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Pomona

Out of Sight, Out of Mind? Relationship Between Obesity Rate and Fast Food Locations in Los Angeles County

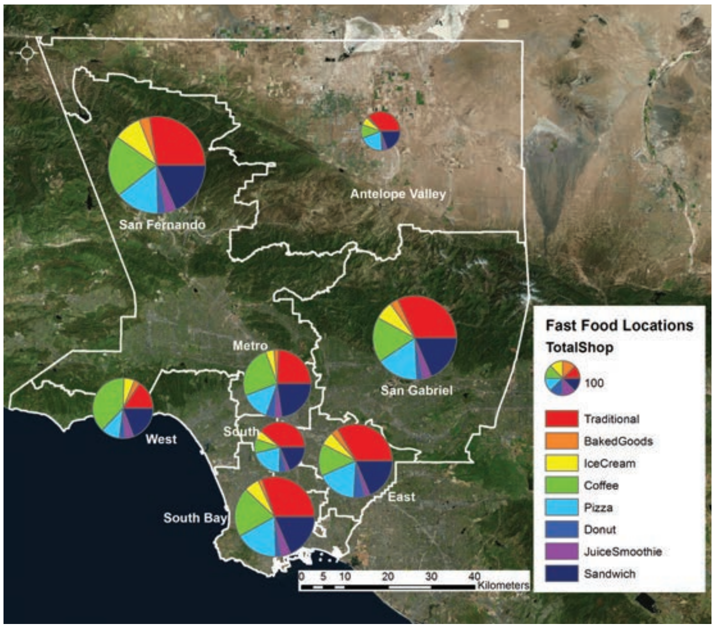

Figure 1: Distribution of fast food chain types located in 8 service planning areas in Los Angeles County in 2015 (Source from ArcGIS Business Analyst, 2018).

Los Angeles County is the most populous county in the United States (U.S. Census Bureau, 2018) and has over 3,500 fast food chains registered as active businesses (ArcGIS Business Analyst, 2018). Previous studies found that the proportion of total population to fast food restaurants is strongly correlated with state-level obesity and serious medical conditions such as diabetes, sleep apnea, osteoarthritis, and hypertension (Burgoine *et al.*, 2016; Flegal *et al.*, 1998; Kipke *et al.*, 2007; Maddock, 2004; Saydah *et al.*, 2014). We used a mixture of 29 major fast food chains with a of total 3,512 locations in Los Angeles County as of 2015, ranging from traditional fast food, pizza, donut, sandwich chains, bakeries to ice cream, coffee, and juice/smoothie shops (ArcGIS Business Analyst, 2018; Figure 1). The numbers of different types of fast food chains are analyzed in eight service planning areas (SPAs) in Los Angeles County (ArcGIS Business Analyst, 2018; Figure 2). Obese is defined by the County of Los Angeles Public Health as body mass index (BMI: in kg/m^2) over 30 and overweight as BMI over 25 but less than 30. For this study, BMI over 25 for both obese and overweight are applied and called obesity rate.

This study contributes to the spatial and temporal analysis of neighborhood fast food environments and obesity rate. Table 1 (page 10) displays that obesity rate defined as BMI of 25 and over has increased in 20 out of 26 health districts in Los Angeles County between 1999 and 2015 along with per capita total fast food sales volume in eight SPAs. Our study found that a few health districts, including Bellflower, Long Beach and the gateway cities region in Southeast Los Angeles County, increased their obesity rates more than 16.50% between 1999 and 2015. Based on fast food sales distribution, its volume and obesity rate in Figure 2 and 3 with Table 1, we observe a few cold spots, representing low obesity rate with high fast food sales per capita area such as the West SPA and high obesity rates with low sales areas per capita such as the gateway cities in Southeast Los Angeles County (South & East SPA). For the low obesity rates with high sales volumes per capita in West, the sales volume from coffee shops is the highest as of 38.92% in the entire Los Angeles County, while the sales volumes of both traditional fast food and pizza shops are the lowest as of 29.88% and 10.51%, respectively (Figure 2). Whereas, the high obesity rate with low fast food sales area per capita of South shows that its combined sales volume of traditional fast food and pizza shops is much higher at 77.28% while the sales volume of coffee shops is the lowest among all SPAs. Our correlation statistics in Table 2 suggests that obesity rate in 2015 is positively correlated with the total fast food sales volume in 2015 along with each different types of sales volume of traditional fast food, pizza, traditional and pizza combined, sandwich shops and donut shops. The correlation between obesity rate and sales volume of coffee shops of the same year yields the lowest positive relationship among all. Further research is required to investigate any relationship between BMI, fast food consumption, access to both healthy food options, and local-level public and park recreation systems in which to engage in physical fitness activities.

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INSIDE

SAVE THE DATE! Please join us at the 2019 ESRI International User Conference in San Diego, California, July 8–12.

Geographic Data Science

We live in an era of increasingly abundant data and as always the challenge is to turn these into information. Geospatial data adds substantially to this challenge, and as presented by Dony, Nara, Rey, Solem and Herman (this issue), this is pointing to the increasing need for educating a workforce trained in both geography and computational thinking, or geo-computational thinking. Geographers worldwide have been at the forefront of geographic data science research, but as these authors present, we need to do a better job preparing our students, while increasing diversity in the geospatial workforce. Given our prominent role in preparing professionals in California, the CSU should be a leader.

Geographic data are rapidly increasing in abundance and availability. Location data can come from many sources, such as GPS or other location services built into smart phones and other devices or interpreted from Twitter feeds, to add to the existing wealth of data with traditional locational sources. On top of our well-established and continually advancing ArcGIS tools, recent developments in R such as the Tidyverse (Wickham & Grolemund 2017), especially coupled with linked advances in spatial structures such as Simple Features (Pebesma 2018), have improved the accessibility and capabilities of structuring data in logical ways as well as enhancing our ability to explore and present our data in informative graphs and maps.

Geographers and others who use geospatial data are discovering new ways to approach the wealth of data sources. Big Data is one thing; big geographic data adds to the challenge, but provides opportunities. Chen, Tsou and Nara (this issue) define big data as having a size or complexity "too big to be processed effectively by traditional software." Government sources at multiple levels remain a key source for the data used in this issue, whether it's data water quality, land-cover and feed-lot permits (Alford & Perez); transportation (Chen, Tsou & Nara); or health (Huh, Abdullah & Williams) and as these authors show these can be related to business data from the fast food industry. And of course, as we've increasingly reported in this journal, we're creating our own data challenges by collecting our own imagery from drones (Wells, Monak & Patsch) and (DaSilva & Patsch), but these sources clearly help us communicate our stories graphically and journalistically.

The CSU is a big system, and as the annual issues of the CSU Geospatial Review shows, we are finding many ways to address geospatial research, in the field and in the lab. But are we doing enough to meet the challenge to prepare the next generation of geo-computational scholars?

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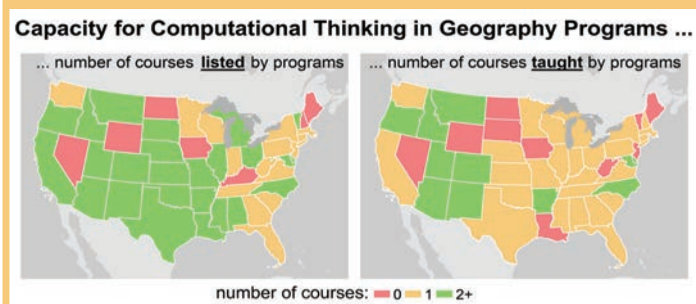
San Diego



Cartography by Hannah Ellingson
(Date: 2 April 2018 | Source: AAG Guide to Geography Programs)

Encoding Geography: Building Capacity for Inclusive Geo-Computational Thinking with Geospatial Technologies

The value and intelligence gained from geospatial innovations such as mobile Global Positioning System (GPS) is such that, in recent years, the geospatial services industry created approximately 4 million direct jobs and generated 400 billion U.S. dollars globally in revenue per year (AlphaBeta, 2017). This is the main reason for the increased demand for graduates with training in both geography and computational thinking (geo-computational thinking), but such students are hard to find. As a consequence, employers across the public and private sectors are constrained and forced to choose between hiring a geographer with limited

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or no computational skills, or a computer science graduate with limited or no expertise in geography and geographic information.

The recent democratization of manufacturing geospatial hardware (Baiocchi & Welser, 2015) is a sign that the geospatial services industry continues to innovate and grow. More importantly, these innovations will generate enormous volumes of geospatial data at even higher rates than we are already facing. We argue that the value of these spatial data will hinge on a workforce that is (1) equipped with geo-computational thinking skills and (2) is diverse and inclusive.

At the K-12 levels, we are still facing long-standing challenges with geography education. In 2015, the Government Accountability Office raised concerns that "throughout the country, K-12 students may not be acquiring adequate skills in and exposure to geography, which are needed to meet workforce needs in geospatial and other geography-related industries". At the college level, geography departments are starting to offer courses that involve computational thinking (Bowlick, Goldberg & Bednarz, 2017), but only a handful have built capacity for certificates or a specialty in geo-computation.

A collaborative effort between the American Association of Geographers (AAG), San Diego State University, UC Riverside, California Geographic Alliance, and Sweetwater Union High School District, will engage in exploratory research to help institutions understand the capacity they need to modernize geography education and to broaden the participation of underrepresented minorities in geo-computational curriculum. This two-year NSF funded project (2018-2020) will initiate the formation of a researcher-practitioner partnership (RPP) to articulate PreK-14 pathways that will expand opportunities for all students to develop spatial and computational (i.e., geo-computational) thinking skills. This pilot RPP is composed of geographers, computer science educators, social science educators and geospatial technology specialists experienced in serving underrepresented minority students and communities. Building capacity for inclusive pathways in computational geography will contribute to key instructional goals in K-12 and postsecondary institutions and increase the potential of all students to contribute to the national innovative ecosystem.

The maps on the previous page show the result of preliminary research conducted by the AAG on a selection of college geography programs to assess their offerings of courses involving computational thinking. The map on the left shows the average number of such courses in each state that are listed on a geography program's website. However, some of the courses listed in geography programs are courses offered by a computer science (or related) program. The map on the right shows the same average but only taking into account courses offered by the geography departments. These maps indicate that, although students have access to courses supporting computational thinking, they are not often taught by a geography professor. On the one hand, this may indicate barriers experienced by geography professors to teach such courses in their department. On the other hand, this may indicate barriers to learning computational thinking if it is not taught in way that would be meaningful to geography students.

This RPP will initiate the design of a long-term mixed-methods approach combining surveys with qualitative data collection to allow other regions or states to design, develop, and implement geo-computational curriculum at all educational levels. The main questions driving further research are: (1) What are barriers experienced by students, teachers, schools or departments in teaching and learning geo-computational thinking? (2) How can RPPs expand access to geo-computational education in K-12 schools?

ACKNOWLEDGEMENTS

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Identifying Concentrated Animal Feeding Operations Location and Proximity to Impaired Streams in California

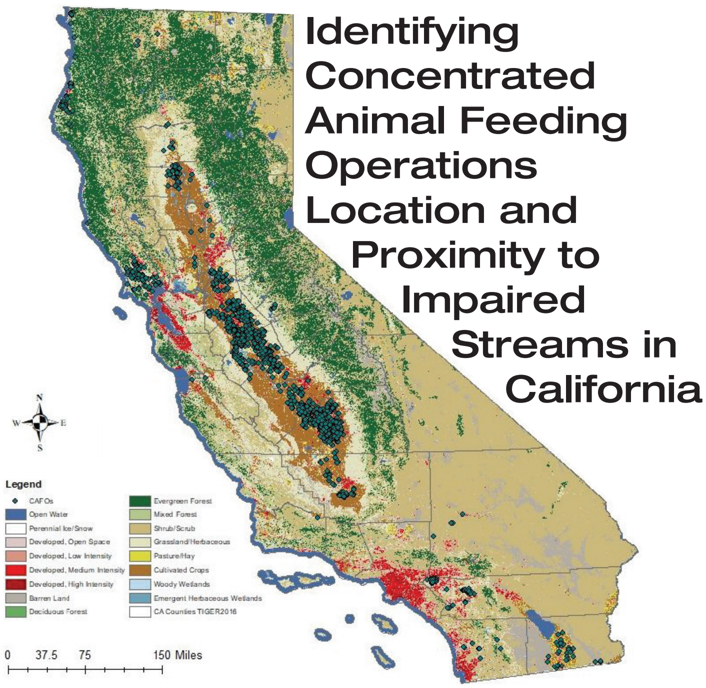

Figure 1: CAFO locations and EPA 303d Impaired and assessed streams in California in ArcGIS.

Livestock production has transitioned from pasture to large building facilities that house high densities of cattle, poultry, and swine called Concentrated or Confined Animal Feeding Operations (CAFOs) (Burkholder et al., 2007; Heaney et al. 2015; Mallin & Cahoon, 2003; Mallin et al. 2015). Waste produced by livestock in CAFOs are collected in wet lagoons or dry piles outside the facilities where it is applied on adjoining fields by aerial spray or subsurface injection. As a result, CAFO waste often introduces excessive nutrients, microbial pathogens, and pharmaceuticals to water at the application site and in surrounding waterways (Burkholder et al., 2007; Mallin & Cahoon, 2003; Mallin et al. 2015). Additionally, humans working in or living near these facilities have experienced adverse health effects including respiratory and infectious diseases from exposure to ammonia (NH_3), *E. coli* and arsenic associated with livestock waste (Hooiveld et al. 2016; Heaney et al. 2014; Liu et al. 2015; Wilson and Serre 2007). Despite these findings, Mallin et al. (2015) notes that US livestock production laws are ineffective in protecting surface water resources and related habitats.

The objective of this study is to identify and spatially illustrate the location of CAFOs in California, their proximity to impaired surface waters listed on the US Environmental Protection Agencies (EPAs) 303(d) list and communities defined as "Pollution Burden" (i.e. affected by and vulnerable to multiple pollution sources) by the CA Office of Environmental Health Hazard Assessment (OEHHA) CalEnviroScreen tool (OEHHA, 2019). Data included: National Pollution Discharge Elimination System (NPDES) Animal Feeding Facility permits, 2011 National Land Cover Data, 2016 Census Tiger County files, the CalEnviroscreen 3.0 geodatabase and EPA WATERS geospatial files. Data

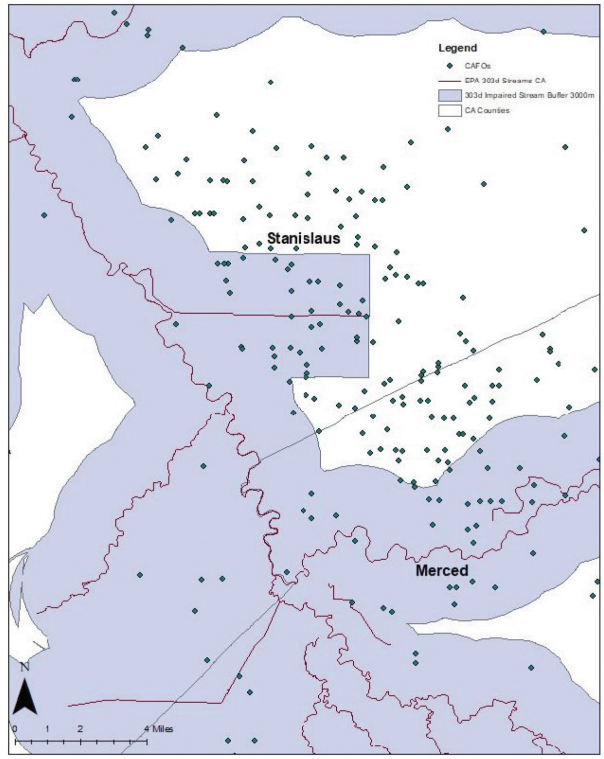

Figure 2: EPA 303d Listed Impaired Stream with a 3000m buffer and CAFOs in Merced and Stanislaus Counties, Central Valley.

Buffer Distance (meters)	100	200	300	1000	3000	6000
Cumulative Percent of CAFOs	2.5%	4.2%	7%	20.5%	47.1%	78.2%
Each buffer distance is in relations to an impaired stream. 100 meters are equivalent to 500ft, 0.67 miles.						

Table 1: Cumulative Percentage of CAFOs by Proximity to Impaired Streams.

were imported into ArcGIS 10.4.1 to create CAFO points and 100, 200, 300, 1,000, 3,000 and 6,000 meter buffers around impaired stream segments. CAFOs located within these buffers were clipped to determine the number of facilities located within a fixed distance from an identified impaired stream segment (Figures 1 and 2). These layers were spatially aligned with the CalEnviroScreen geodatabase to identify community characteristics and environmental health risk (e.g. poor air and water quality) of communities with high densities of CAFOs and impaired stream segments.

Results indicate that a majority of NPDES permitted CAFOs (78 percent of the total) are located within 6,000m of an impaired stream in California and 47 percent of the total CAFOs are located within a 3,000m of an impaired stream (Table 1, Figure 2). Although CAFOs are found within all regions of California, high densities occur in the Central Valley on agricultural land types in Tulare, Merced, and Stanislaus Counties (Table 2, Figure 2). CAFOs are also located near urban centers in Marin County, north of San Francisco, and the cities of Ontario and Chino in Southern California (Figure 1). Counties with the highest number of CAFO facilities (Table 2) were ranked in the 91-100 and 81-90 percentiles according to the CalEnviroScreen, especially in relation to poor air and water

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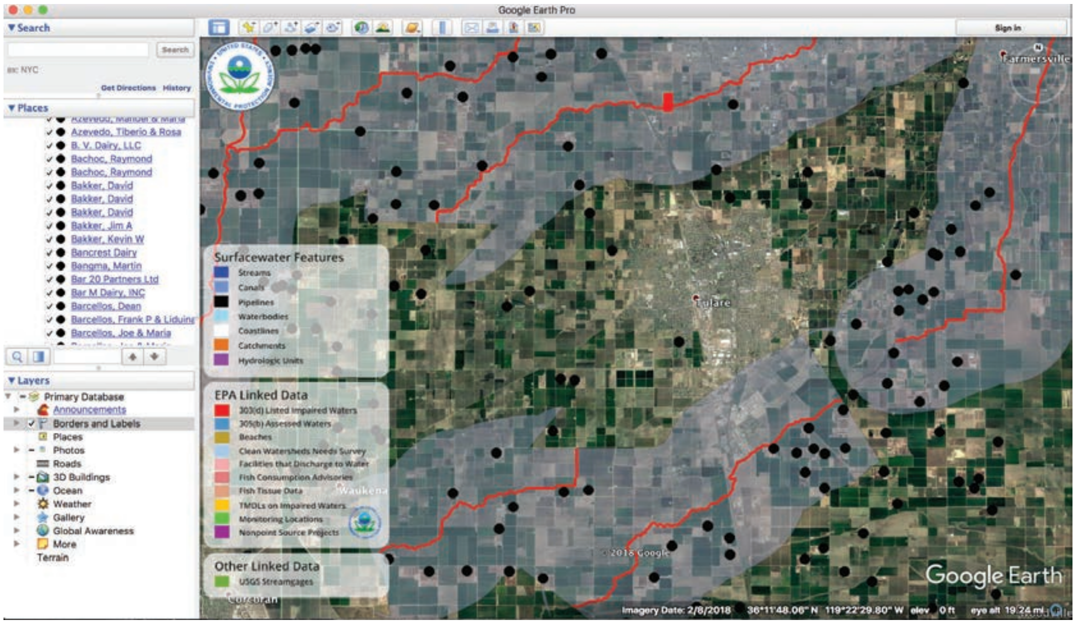

Figure 3: ArcGIS files displayed in Google Earth with 303d Impaired Streams, CAFOs and Stream Buffers.

County	number of CAFOs	Region
Tulare	306	5F – Central Valley
Merced	256	5S – Central Valley
Stanislaus	234	5S - Central Valley
Kings	175	5F – Central Valley
San Joaquin	118	5S- Central Valley
San Bernardino	87	8 - Santa Ana
Fresno	74	5F – Central Valley
Kern	69	5F – Central Valley
Sonoma	69	1 – Northern Coast
Humboldt	64	1 – Northern Coast

Ranking of Counties with the top 10 number of CAFOs with their country and respective regions.
n=1,452 CAFOs

Table 2: Ranking of CA Counties by total CAFOs.

quality metrics. In addition, these locations have populations with 16%-25% of children under 10 years of age who are vulnerable to the exposure to excessive pollution sources. Results suggests that CAFO related activities in these locations could be contributing to these environmental and public health characteristics.

Once the initial analysis was completed, ArcGIS files were converted to KML files and imported into Google Earth to provide an interactive platform for engaging stakeholders in understanding spatial relationships between CAFOs, impaired surface water resources and "pollution vulnerable" communities (Figure 3). This project is ongoing and the socioeconomic characteristics of hydrological units with high densities of CAFOs and impaired streams are being assessed. Currently, the Google Earth based files are used in course activities for students to surf their watershed and explore the spatial context of impaired streams, CAFOs and communities impacted by various pollution sources across multiple geographical scales.

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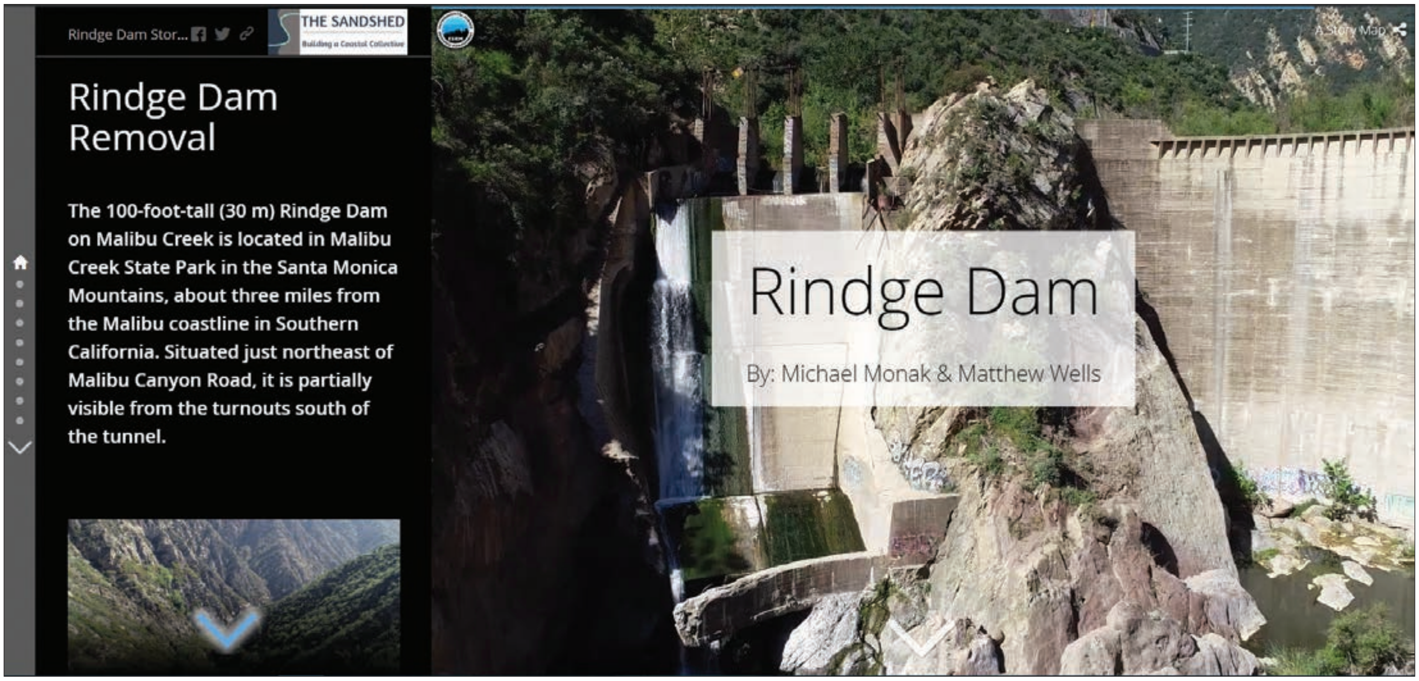

Figure 1: Aerial footage from the UAV flight was used to create an impressive launch screen for the Story Map project created by Monak and Wells.

Communicating Geospatial Science with Story Maps

Geospatial tools are becoming more powerful every day while our ability to communicate spatial information has advanced at a slower pace. Traditionally, static maps were the most efficient way a mapmaker could convey geospatial information. Like all other professions reshaped by the computer age, cartography is no different. ESRI's interactive Story Map web application is revolutionizing the way we design maps and communicate geospatial information. By incorporating interactive maps (both two-dimensional and three-dimensional), photos, videos, and hyperlinks, map makers can convey a plethora of information in a cohesive package. This multidimensional framework allows users to engage with our maps on a much deeper level and at their own pace, most often leading to a deeper connection to, and understanding of the material.

Professors at California State University Channel Islands are teaching students how to use Story Maps to create projects that communicate the findings of their geospatial research. During the spring semester of 2018, students enrolled in an intermediate GIS course taught by Kiki Patsch and Cynthia Hartley were given the unique opportunity to work hand-in-hand with community partners (e.g. CI's Facilities Services, Los Angeles and Ventura Chapters of Surfrider, Ventura Land Trust, US Fish and Wildlife, and Ventura Audubon; Table 1). Students met periodically with their community partners and provided each organization with a detailed GIS analysis furthering the research goals of their partners. Using this analysis students then created Story Maps to convey their research efforts and the mission of their partner organization to the public in a way that could be easily understood.

Working with the Los Angeles Chapter of the Surfrider Foundation, Michael Monak and Matthew Wells, two students, used a combination of GIS techniques, unmanned aerial vehicles (UAVs), and ESRI's Story Maps application to tell the complex story of the proposed removal of Rindge Dam (Figure 1) on Malibu Creek in Southern California. Constructed 92 years ago, Rindge Dam rapidly infilled with sediment, quickly rendering the dam useless and severely affecting the ecosystem functions of the 109 square mile Malibu Creek Watershed. The construction of Rindge Dam severed a once vital spawning artery for endangered steelhead trout and began depriving local beaches of badly needed sediment. The combining of geospatial analysis with new UAV technology and flying techniques allowed the students to communicate the history of the Rindge Dam, including its impact to the ecosystem of Malibu Creek watershed, reduction of sand supply to the Malibu coastline, and the controversy surrounding the current proposal for removal.

Using a DJI Phantom 4 Pro, the students were able to capture photos and video for GIS analysis as well as engaging media to articulate the background and need to remove Rindge Dam. Using structure-from-motion (SfM) photogrammetric software to process UAV images, the students created high-resolution orthomosaic aerial images, point clouds, digital surface models (DSMs), and 3D textured mesh images to communicate to readers the history of sediment impaction, and the necessity of dam removal. In addition, digital surface models illustrated elevation differences between the impacted area above the dam and the dam itself. Eleven historical aerial photos, the first dating back to 1928, were georeferenced to show the rate at which the dam initially became impacted with sediment and ceased to function, somewhere between 1960 and 1971. The students used ArcPro to run a series of analyses to develop a new watershed map and used multispectral filters to look at plant health in the riparian corridor above and below the dam (Figure 2). The students used

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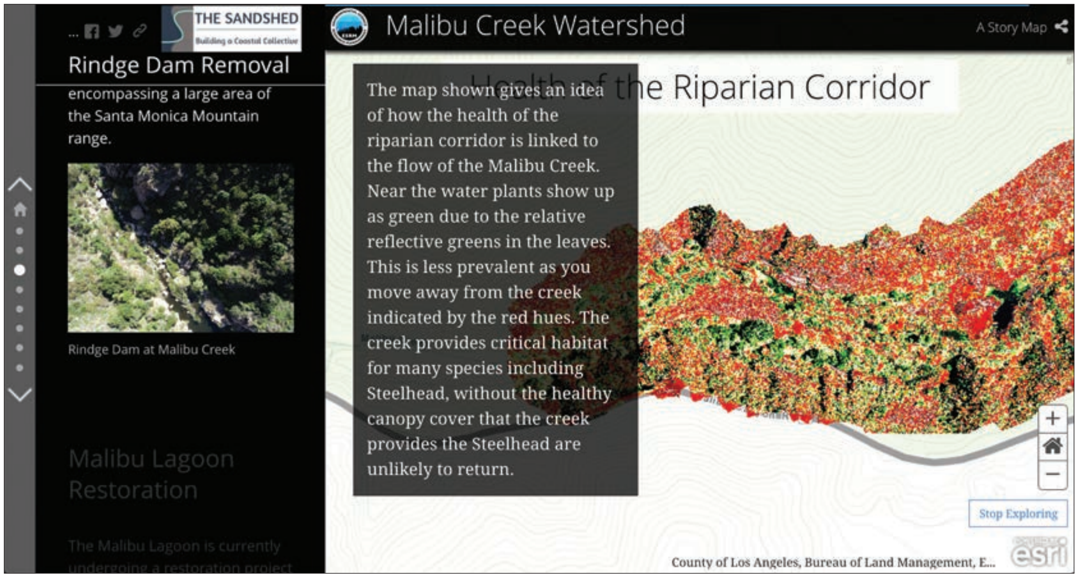

Figure 2: Analysis was done using multispectral filters to look at plant health in the riparian corridor above and below the dam.

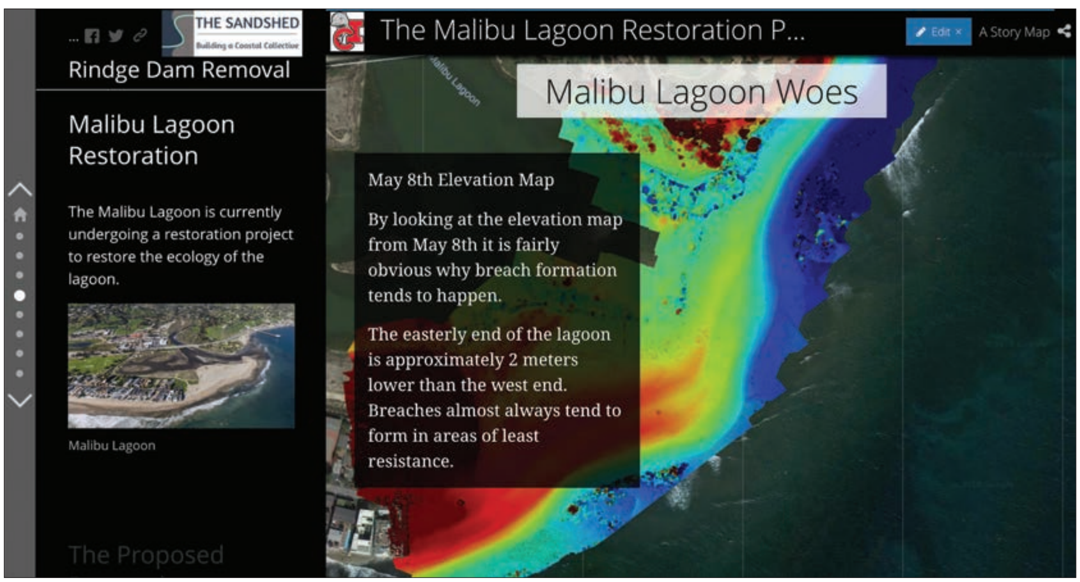

Figure 3: DEM showing changes in elevation at Malibu Lagoon barrier beach created using aerial imagery. Showing differences in Used to discuss potential impacts of Dam removal on the surrounding environment.

similar techniques to show how the beach morphology at Malibu Lagoon has been impacted by the sediment trapped upstream (Figure 3). As a result of this project, the students are now assisting a professional documentary filmmaker with imagery and GIS analyses for their film on the construction and potential removal of Rindge Dam as well as providing GIS data to the City of Malibu and The Surfrider Foundation Local Chapter on patterns of inlet formation at the Malibu Lagoon barrier beach. The complete story map can be viewed at https://arcg.is/1TSD8X.

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Determining the Efficacy of Solar Panels on Campus Rooftops using GIS, UAVs, and Area Solar Radiation Models

California now leads the U.S. in renewable energy since Jerry Brown signed “The 100 Percent Clean Energy Act” into law in early September 2018. This new law puts the state on a path to produce 100% renewable energy by the end of the year 2045 (§399.11(B)). According to the International Energy Agency (IEA), solar energy is the fastest-growing renewable source of power in the world; knowing where to get the most solar radiation can help ensure California reaches its goal. Solar radiation maps give an accurate representation of how much solar insolation any given area will have, whether a building rooftop or an open field. This helps in estimating the theoretical kilowatt-hours (kWh) an area could provide with solar panels, which in turn helps in determining the best placement for a new energy system.

California State University Channel Islands (CSUCI) prides itself on being a green campus and received a Gold STARS (Sustainability Tracking, Assessment, and Rating System) rating. CSUCI has taken great steps towards sustainability with their hydration stations, multiple recycling bins across campus, rain barrel systems, and “Green Screens” that display sustainability content on campus. The next major step is to adopt renewable energy. This will help reduce the university’s net greenhouse gas emission and foster climate literacy across the whole campus. In 2017, CSUCI used an average of 943,842 kWh of electricity and usage is expected to rise annually due to its increasing student body. ESRI’s ArcGIS software can help determine where on campus the most kWh can be obtained with efficient solar panels.

Focusing on the suitability CSUCI building rooftops, unmanned aerial vehicles (UAVs, or drones) captured a sequence of images of our newest campus building, Sierra Hall. These aerial images were processed using structure-from-motion (SfM) photogrammetry software, PIX4D, to generate 3D point clouds, digital surface models, and orthomosaic images as well as rasters for aspect and slope for the rooftop outlines. Using the generated rooftop data, GIS tools allow us to process an Area Solar Radiation (ASR) analysis, which quantifies solar energy potential using atmospheric effects, site latitude, elevation, slope, aspect, daily and seasonal shifts of the sun angle, and the effects of shadows cast by surrounding topography. In order to provide a good range of the amount of solar insolation a building can get, which varies seasonally depending on the daylight hours, two ASR analyses were run simulating one day in the middle of summer, July 2 (Figure 1), and one day in the middle of winter, December 21 (Figure 2), which is the winter solstice.

To determine the total solar kWh possible for a given area on a given day with the installation of solar panels on Sierra Hall, the surface area of the rooftop, 731.12 m^2 was multiplied by the converted kWh/m^2 solar radiation of the rooftops given from the ASR maps and then multiplied by an efficiency coefficient (Table 1). Solar panel technology is advancing quickly and becoming more efficient as new technologies are discovered and implemented. Currently, the most efficient solar panel converts 22.5% of solar radiation into actual energy and considers the standard test illumination for photovoltaic modules, temperatures effects, and cable and inverter losses (Aggarwal 2018). These calculations can aid in determining if a solar panel system would be cost-effective on any particular building.

The 2017, CSUCI paid a monthly average rate for electricity of $0.30 per kWh. Sierra Hall used an average of 46,371 kWh per month, which means the electricity cost of Sierra Hall was nearly $14,000 per month. According to the calculations derived from this project, in the month of July, Sierra Hall could generate 29,578 kWh of energy if solar panels covered the measured surface area. Thus, only 16,793 kWh, on average, would need to be bought directly from the utility at $0.30 per kWh, or roughly $5,000. This would provide a savings of approximately $8,800 per month just for Sierra Hall alone.

Determining the best placement and potential solar energy an area provides can further be refined by having accurate geospatial data, which in this study was gathered using innovative UAV technology. The size and efficiency of particular solar panels option will help quantify the actual energy generated and assist in the decision to choose this green-energy option. In addition to saving campuses money in the long run, utilizing solar energy across California State University campuses will reduce greenhouse gas emissions. ASR maps can provide architects with the most optimum locations for small- and large-scale solar systems and even help in the decision of what kind of system would be most cost-effective for the given area. In addition to rooftops, many open areas and hillsides can be analyzed for solar insolation thus further expanding the abilities of this geospatial tool.

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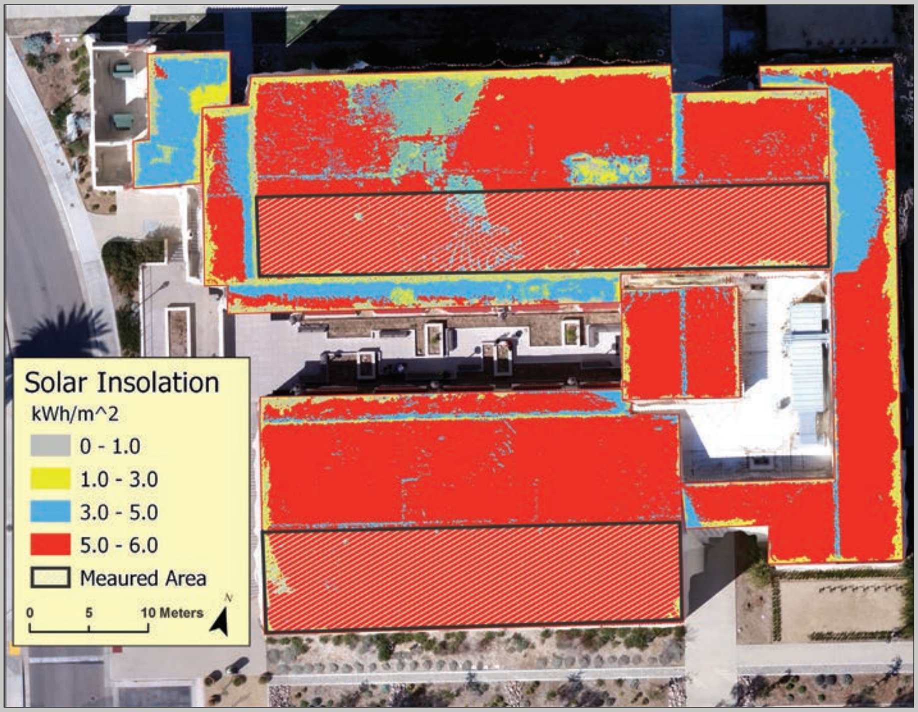

Figure 1: Predicted solar insolation (in kWh per square meter) for Sierra Hall on July 2. This Area Solar Radiation (ASR) map shows an abundance of solar insolation in the middle of summer. With proper battery usage, excess energy can be stored for use during cloudy days (which are limited in southern California).

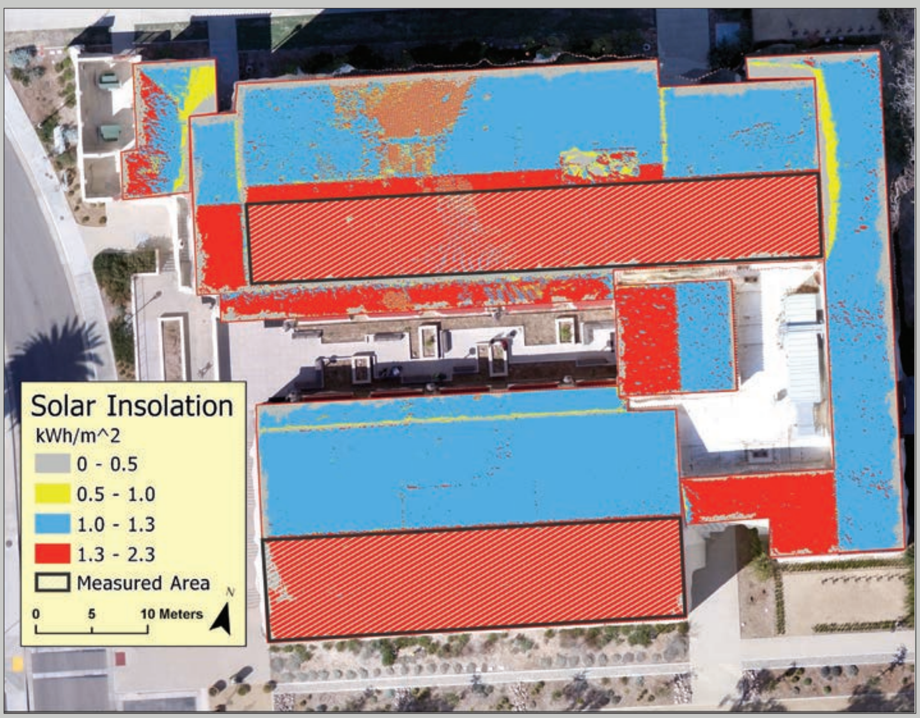

Figure 2: Predicted solar insolation (in kWh per square meter) for Sierra Hall on December 21. This Area Solar Radiation (ASR) map shows a great deal of solar insolation, even during the day with the fewest daylight hours in the year. During the winter, the sun lays low in the sky and rises and sets at an angle. This affects the length of daylight which consequently affects the amount of solar insolation during the winter.

Month	Solar Insolation kWh per square meter	Roof top Area in square meters	Efficiency Percentage	Number of days in the month	Total kWh/Month
December	1.5	731.12	22.5%	31	7,649
July	5.8	731.12	22.5%	31	29,578

Table 1: Calculated monthly kWh based on insolation from ASR maps using the equation: Solar Insolation x area x efficiency of solar panels x days per months

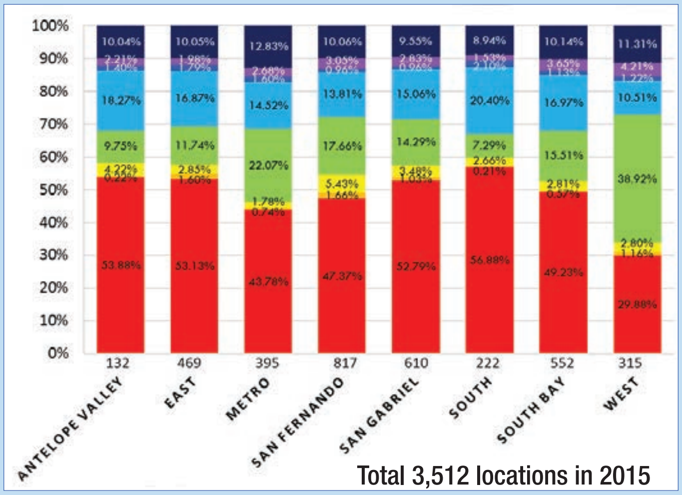

Figure 2: Detailed distribution of different types of fast food chains in 8 service planning areas in Los Angeles County. The total number of fast food chains for each area is shown under the bar.

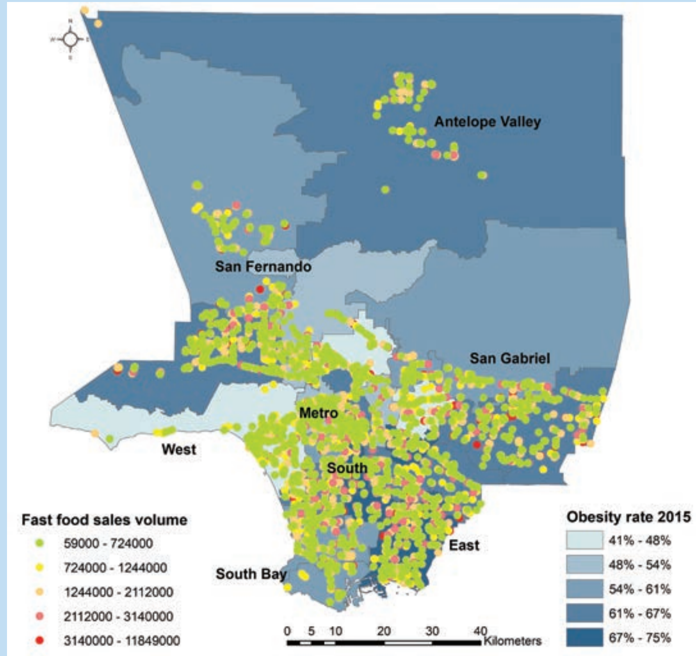

Figure 3: The relationship between fast food sales volume and obesity rate of BMI of 25 and over by 26 health districts in 8 service planning areas (SPAs) of Los Angeles County in 2015.

Health District	1999	2015	Change (2015-1999)	Service Planning Area (SPA)	Per capita fast food sales volume per fast food location in 2015
Antelope Valley	57.40%	66.60%	9.20%	Antelope Valley (SPA1)	424.56
San Fernando	47.90%	59.60%	11.70%	San Fernando (SPA2)	409.55
East Valley	49.60%	53.40%	3.80%		
West Valley	49.20%	61.10%	11.90%		
Glendale	46.60%	47.70%	1.10%		
Alhambra	37.10%	44.20%	7.10%	San Gabriel (SPA3)	408.60
El Monte	61.60%	66.30%	4.70%		
Foothill	52.50%	54.40%	1.90%		
Pasadena	43.10%	58.70%	15.60%		
Pomona	50.50%	65.20%	14.70%		
Central	47.00%	63.30%	16.30%	Metro (SPA4)	364.14
Hollywood-	46.20%	53.40%	7.20%		
Northeast	56.60%	54.00%	-2.60%		
West	42.00%	41.40%	-0.60%	West (SPA5)	500.75
Compton	67.90%	71.60%	3.70%	South (SPA6)	271.99
South	74.40%	74.00%	-0.40%		
Southeast	55.70%	72.20%	16.50%		
Southwest	56.00%	59.70%	3.70%		
Bellflower	50.40%	68.90%	18.50%	East (SPA7)	425.51
East LA	62.60%	74.70%	12.10%		
San Antonio	65.30%	65.00%	-0.30%		
Whittier	64.60%	63.30%	-1.30%		
Harbor	60.00%	57.20%	-2.80%	South Bay (SPA8)	403.33
Inglewood	55.80%	64.50%	8.70%		
Long Beach	50.70%	67.30%	16.60%		
Torrance	52.40%	54.40%	2.00%		

Table 1: Obesity rates of age over 18 years and its change between 1999 and 2015 in 26 health districts within 8 service planning areas (SPAs) in Los Angeles County along with per capita fast food sales volume per location. Obesity rates are based on self-reported data by a random sample of adult population in Los Angeles County data, achieved from the County of Los Angeles Public Health. The obesity rate defined for this study is BMI of 25 and over, meaning both obese and overweight.

The numbers of obesity from each 8 SPA in 2015	Correlation (r value)
with sales volume of all fast food	0.9487
with sales volume of Traditional Fast food	0.9804
with sales volume of Pizza shops	0.9871
with sales volume of Traditional + Pizza shops	0.9839
with sales volume of Sandwich shops	0.9136
with sales volume of Donut shops	0.8273
with sales volume of Ice Cream shops	0.8166
with sales volume of Baked Goods shops	0.7712
with sales volume of Juice & Smoothie shops	0.7677
with sales volume of Coffee shops	0.5335

Table 2: Pearson's Correlation Coefficient (r value) of fast food sale volume by types in 8 service planning areas of Los Angeles County.

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Out of Sight, Out of Mind? *continued from previous page*

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Analysing Transportation Big Data *continued from back cover*

time visualization application in the future. We wrote Python programs to parse the original large data into smaller datasets. The smaller datasets were converted into both PostgreSQL and MongoDB databases and linked them with ArcGIS Pro. This study used two types of data, vehicle points and roads. The points dataset is a series of GPS points extracted from the randomly selected vehicles from the SPMD database in April 2013. Those points contain basic safety messages (BSM) for a vehicle such as speed, location, direction, yaw rate, and heading collected at the rate of approximately 10 Hz. A road line dataset contains major road condition and speed limit, which comes from the Southeast Michigan Council of Governments (SEMCOG) Annual Average Daily Traffic (AADT) program.

To find the vehicle points with over-speeding cases, we used sampled SPMD data (0.1%) with ESRI ArcGIS Pro and buffered the roads at 5 meters wide since the major roads should have a shoulder that is at least 5 meters wide. Then we used a spatial join to aggregate vehicle points data into the road buffers. We compared speed recorded at each vehicle point with the road speed limit and extracted four categories of over-speeding clusters: class 1: Over speed 1-5 MPH; class 2: Over speed 5-10 MPH; class 3: Over speed 10-20 MPH; class 4: Over speed more than 20 MPH. We visualized these data on GIS maps to identify their spatial patterns and point density. Figure 1 illustrated the severity of over-speeding vehicles and their cluster patterns. The visualization result showed that points with more than 10 MPH over-speeding mostly occurred in the intersections of major highway segments and ramps. In addition, it also appeared when the speed limit changes between two segments of local roads. Finally, most over-speeding less than 10 MPH occurred in the Ann Arbor downtown. The spatial pattern of over-speed activity can be further evaluated in the future using advanced machine learning methods.

The automatic detection of aggressive driving behaviors can facilitate the investigation of behavioral and environmental risks in space and time from a large collection of sensor-based datasets. Identifying and addressing those risks is one of the central factors in building a safe transportation system, especially with the potential of autonomous vehicles and self-driving cars in the near future. This pilot study helps us to understand the potential and challenges of using GIS to analyze transportation Big Data. We continue to strive for finding better approaches to challenges in big data analytics, such as data partitioning, data sampling from the original datasets, big data visualization, and developing parallel computation algorithms.

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Analyzing Transportation Big Data with GIS: Detecting Over-speeding Vehicles from Traffic GPS Data

With the popularity of automobiles and increasing volume of vehicles, the traffic accident rates in U.S. cities are increasing year by year. The aggressive driving behaviors can be considered as one of the main reasons to lead to serious traffic crashes according to AAA (American Automobile Association) Foundation for Traffic Safety. Over-speeding is one major problem in the category of aggressive driving behaviors. The Center for Human Dynamics in the Mobile Age (HDMA) at San Diego State University is cooperating with Virginia Tech Transportation Institute to study "Big Data Visualization and Spatiotemporal Modeling of Aggressive Driving" under the Safety Through Disruption (SAFE-D) Project (SAFE-D, 2018) funded by US Department of Transportation. This project aims to identify aggressive driving behaviors and visualize them by using various big data analytics and spatial analysis technologies. We utilized the experimental data for Safety Pilot Model Deployment (SPMD) program, which was a real-world data collection program with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication devices in October 2012 and April 2013 in Washtenaw County, Michigan (Gold, 2012).

Big Data are commonly defined as the size or the complexity of data that are too big to be processed effectively by traditional software. For example, the one-month GPS tracks of SPMD data contains more than 1.5 billion GPS points (205 GB in a comma-separate value file format), which cannot be handled by traditional GIS software easily. The purpose of this study is to utilize various SQL and No-SQL databases to process big data and to detect over-speeding vehicles or aggressive driving behaviors using environmental GIS layers with GPS trajectory data. It will help transportation researchers to develop a real-

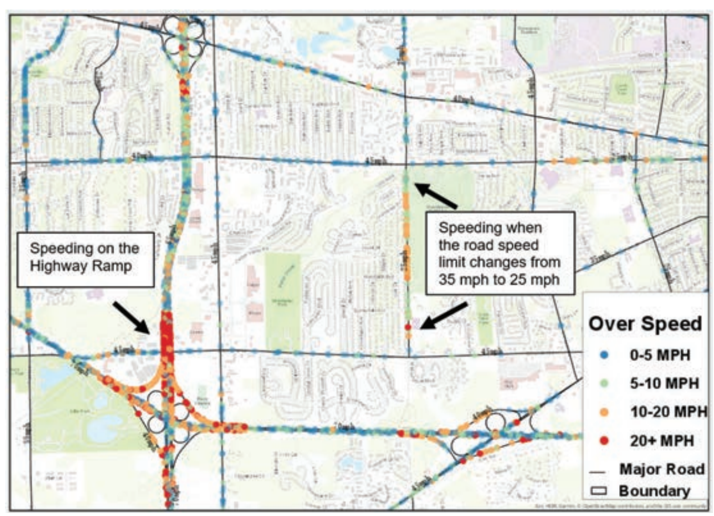

Figure 1: Zoom-in view of the over-speeding locations in major roads.

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