The Effect of the COVID-19 Pandemic on the Spatial Distribution of Traffic Crashes

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GEOG 596A
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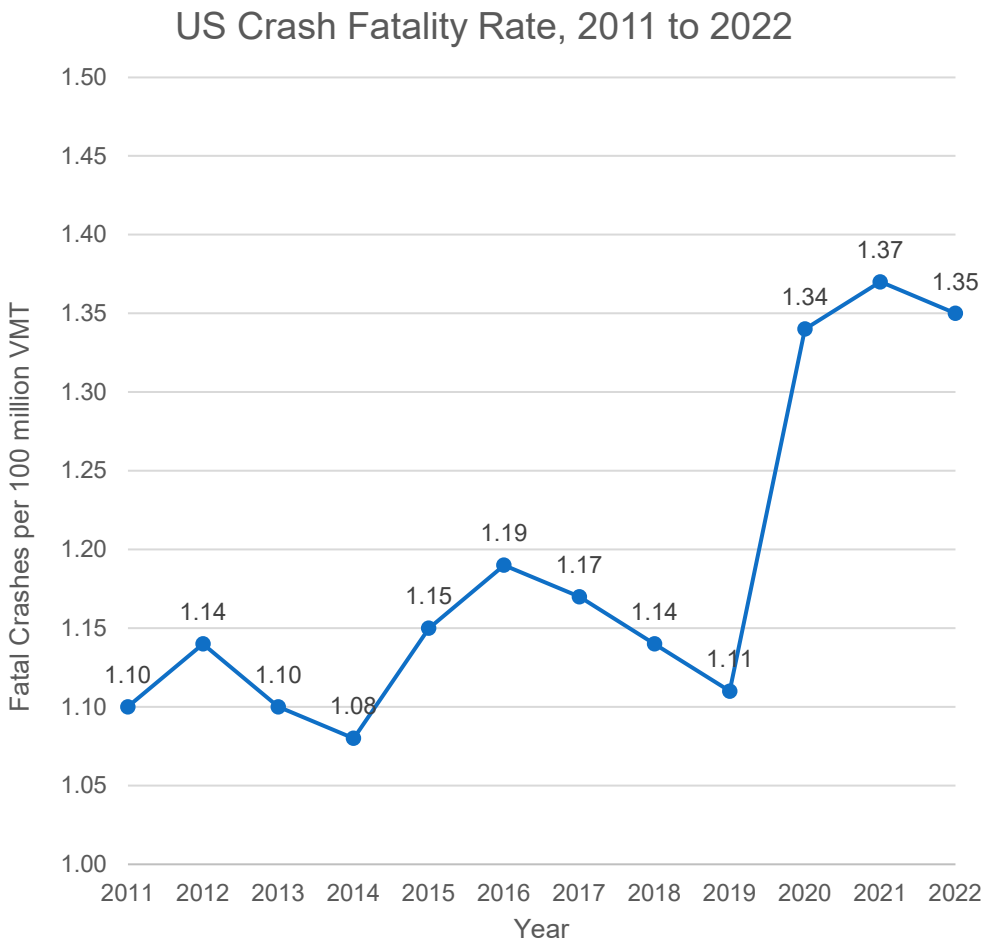
COVID-19 and Traffic Crashes

- Traffic fatalities generally decreased from the 1960s until 2014, then started rising
- Dramatic increase in fatalities in 2020
  - 20.7% increase in fatality rate
  - Continued increase in 2021
  - Leveled off at a new-normal high in 2022
- Overall number of crashes decreased, but severity increased
- "Why" fatalities increased has been studied, but not "where"



Source: "NHTSA Estimates for 2022 Show Roadway Fatalities Remain Flat After Two Years of Dramatic Increases | NHTSA."

Research Question

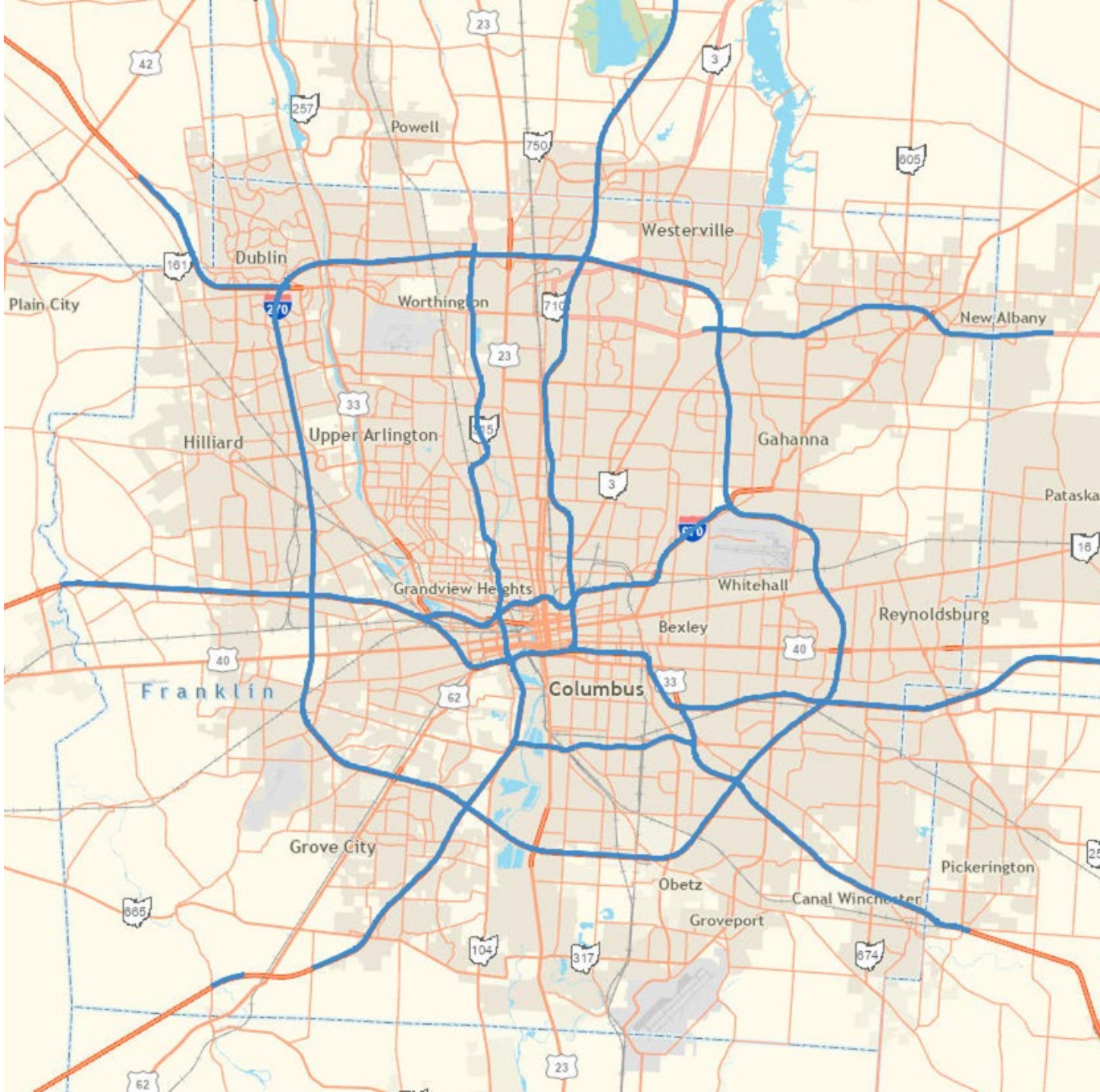
- **What effects did the COVID-19 pandemic and its related shifts in traffic patterns have on the location and characteristics of traffic crash hotspots on the urban freeway network of Columbus, Ohio?**
  - Define hotspots before, during, and after pandemic
  - Compare hotspot locations and features
  - Test and refine methodology on a single urban area

Columbus, Ohio

- Capital and largest city in Ohio
- Fastest growing metro area in the Midwest
- 2.13 million people in 2020; estimated to rise to 3.15 million by 2050
- Heavily car-reliant
- Local and state agencies have strong focus on managing increased volumes and improving safety

Study Area

- Urban interstates and highways in the Columbus Metropolitan Area
- Highways defined as roadways in Functional Class 1 or 2 according to FHWA criteria
- “Urban” distinction from ODOT roadway data



Time Periods

- Define hotspots in three time periods:
  - Pre-Pandemic: January 2018 to February 2020
  - Mid-Pandemic: March 2020 to December 2021
  - Post-Pandemic: January 2022 to December 2023
- Further refinement of date ranges to come from analysis of traffic volumes
  - When did volumes drop?
  - When did traffic recover?

Research Methodology

1. Acquire data from public sources
2. Query and filter data to the study area in the time periods
3. Conduct Network Kernel Density Estimation to create crash density raster
4. Develop density threshold to define as a “hotspot”
5. Create polylines of hotspot areas
6. Enrich hotspot polylines with roadway information
7. Compare hotspot areas with in the three time periods

Data Sources

Crash Data: Ohio Crash Statistics System

Log of all crashes in the state

Data comes from law enforcement completing OH1 crash reports

Data includes detailed information about how and where crash occurred

Roadway Information: Ohio Traffic Information Management System (TIMS)

Traffic Counts: ODOT Transportation Data Management System

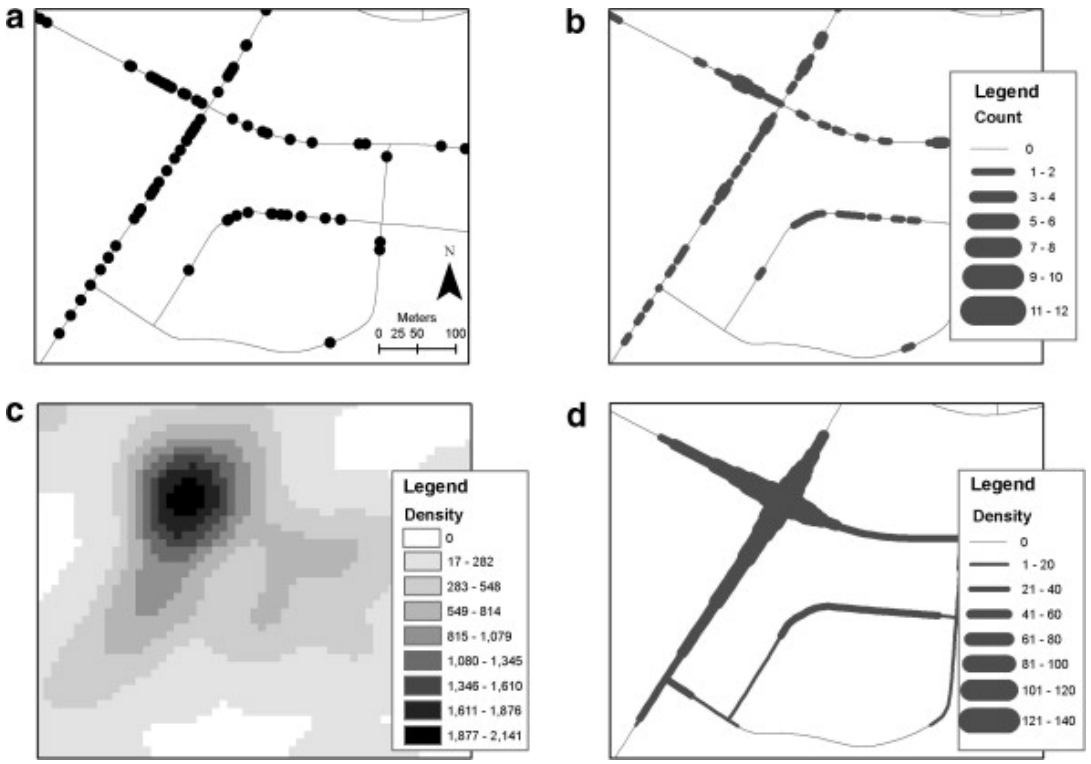
All publicly available for download and known to be reliable

Hotspot Identification

- Several methods of identifying crash hotspots
- Kernel Density Estimation (KDE) is popular for crash analysis (Xie and Yan, Harirforoush and Bellalite, Benedek et al., Mohaymany et al.)
- KDE is density-based, relying on first-order properties
- Second-order properties (such as kriging or nearest-neighbor distances), measure spatial dependence, and crashes are discrete events

Network-Based Analysis

- Traditional KDE is “planar”, and assume events are in two-dimension space
- Road networks are one-dimensional (forward and backward on the roadway)
- Researchers have developed network-based versions of many geospatial analysis techniques, including KDE
- Software such as SANET and R can do Network KDE



Planar vs. Network KDE. Source: Xie and Yan, “Kernel Density Estimation of Traffic Accidents in a Network Space.”

Hotspot Characteristics

Density	Crash density will vary based on time period
Roadway information	Number of lanes, speed limit, lane width, near ramp
Traffic Volume	Can be used to normalize crash densities

Comparison

Comparing time periods

Did the hotspots move from period to period?

- Use Pearson correlation (0 to 1, no correlation to exact correlation) to quantify similarity over time periods

How did hotspots change when normalized for traffic volumes?

How did the density of crashes change?

Comparing attributes

Are certain roadway attributes no longer prominent in hotspots?

Can changes in hotspot roadway features be attributed to the pandemic?

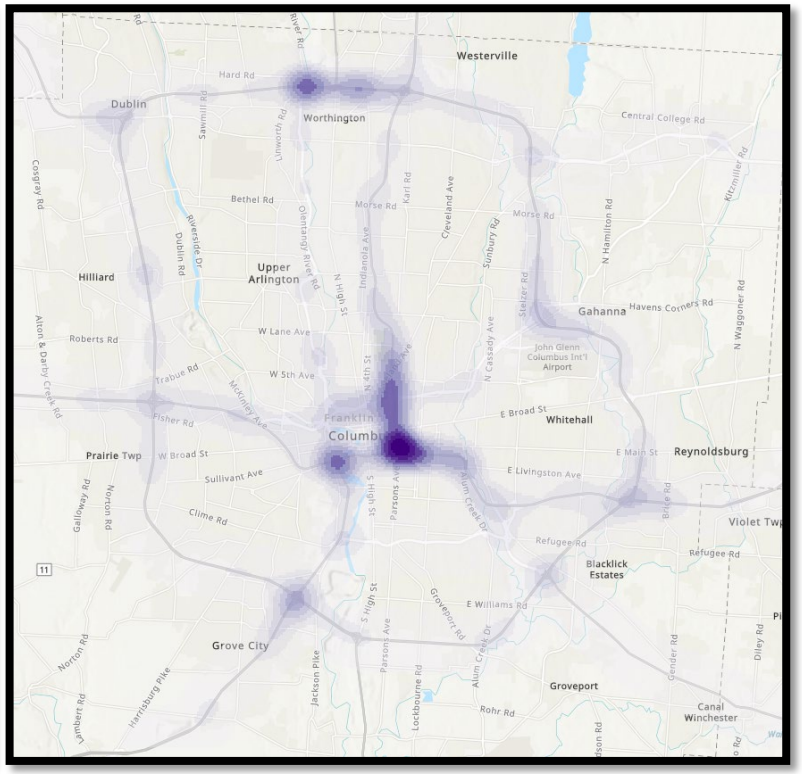
Expected Results

- Expect to see a more even distribution of crashes during the pandemic
- Less traffic means fewer crashes in congestion, fewer interchange crashes
- Reversion toward the norm after the pandemic, but with noticeable differences

Preliminary Work

Planar KDE analysis for quick look at data

1. Pre-Pandemic



2. Mid-Pandemic

3. Post-Pandemic

Note: different scale used for each time period

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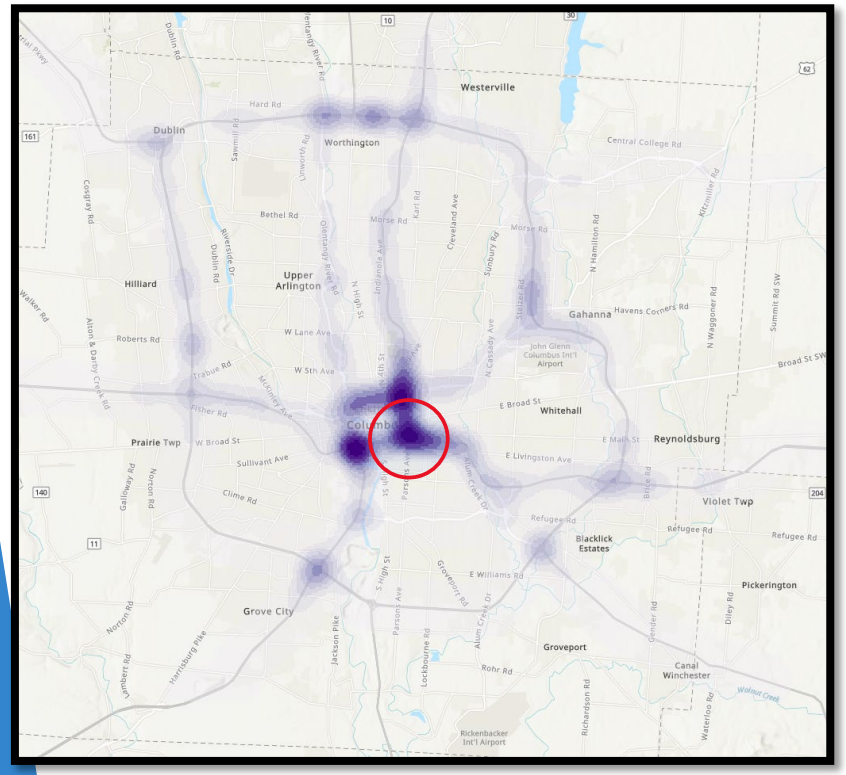
Planar KDE analysis for quick look at data



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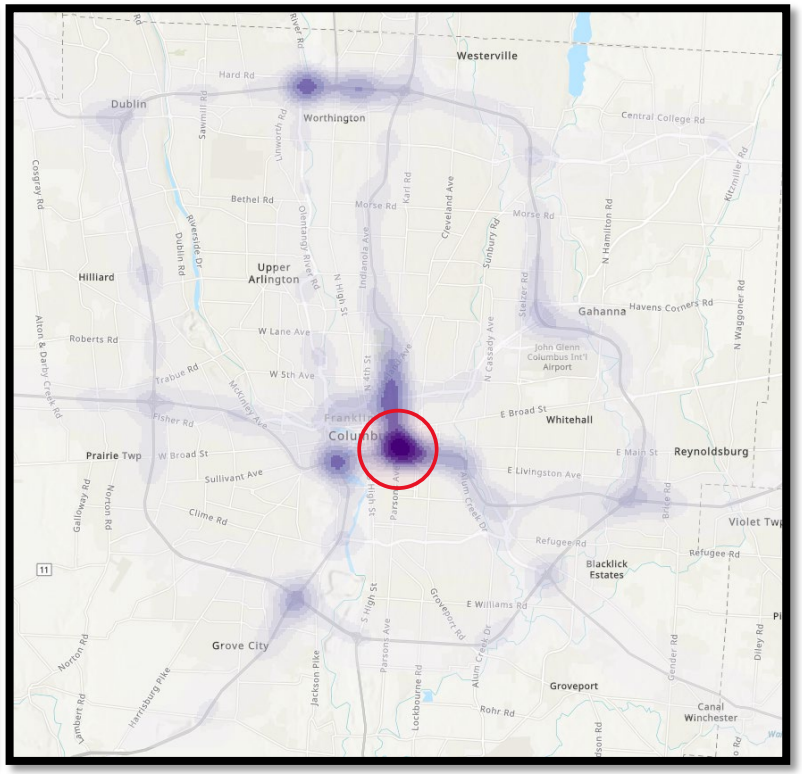

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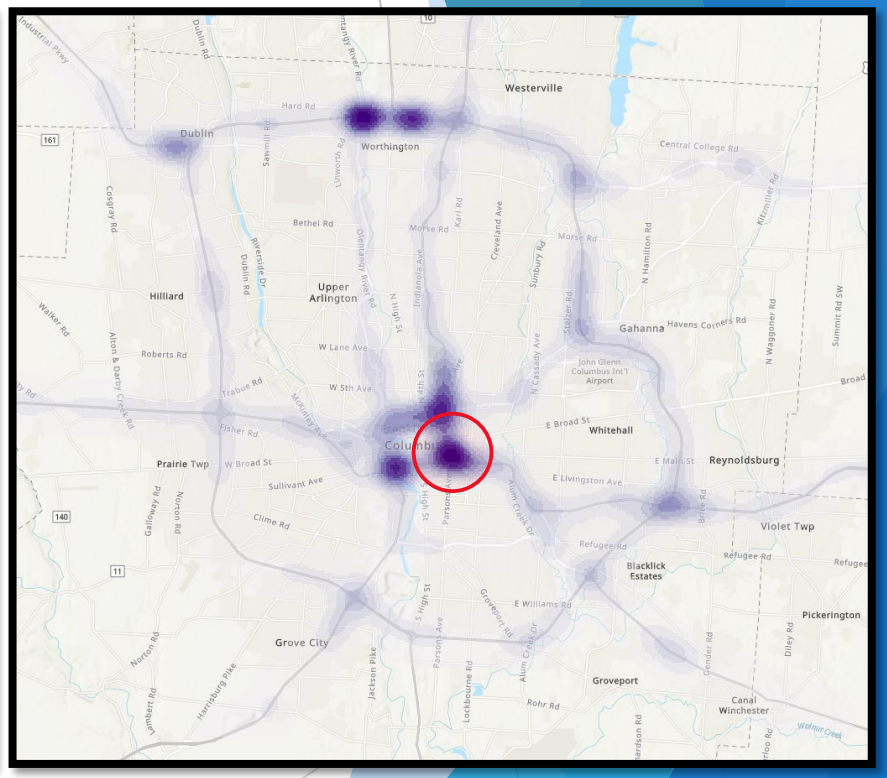

3. Post-Pandemic

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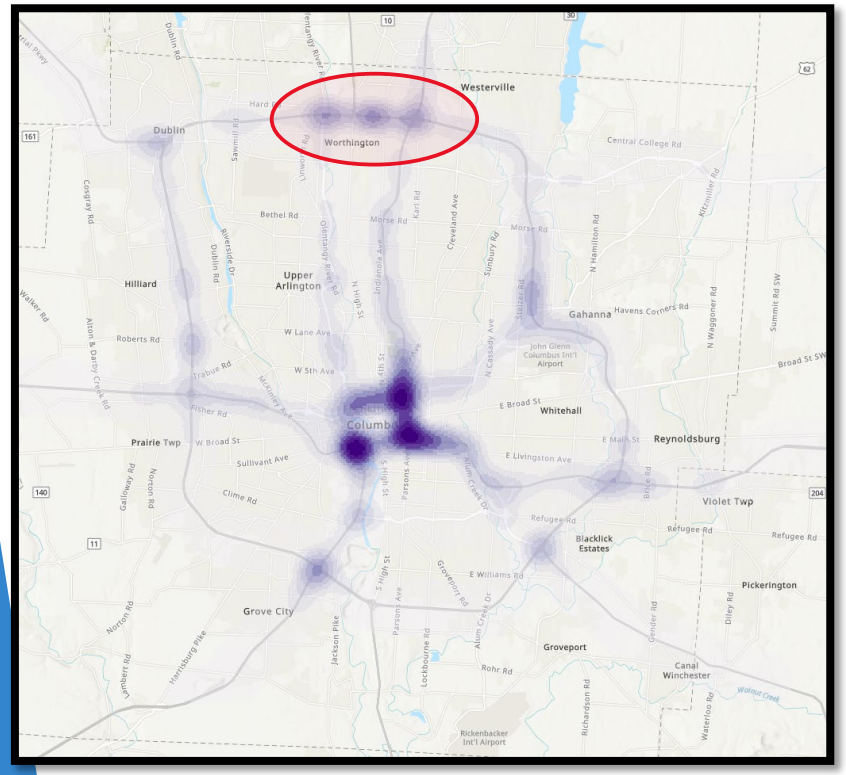

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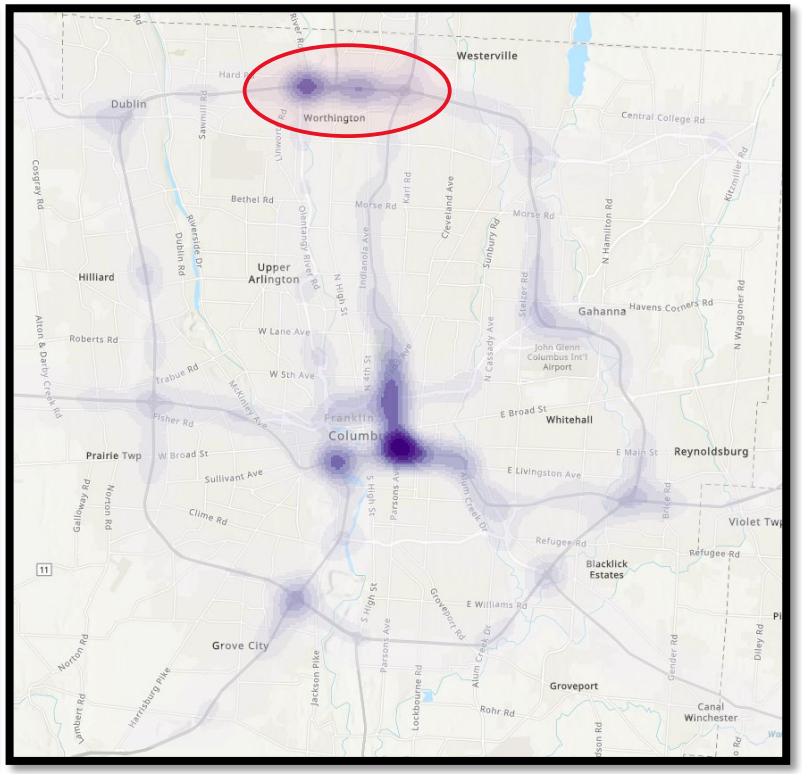

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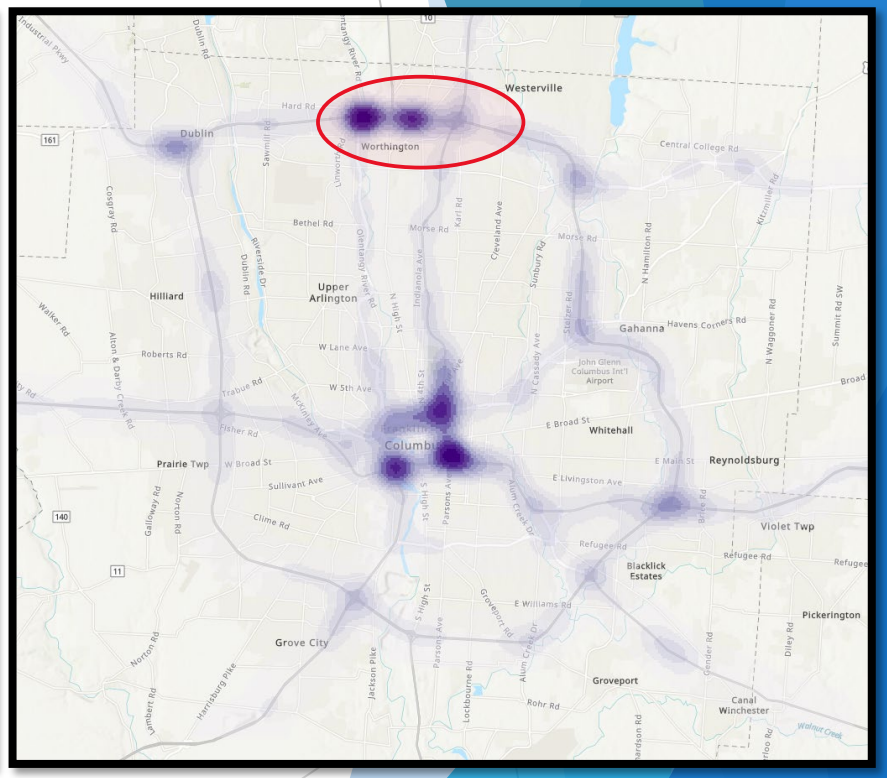

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Conference Presentation

- Aiming for AASHTO GIS-T Symposium in April
  - Largest GIS conference for the US transportation sector
  - Atlanta, April 2-5, 2024
  - Call for Abstracts open now
- Would be interested in presenting internally if abstract is not for AASHTO GIS-T

Questions and Contact Info

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