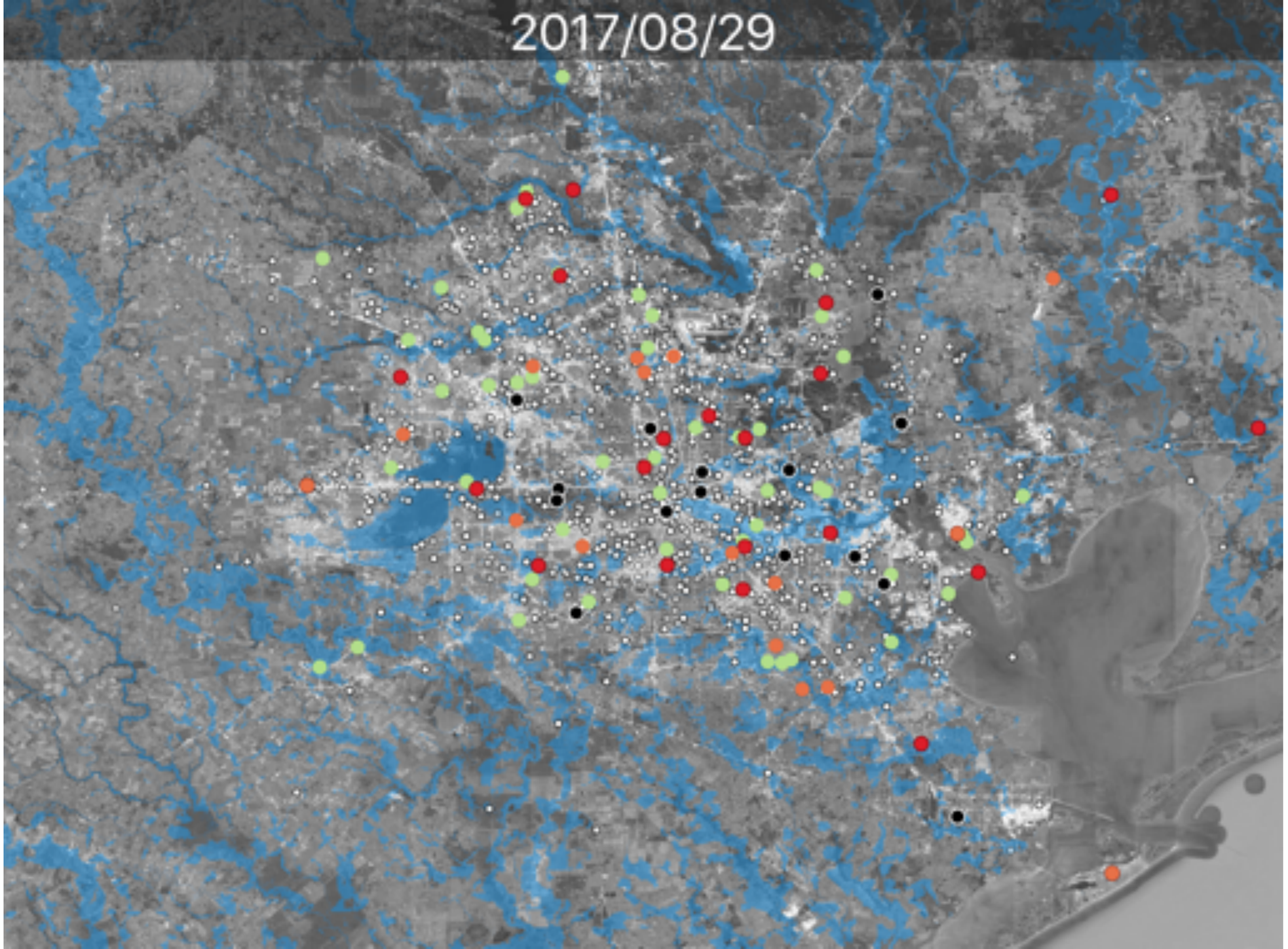
- Two location information types:
  - *Tweet-from* location
  - *Tweet-about* location

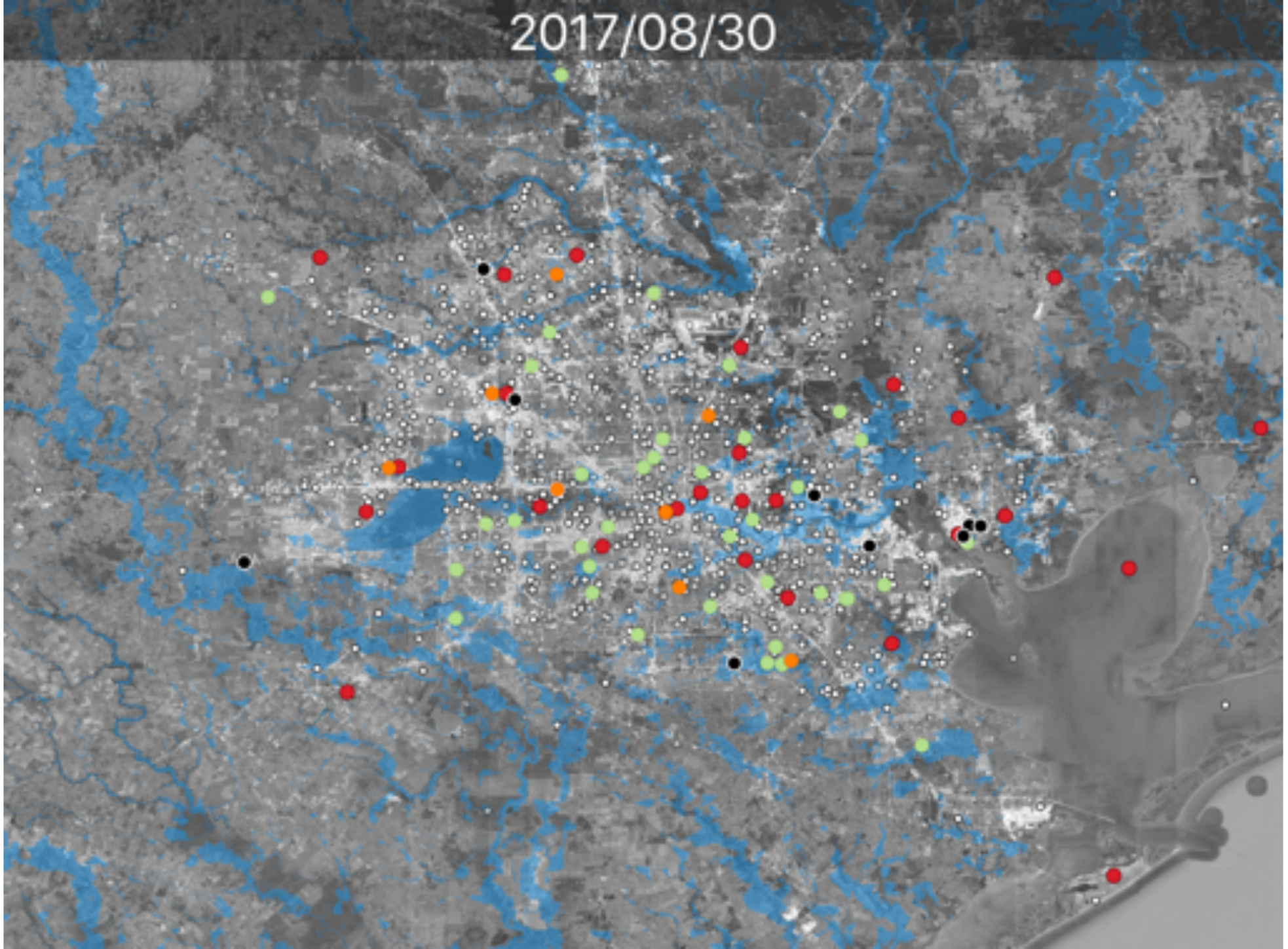
Geoparser:

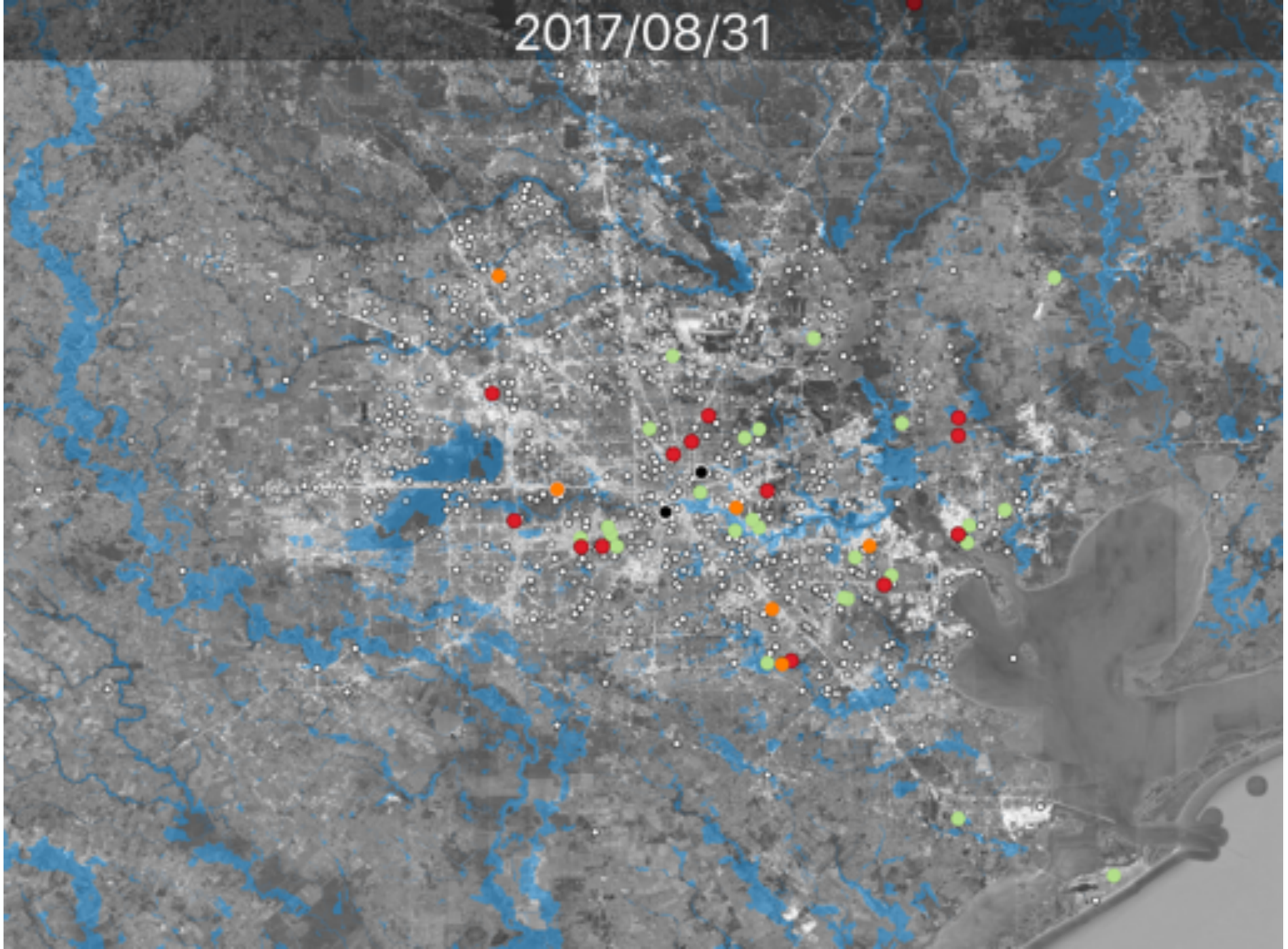
- NLP
  - Natural Language Processing (NeuroNER)
- Local Gazetteer
  - GeoNames (the most comprehensive gazetteer): city and town names
  - TIGER: road network names

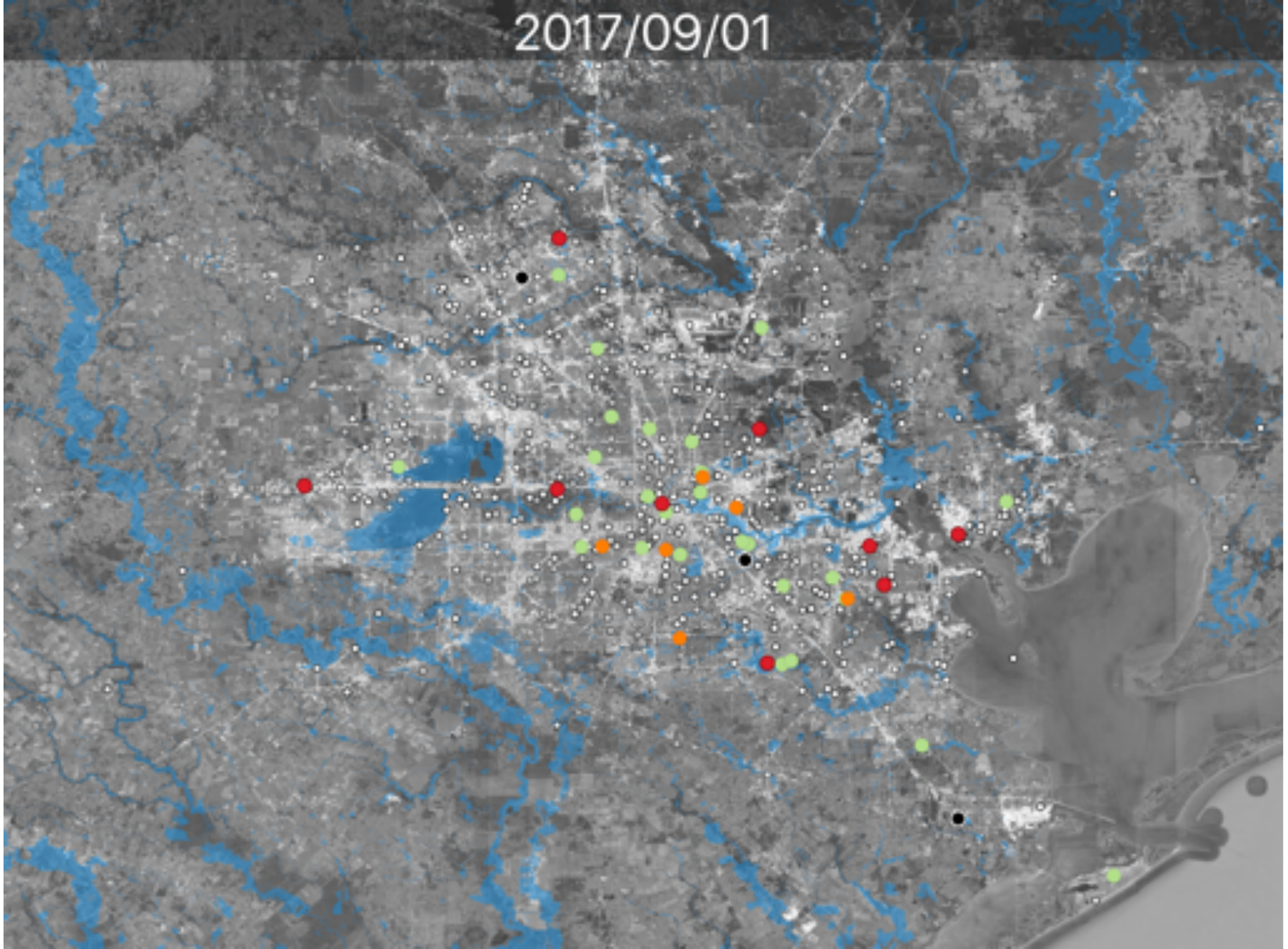
Wang et al., IEEE Access 2020

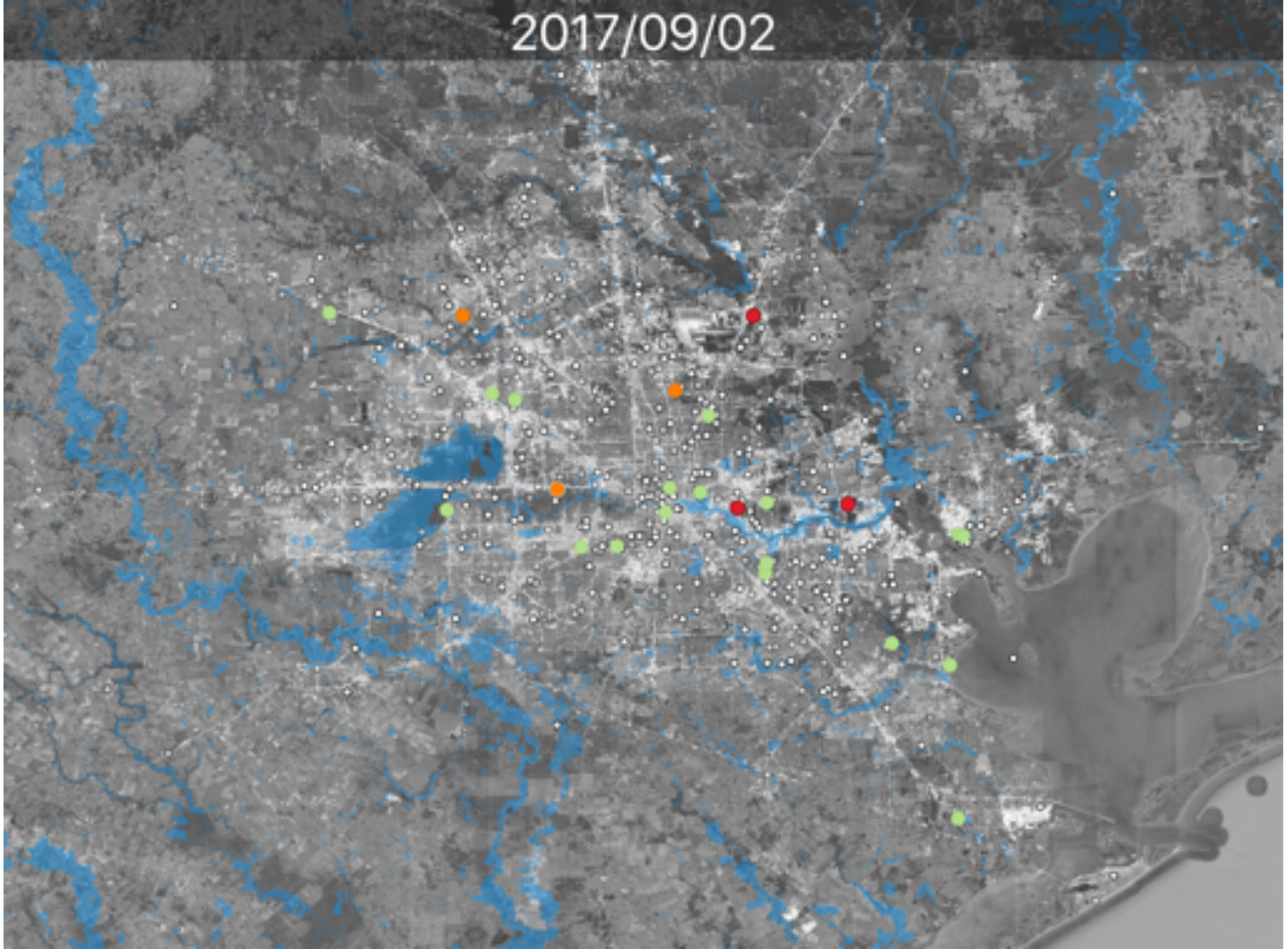

2017/08/28

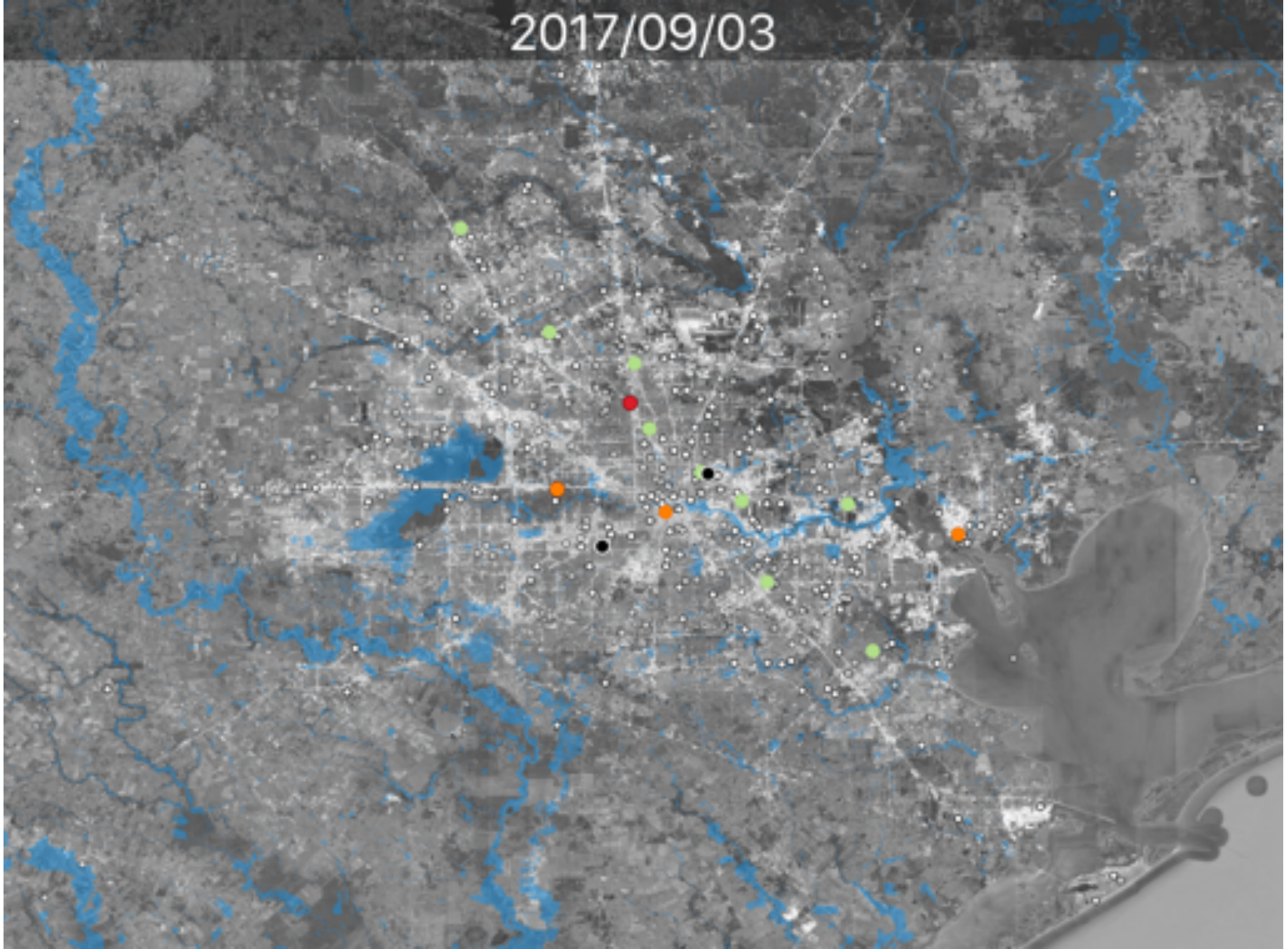

2017/08/29


2017/08/30


2017/08/31


2017/09/01


2017/09/02


2017/09/03

First-hand witness photos

- Manually picked from the “Impact” category to shrink the dataset to 698 high-value images
- Wide spectrum of emergency issues: flooding in nursing houses, flood trapped animals (e.g. horses, dogs), unusual animal presence in the city such as crocodiles, snakes, and fire-ants, the emergency of fountaining sewer manholes, road damages, and indoor floods.

Wang et al., IEEE Access 2020

Manual processing for comprehensive situation awareness and a passive hotline

High level address help shrink the pool

Wang et al., IEEE Access 2020

What's the best use of AI-processed tweets?

- High uncertainty makes mapping difficult
  - Difficult to be used to map inundation
  - Difficult to be used to calibrate and validate numerical models

- Good to
  - Capture phase transition for disaster management
  - Establish passive hotline

Wang et al., IEEE Access 2020

A recent disaster

Extracting information from almost no data

Edenville Dam Collapse

- On May 19, 2020, 5:46 p.m.
- Due to massive inflow from heavy rains in the area,
- The eastern side of the dam collapsed.
- Governor declared a state of emergency, and
- announced an investigation into the dam's operators.
- Over 10,000 local residents were ultimately evacuated during the COVID-19 pandemic.

Source: fox2detroit

Source: Detroit news

On the TV news

Final video

Please find more details at:

https://youtu.be/2KbMETrItME

or

https://www.bilibili.com/video/BV1vV411k7pU/

Announcement of ARIC 2020

ARIC 2020

3rd ACM SIGSPATIAL
International Workshop on Advances
in Resilient and Intelligent Cities
(ARIC 2020)
Tuesday, November 3, 2020
Seattle, Washington, USA



https://urbands.github.io/aric2020/

Deadlines

Paper submission: August 15th, 2020

Acceptance decision: September 15th, 2020

Camera ready version: September 30th, 2020

CAWRA

- Website: cawra.net
- To subscribe our mailing list: send email to

  Hui Rui huirui0821@gmail.com

- Looking for new webinar speakers

Reference

- Wang, R. Q., Mao, H., Wang, Y., Rae, C., & Shaw, W. (2018). Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data. *Computers & Geosciences*, *111*, 139-147.
- Wang, R. Q., Hu, Y., Zhou, Z., & Yang, K. (2020). Tracking Flooding Phase Transitions and Establishing a Passive Hotline with AI-Enabled Social Media Data. *IEEE Access*.
- Yuan, Wang, Bazzett, Padnani (2020). Unlocking data from the online footage of the Edenville Dam Failure. Submitted to GeoEx 2021, DOI: 10.13140/RG.2.2.14763.67363

Acknowledgement

Yingjie Hu (University of Buffalo)

Yixing Yuan, Huina Mao, Yuan Wang

Chris Rae and Wesley Shaw (Blue Urchin)

Kevin Yang (Union County Magnet High School)

David Bazzett (Rutgers)

Rishika Padnani (Rutgers)

Zikai Zhou (Rutgers)

Chao Fang (Toyota Research Institute)

Yuqian Zhang (Rutgers)

Cole Waterman (MLive)

Thank you

RUTGERS

MyCoast

SAGES

Scottish Alliance for Geoscience, Environment and Society