Integration of Geospatial Data: Examples & Implications

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Bureau of Labor Statistics

Location Powers: Data Science Summit November 2019

Acknowledgements

- FCSM Federal Committee on Statistical Methodology Geospatial Interest Group (GIG)
- FCSM Working Group on Transparent Quality Reporting on the Integration of Multiple Data Sources – Workshops
- Especially grateful to
 - ► Ed Strocko, Dan Flynn Department of Transportation
 - Harvey Miller, The Ohio State University
 - ► Mike Ratcliffe, Matthew Graham US Census Bureau
 - Claire Boryan, Zhengwei Yang NASS
 - Dave Hiles, Peter Meyer Bureau of Labor Statistics
 - Samantha Wotiz, Heather Strosnider CDC



Way Ahead

- Goals:
 - ► Motivate following discussion
 - Provide information on resources

- Examples of outcomes
- Issues to think about





Examples of Outcomes

- Products from integrating data sources
 - **▶** Bureau of Transportation Statistics
 - Census Bureau
 - ► National Agricultural Statistics Service
 - ► Centers for Disease Control
 - Bureau of Labor Statistics











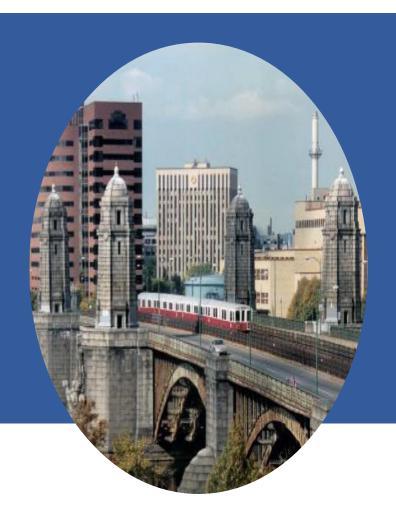


Transportation



Safety Applications of Crowd-Sourced Traffic Data

Dan Flynn, PhD Erika Sudderth, PhD





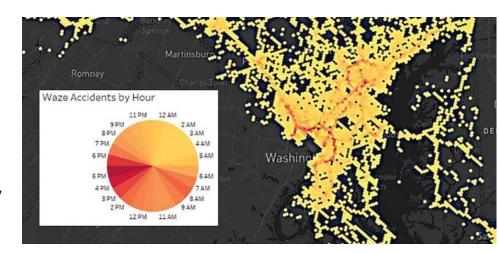
Waze Pilot Project and Case Studies

- U.S. DOT Safety Data Initiative: Integrate datasets and use advanced analytical tools with compelling visualizations to identify transportation safety risks.
 - Leverage new data sources (Waze Connected Citizens crowdsourced data) and "traditional" transportation data (roadway information, weather, police reports, ...)
- Waze pilot: Integrate transportation data to develop rapid crash indictors
 - Phase 1: State-wide indicators of police-reportable traffic crashes
 - Phase 2: State and local applications of Waze analysis pipeline
 - Tennessee: Crash propensity model to target safety risk with highway patrols
 - Bellevue: Crash risk model to inform Vision Zero action plan



State-Wide Crash Models using Waze data

- Assessed spatial and temporal relationships between Waze events and police-reported traffic crashes
- Integrated statewide Waze, traffic volume, road miles, historical crashes (FARS), demographics, and weather data for MD, VA, CT, and UT
- Applied machine learning to reliably estimate hourly police reportable crashes in four states
- Created interactive Tableau dashboards: when and where are model estimates accurate?



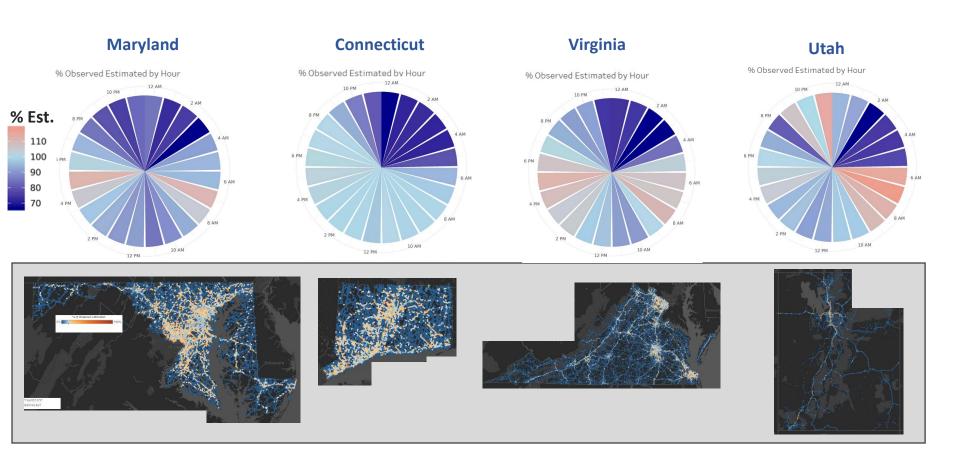
Our Waze data integration, modeling, and visualization pipeline can support nationwide studies or state and local applications

https://rosap.ntl.bts.gov/view/dot/37256

State-Wide Crash Models using Waze data – Details

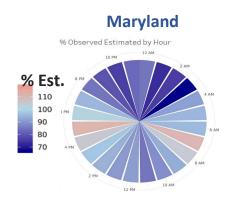
- Overall goal to assess how well Waze data can be used to estimate police-reportable crashes.
- Time scale: full year of data, 2018.
- Spatial scale: all of Maryland, Virginia, Connecticut, or Utah (separate models for each state).
- Response variable: presence of a police accident report in a grid cell, in an hour.
- Predictor variables: Counts of Waze traffic incidents (crashes, jams, weather / hazards, road closures), traffic volume (AADT), miles of roadway of different functional classes, historical fatal crashes, and census socioeconomic data.
- Method: Random Forest models trained on 70% of full data set, validated on remaining 30% of data set.

Models perform well across multiple states Variation by hour and location related to Waze coverage

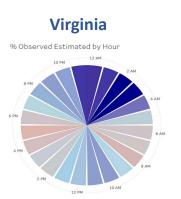


Models perform well across multiple states Variation by hour and location related to Waze coverage

- Performance varies by time and space
- <u>Time of day</u>: Models tuned towards slight over-estimation.
 - When Waze signal is weakest (e.g., 2am), the models tend to slightly underestimate the number of crashes.
 - When Waze signal is the strongest (commuting times), the models tend to slightly overestimate the number of crashes.
- **Spatially:** the dominant colors are dark blue (true zeros, Waze signal present but no Waze accident and no police-reported accident) and white (true positives) where the correct number of crashes was estimated.



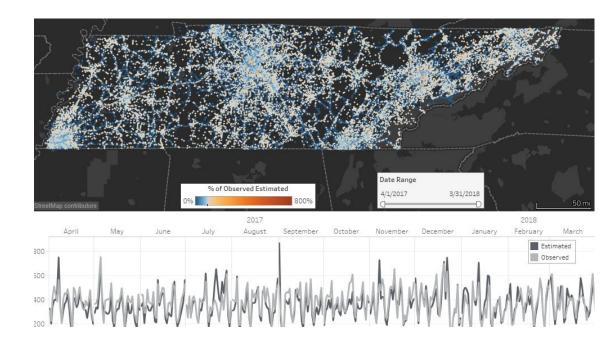






Phase II: Tennessee Case Study

- Highway Patrol uses machine learning to predict crash propensity and target patrols
- Integrating Waze data with existing grid models improves estimates
 - Spatial resolution: 42 to 1 sq mile
 - Temporal resolution: 4 hrs to 1 hr
- Results will help HP better target high crash risk locations and times

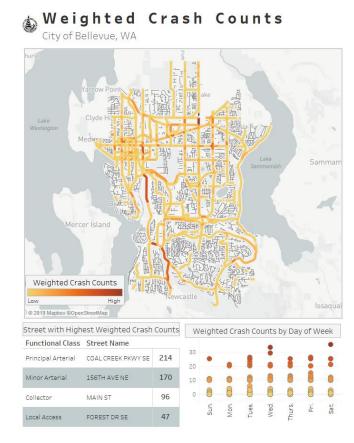


Insights – What Have We Learned?

Waze data provide important contextual information to inform state and local safety applications

- Crash models based on integrated Waze, traffic volume, job, and weather data give reliable estimates
- Tennessee Highway Patrol will more effectively target high-risk times and areas
- Crash propensity models will guide city-wide safety investment decisions

Crowd-sourced traffic data can enhance other roadway data to illuminate safety risk patterns and inform decision making





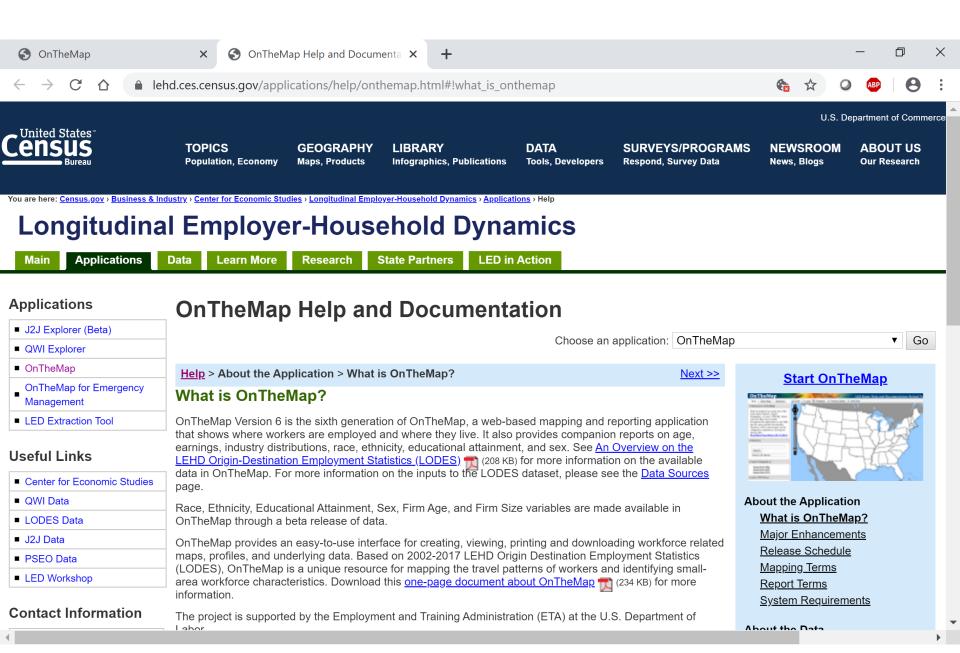
Disasters

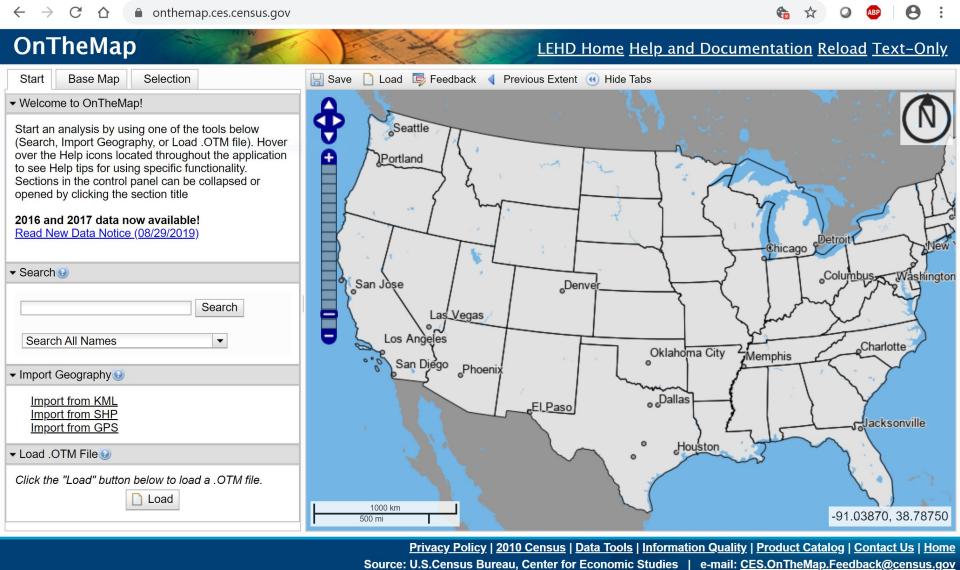


OnTheMap – Census Bureau

- A web-based mapping and reporting application that shows where workers are employed and where they live.
- Provides an interface for creating, viewing, printing and downloading workforce related maps, profiles, and underlying data





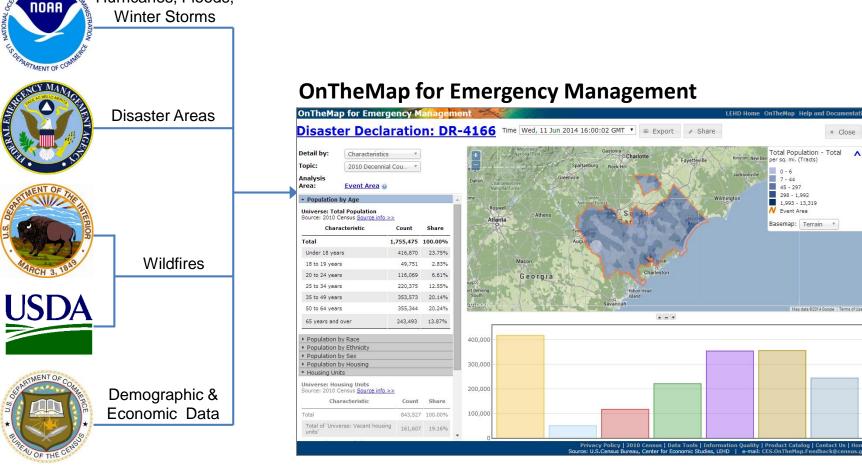


OnTheMap

https://onthemap.ces.census.gov/

Data Sources

Hurricanes, Floods,



https://onthemap.ces.census.gov/em/

Public Health

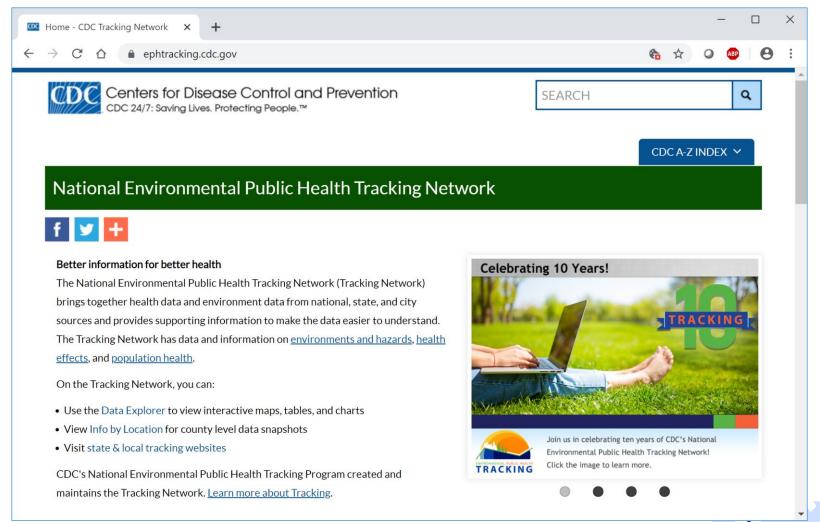


CDC Environmental Public Health Tracking

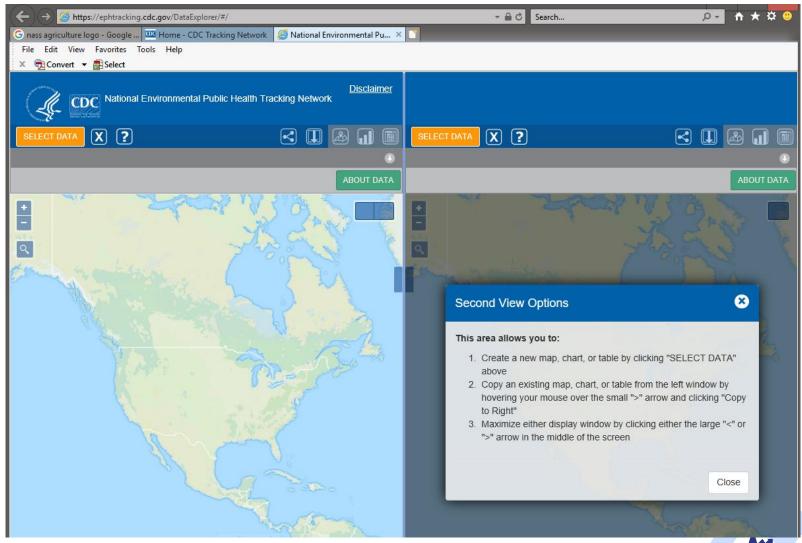
- The Tracking Network has data and information on environments and hazards, health effects, and population.
- Data Explorer: https://ephtracking.cdc.gov/DataExplorer/
- Downloadable data sets
- Data sources: national, state, and city:
 https://www.cdc.gov/nceh/tracking/data-sources-2018/data-sources-2018.html
- Brings together standardized data from multiple sources



CDC Environmental Public Health Tracking



CDC Environmental Public Health Tracking



EPH Tracking Applications

- Minnesota
 - Legislation banned smoking in almost all indoor venues
 - ▶ Tracking data quantified evidence showing decreased secondhand smoke exposure
- California
 - Concerned about nitrate in drinking water
 - ► Tracking program tool helped map water systems
 - ▶ ID areas of concern & propose remedition



Agriculture



Near Real-Time Flood Mapping of Agriculture USDA National Agricultural Statistics Service

Disaster Analysis Website:

https://www.nass.usda.gov/Research and Science/Disaster-Analysis/index.php







Nebraska National Guard

Claire G. Boryan, Avery Sandborn, Patrick Willis and Zhengwei Yang National Agricultural Statistics Service

Claire.Boryan@usda.gov





Recent Disasters – Hurricanes



FL

Hurricane Harvey, 2017

Hurricane Irma, 2017



Hurricane Michael, 2018



Hurricane Florence, 2018



Hurricane Dorian, 2019





Background

- Agricultural flood mapping and assessment are important for food security, disaster assistance, crop insurance, agricultural statistics, and decision support.
- Optical sensors, commonly used in agricultural remote sensing, are affected by cloud cover and cannot acquire useful data during the night for flood disaster assessment.
- Synthetic Aperture Radar (SAR), however, can observe the Earth day and night and through most weather conditions. This makes SAR particularly useful for flood mapping in near real time.

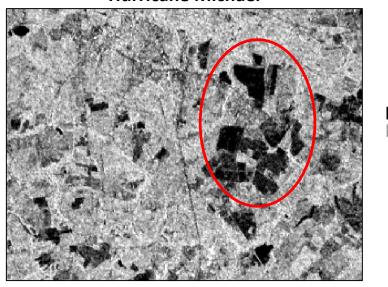




Copernicus Sentinel-1 Synthetic Aperture Radar

- Launch: 2014 (1A), 2016 (1B)
- **Instrument:** C-band synthetic aperture radar (SAR)
- Revisit Time: 6 days with 2-satellite constellation
- Operational Mode: Inferometric wideswath at 250km and 5x20m resolution
- Product Type: Ground Range Detected (GRD)
- Software: European Space Agency (ESA) Sentinel Application Platform (SNAP)
- Download: Freely available within 24 hours of acquisition on ESA site

Flooding in Greene County, NC Hurricane Michael



October 13, 2018

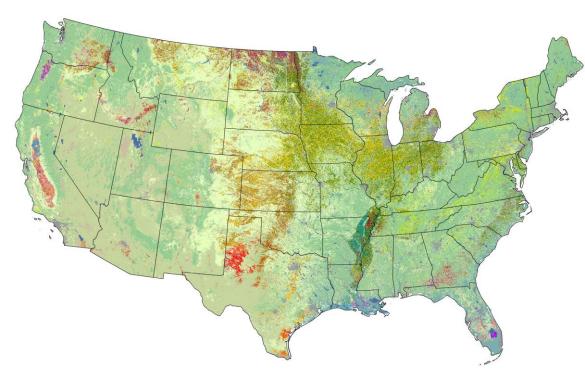
Website: https://sentinels.copernicus.eu/web/sentinel/home





Other

NASS Cropland Data Layer (CDL)



CropScape: https://nassgeodata.gmu.edu/CropScape/

- Annually released, geo-referenced, 30 meter, crop-specific land cover data set
- Produced with optical imagery from multiple satellites spanning the growing season
- Multiple versions produced during the growing season to obtain independent acreage estimates
- National scale since 2008
- The 2018 CDL was released to the public on February 15, 2019





NASS Cropland Data Layer

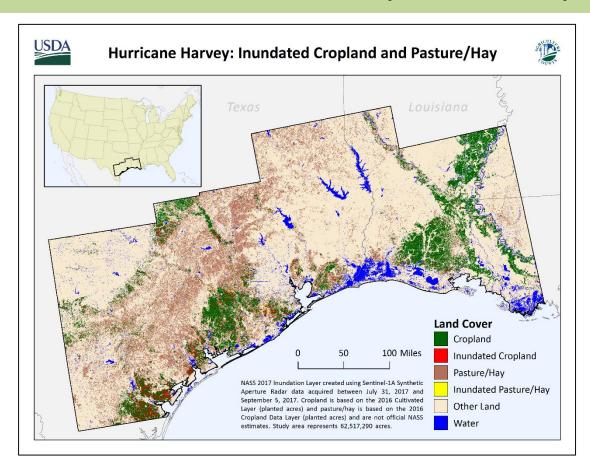
_							
1	Corn	41	Sugarbeets	73	Other Tree Fruits	227	Lettuce
2	Cotton	42	Dry Beans	74	Pecans	228	Cucumbers
3	Rice	43	Potatoes	75	Almonds	229	Pumpkins
4	Sorghum	44	Other Crops	76	Walnuts	230	Lettuce/Durum Wht
5	Soybeans	45	Sugarcane	77	Pears	231	Lettuce/Cantaloupe
6	Sunflower	46	Sweet Potatoes	80	Other Non-Tree Fruit	232	Lettuce/Upland Cotton
10	Peanuts	47	Misc. Vegs. & Fruits	92	Aquaculture	233	Lettuce/Barley
11	Tobacco	48	Watermelons	204	Pistachios	234	Durum Wht/Sorghum
12	Sweet Corn	49	Onions	205	Triticale	235	Barley/Sorghum
13	Pop. or Orn. Corn	50	Pickles	206	Carrots	236	WinWht/Sorghum
14	Mint	51	Chick Peas	207	Asparagus	237	Barley/Corn
21	Barley	52	Lentils	208	Garlic	238	WinWht/Cotton
22	Durum Wheat	53	Peas	209	Cantaloupes	239	Soybeans/Cotton
23	Spring Wheat	54	Tomatoes	210	Prunes	240	Soybeans/Oats
24	Winter Wheat	55	Caneberries	211	Olives	241	Corn/Soybeans
25	Other Small Grains	56	Hops	212	Oranges	242	Blueberries
26	Dbl. Crop WinWht/Soy	57	Herbs	213	Honeydew Melons	243	Cabbage
27	Rye	58	Clover/Wildflowers	214	Broccoli	244	Cauliflower
28	Oats	59	Sod/Grass Seed	216	Peppers	245	Celery
29	Millet	60	Switchgrass	217	Pomegranates	246	Radishes
30	Speltz	61	Fallow/Idle Cropland	218	Nectarines	247	Turnips
31	Canola	62	Pasture/Grass	219	Greens	248	Eggplants
32	Flaxseed	66	Cherries	220	Plums	249	Gourds
33	Safflower	67	Peaches	221	Strawberries	250	Cranberries
34	Rape Seed	68	Apples	222	Squash	251	Corn - Non-Irrigated
35	Mustard	69	Grapes	223	Apricots	252	Soybean - Non-Irrigated
36	Alfalfa	70	Christmas Trees	224	Vetch	253	WinWheat - Non-Irrigated
37	Other Hay	71	Other Tree Nuts	225	WinWht/Corn		
38	Camelina	72	Citrus	226	Oats/Corn		

CropScape: https://nassgeodata.gmu.edu/CropScape/





Inundation Map and Analysis



Сгор Туре	Percent Inundated				
Corn	14.54%				
Cotton	14.53%				
Fallow/Idle Cropland	9.47%				
Oats	10.39%				
Rice	7.43%				
Sorghum	25.72%				
Winter Wheat	11.45%				
Total Cropland	10.16%				
Pasture/Hay	3.68%				

Total Area Analyzed

Total: 62,517,290 acres Cropland: 7,061,403 acres Pasture/Hay: 9,448,350 acres





Disaster Analysis Website

Website: https://www.nass.usda.gov/Research and Science/Disaster-Analysis/index.php

Files Available for Download

- Maps
- Assessment reports
- Geospatial data
- Metadata
- Methodology paper







Hurricanes



BLS – QCEW

- Quarterly Census of Employment and Wages
- Serves as an establishment 'population'
- Count of employment and wages
- Covers more than 95% of US jobs
- Over various geographic areas
- Easy to download data

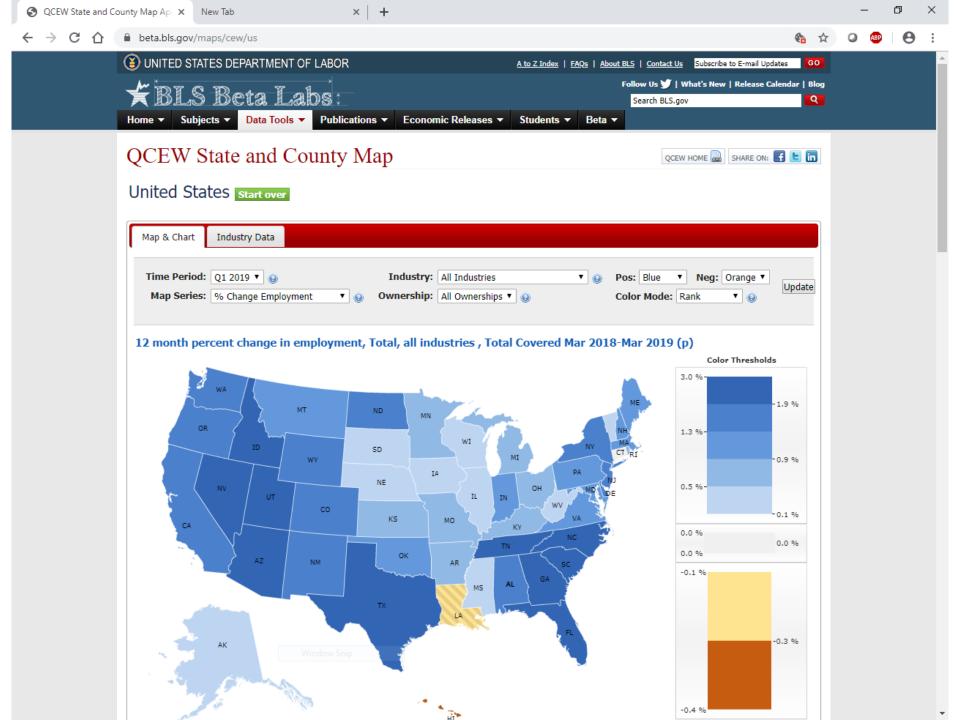


BLS – QCEW

- QCEW can construct maps & download data
 - ► Different statistics
 - ► Industries
 - Years, quarters

https://beta.bls.gov/maps/cew/us



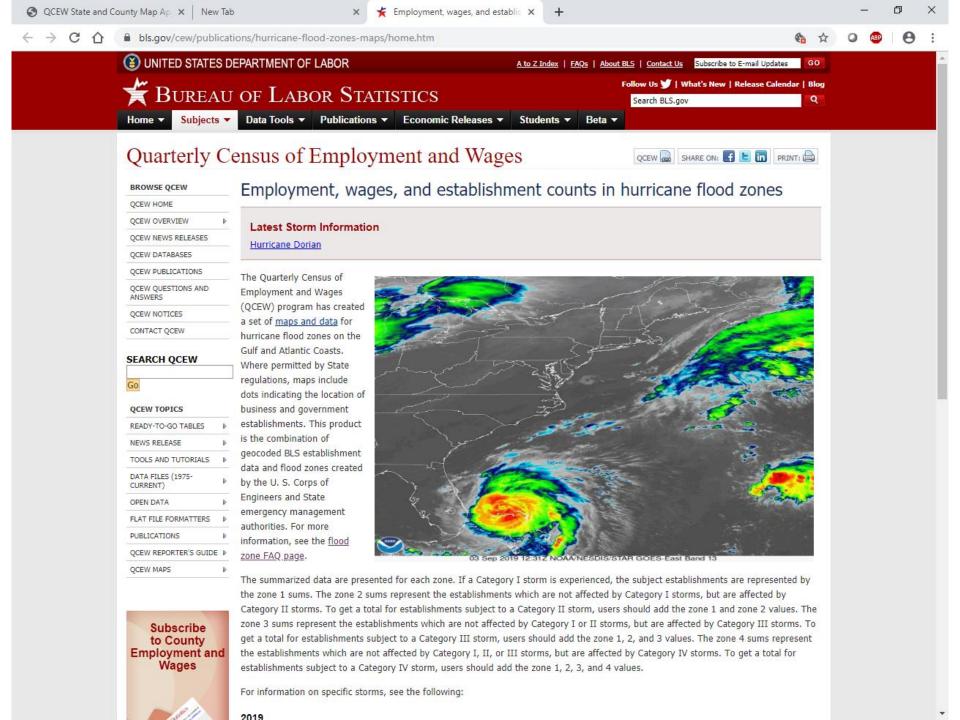


QCEW Hurricane Maps

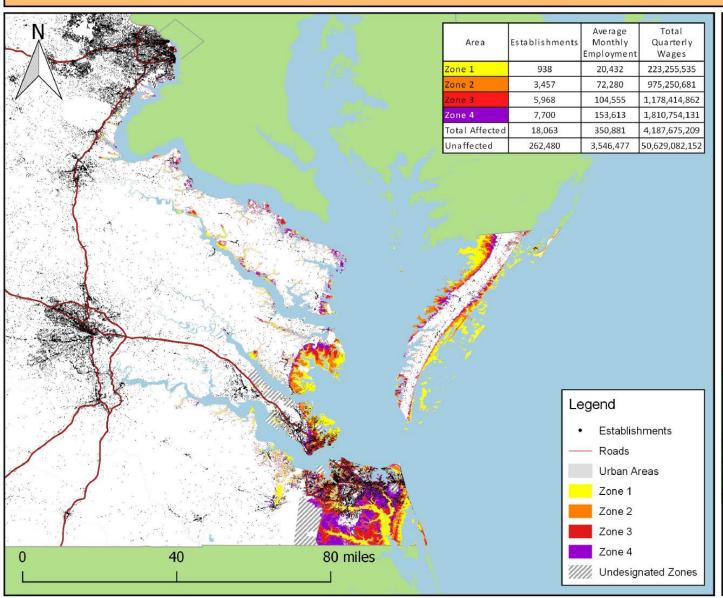
- Hurricane zone maps use Quarterly Census of Employment and Wages (QCEW)
- Show total employment, wages, & establishment counts for every county for hurricane flood zones
- Linked QCEW with data from U.S. Corps of Engineers and State emergency management

https://www.bls.gov/cew/hurricane_zones/home.htm





Employment in Hurricane Storm Surge Flood Zones, Virginia



Note: Flood zones represent a conservative estimation of areas that would experience flooding in the event of a hurricane. Zone 1 is the area that would be flooded by a Category I hurricane. A Category II hurricane would cause flooding in Zones 1 and 2. The hurricane categories reference the Saffir-Simpson Hurricane Scale.

Each black dot represents at least one establishment.

Data Source: U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages; 2018 Third Quarter https://www.bls.gov/cew

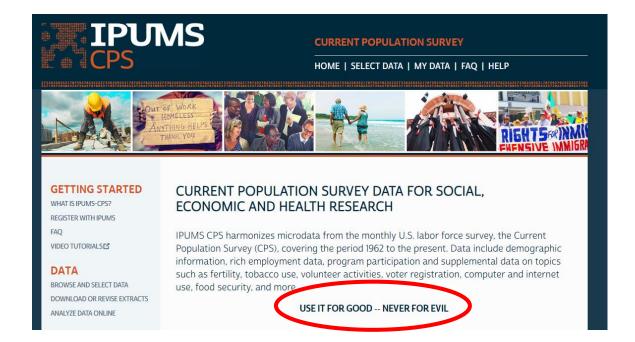
Flood Zone Source: National Hurricane Program



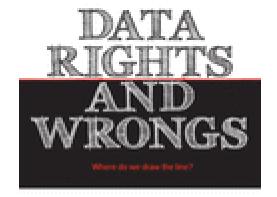


Geospatial Data Ethics

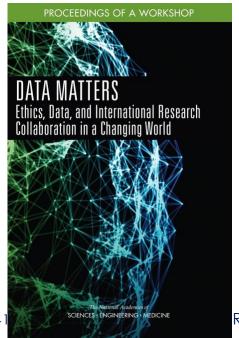














Statisticians, Data Scientists, and others...

...using our analytic skills...

Data For Goo

...on volunteer projects...

...to help people and a make better world



What is Data Ethics?

- Ethics ...
 - ► Is the study of right and wrong
 - Is the set of moral principles governing our behavior
 - ► Is often abstract guidelines
- Data Ethics is "branch of ethics ... moral problems related to data, ... algorithms, ... and corresponding practices.



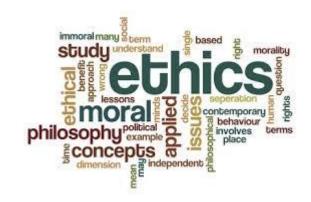
Three Axes of Data Ethics

- Ethics of Data Collection and analysis of large datasets
 - ► Re-identification of individuals geospatial concern?
 - Trust and transparency
- <u>Ethics of Algorithms</u> Increasing complexity and autonomy of algorithms (e.g., Internet of Things)
- Ethics of Practices Responsible innovation, R&D, usage foster innovation and protect rights
 - Informed consent (Web-scraping??)
 - User privacy and surveillance
 - ► Secondary use integration of data sets
 - Unintended use

https://royalsocietypublishing.org/doi/full/10.1098/rsta.2016.0360



Stories ...

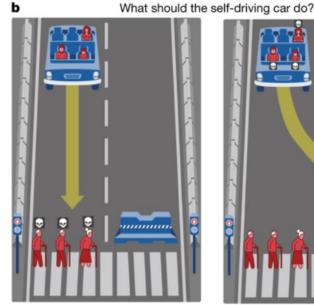


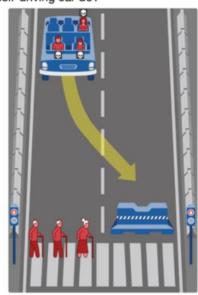
- Algorithms
 - ► Racial bias in medical algorithms
 - Underestimates health needs of sickest black patients
 - Mapping highest scores showed concentration in affluent suburbs
- Predictive policing software
 - Focus on already hotspot areas
 - Geographic profiling
 - ► Add police increase in reports
 - Resulting spike used as justification



Stories ...

- Autonomous vehicles what should vehicle algorithm do?
 - Assume accident is unavoidable
 - ► Minimize damage to car?
 - ► Save car passengers?
 - ► Save pedestrians?
- The Moral Machine
- http://moralmachine.mit.edu/







Implications to Consider



GIG Workshop on DQ – Data

- What are the unique aspects of geospatial data we should consider when determining data quality in the context of integrated data products – Inputs, Processing, and Outputs?
 - Geospatial representation
 - Error models
 - ▶ Geometry
 - ► Spatial relationships
- Emphasized transparency & metadata





GIG Workshop – Relationships

- Some critical issues when modeling & integrating
- Geometry of geospatial objects is scale-dependent.
 - What level of geometry at different scales?
 - ► How can we integrate data at different scales/resolution?
- Spatial relationships between objects
 - Overlap or inclusion
 - Direction
 - Distance



More Food for Thought

- Testing algorithms to remove inherent bias?
- How robust or sensitive are data integration and algorithms?
- Data stewardship: validation, cleaning => integration
- Geospatial technologies privacy and surveillance concerns?
 - Drones, cameras
 - Image processing software
- The Internet of Things ethical decisions?
 - Location-aware devices monitor our environment
 - Processing/algorithms in autonomous decision support systems



References & Resources



Links to Workshops

- There were a series of workshops looking at data quality of integrated products in federal arena.
- Links to slides

http://washstat.org/presentations/

■ Links to videos — see playlists

https://www.youtube.com/channel/UCblmtGTydPN4978pSy55b3A/playlists

Links to Ethics Examples

- https://www.nature.com/articles/d41586-018-07135-0
- https://www.reuters.com/article/us-amazon-com-jobs-automationinsight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-againstwomen-idUSKCN1MK08G
- https://washingtonmonthly.com/magazine/junejulyaugust-2017/code-of-silence
- https://www.washingtonpost.com/health/2019/10/24/racial-bias-medicalalgorithm-favors-white-patients-over-sicker-black-patients/
- https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/



Now for the panel ...



Some References

- Beyond Accuracy: What Data Quality Means to Data Consumers Author(s): Richard Y. Wang and Diane M. Strong Source: *Journal of Management Information Systems*, Vol. 12, No. 4 (Spring, 1996), pp. 5-33. http://mitig.mit.edu/Documents/Publications/TDQMpub/14 Beyond Accuracy.pdf
- Transparency in the Reporting of Quality for Integrated Data: A Review of International Standards and Guidelines, John L. Czajka and Mathew Stange , https://www.mathematica-mpr.com/our-publications-and-findings/publications/transparency-in-the-reporting-of-quality-for-integrated-data-a-review-of-international-standards
- National Academies of Sciences, Engineering, and Medicine. 2017. Federal Statistics, Multiple Data Sources, and Privacy Protection: Next Steps. Washington, DC: The National Academies Press. https://doi.org/10.17226/24893 or https://doi.org/10.17226/24893 or https://doi.org/10.17226/24893 or https://doi.org/10.17226/24893 or https://doi.org/10.17226/24893 or https://nap.edu/24893
- National Academies of Sciences, Engineering, and Medicine. 2017. *Innovations in Federal Statistics: Combining Data Sources While Protecting Privacy*. Washington, DC: The National Academies Press. https://doi.org/10.17226/24652



Waze Pilot: Next Steps

- Transfer data integration, modeling, and visualization approaches to state and local case study partners (grid and segment models)
 - Tennessee: Deploy updated crash propensity models with Waze data at finer spatial and temporal resolution
 - Bellevue: Transfer analytical methods and dashboard development process.
- Explore safety applications with other state and local partners

https://www.volpe.dot.gov/news/using-crowdsourced-data-estimate-crash-risk https://www.wired.com/story/waze-data-help-predict-car-crashes-cut-response-time/





Phase II: Bellevue Case Study

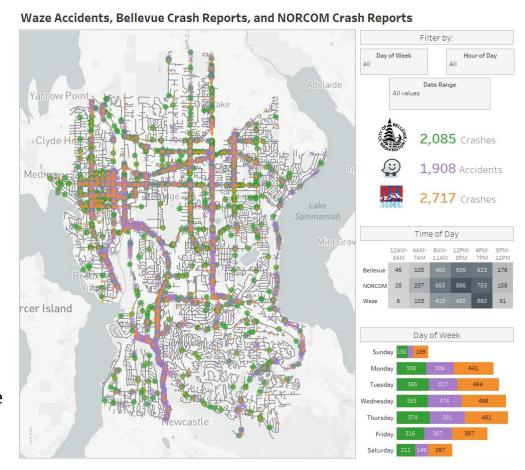
Crowdsourced traffic incident data to improve traffic safety management

Approach:

- Integrate data sources and create dashboards
- Develop crash estimation models: conditions, times, locations with high propensity
- Road-segment instead of grid-scale
- Transfer methods to Bellevue (CCP partner)

Outcomes:

- First integrated view of 3 traffic crash datasets highlights unique contributions of each by time and location
- Segment-level crash models will guide city-wide transportation safety investment decisions



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