

Mapping Social Determinants of Health in Utah: A Data-driven Approach for Public Health and Clinical Decision-making

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GitHub https://github.com/lwynholds/BMI6016_SDOH

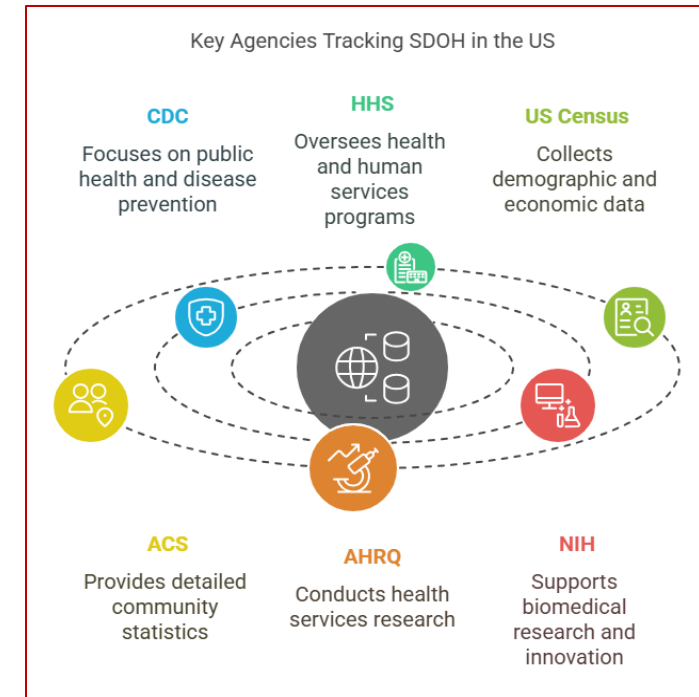
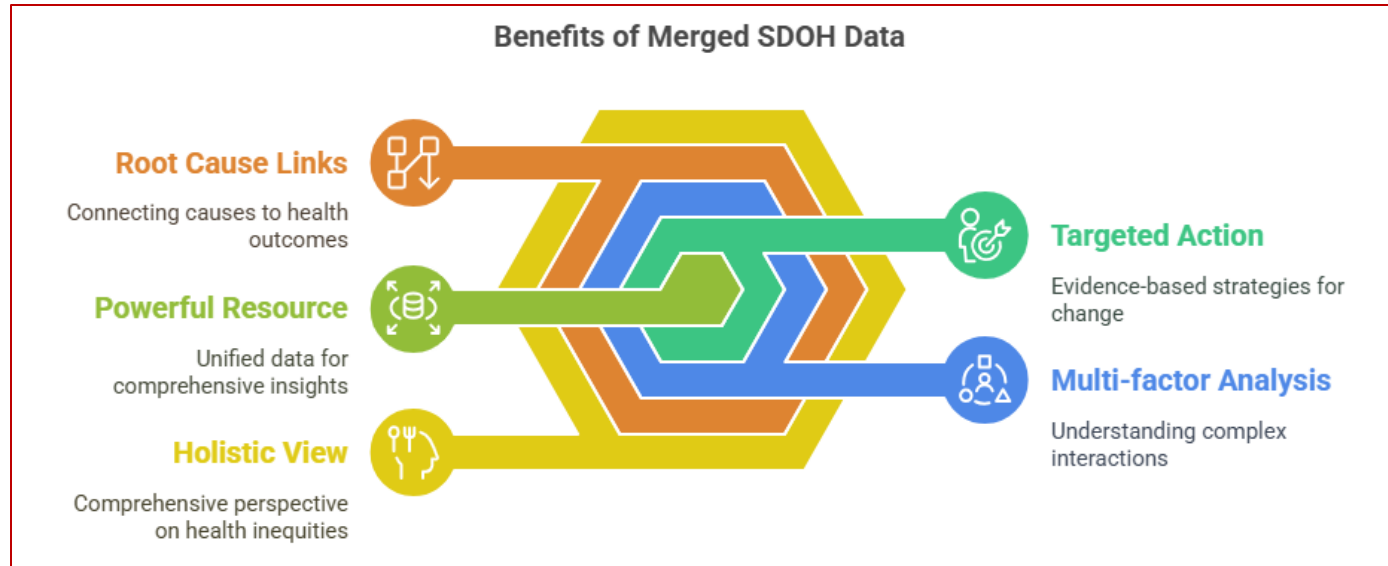
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BACKGROUND AND MOTIVATION

- **Social Determinants of Health (SDOH)** are *“the circumstances in which people are born, grow up, live, work and age, and the systems put in place to deal with illness. These circumstances are in turn shaped by a wider set of forces: economics, social policies, and politics”*
- In 2018, Cantor et al. published their Factors Affecting Communities and Enabling Targeted Services (FACETS) open-data model
 - to standardize and compile SDOH-related data at the census-tract level in New York City, and
 - to integrate community-level determinants with patient health records in clinical settings



- **We propose to develop a FACETS-based model tailored to the state of Utah**, by integrating Utah-specific SDOH data, including environmental data, into a framework, we aim to provide a comprehensive tool for assessing community-level health determinants to support informed public health interventions and patient-level clinical decision-making

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PROJECT OBJECTIVES

- To **standardize Utah's SDOH data at the US census-tract level** by integrating multiple sources of publicly available and state-specific data, using:
 - ACS and US Census Bureau, CDC, Environmental Protection Agency (EPA), and US Department of Agriculture Food Access Research Atlas (USDA) data (data sources from the original FACETS study that are also relevant to Utah)
 - State datasets from the Utah Department of Health and Human Services
 - State SDOH variables not otherwise specified that are particular or pertinent to Utah (e.g., urban/rural, electoral participation)
 - Temporal, categorical, or spatial crosswalks, where necessary
- To **create an interoperable dataset** of census tracts, within which an individual patient's address can be mapped to a Utah FACETS characterization of SDOH context
- To **characterize disparities in health outcomes** based on the intersection of air quality with other environmental health factors and SDOH.
- To **give context to any individual patient's health status** and assist patients and providers in deciding how best to improve that patient's health.

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DATASETS



Social Vulnerability Index

SVI percentile ranking •
English proficiency (2020)



Census tract geodata •
Urban-Area classification
(2020)



PM_{2.5} Max Value •
Respiratory hazard/cancer
risk (2020)



Asthma prevalence
(2022)



Agency for Healthcare Research and Quality

Total population • Citizenship • Racial/Ethnic diversity •
Unemployment • Health insurance status • Housing •
Education • Poverty • Household income • Walkability •
GINI Index of Inequality (2020)

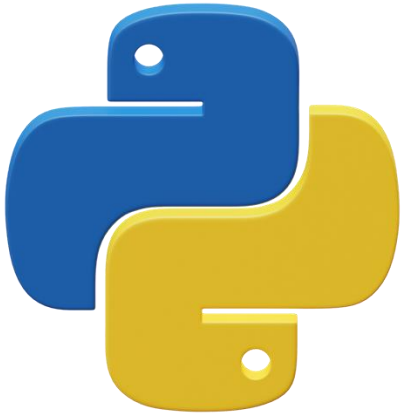


Law enforcement and
municipal geodata •
Crime (2022)

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DATA PROCESSING AND WRANGLING



+

=

CDC, USDA
EPA CSVs

AHRQ_SDOH CSVs
(338 variables)



Shapefiles .cpg, .dbf,
.prj, .shp, .shx
(716 records)

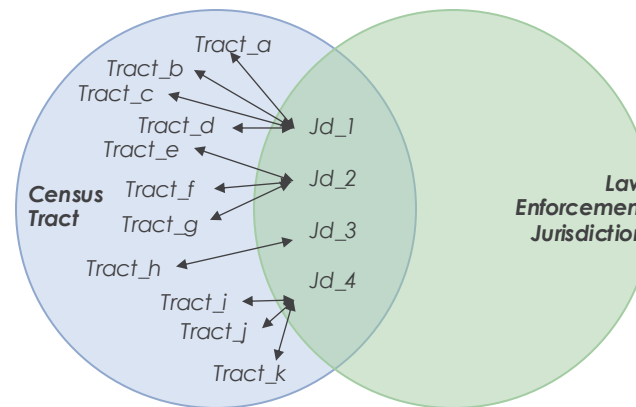
Remove unwanted
and redundant
attributes
and anomalies

YEET

BYE

| | A | B | C | D | E |
|----|----------|---------------------|----------|--------------|------------|
| 1 | Num_DODs | Britney_Spears_Fans | Disabled | Has_Parakeet | Unemployed |
| 2 | | | | | |
| 3 | | | | | |
| 4 | | | | | |
| 5 | | | | | |
| 6 | | | | | |
| 7 | | | | | |
| 8 | | | | | |
| 9 | | | | | |
| 10 | | | | | |
| 11 | | | | | |
| 12 | | | | | |
| 13 | | | | | |

Turn jurisdictional and county data into census
tracts with CROSSWALKS



Merge, join, and transform variables into domains, themes, and layers.

First a lot of this ...

```
# Slim down the df
svi_kept_var = ['ST', 'STATE', 'ST_ABBR', 'STCNTY', 'COUNTY', 'FIPS', 'LOCATION',
               'AREA_SQMI', 'E_TOTPOP', 'RPL_THEMES', 'EP_LIMENG']
svi_dff = svi_df[svi_kept_var].copy()

#Fix the joining variable (it has 11 digits already; just needs to be a string
and renamed) and put it near the other variables
svi_dff['GEOID20'] = svi_dff['FIPS'].astype("string")
svi_dff = svi_dff[['ST', 'STATE', 'ST_ABBR', 'STCNTY', 'COUNTY', 'GEOID20'] +
                 [col for col in svi_dff.columns if col not in ['ST', 'STATE', 'ST_ABBR',
                 'STCNTY', 'COUNTY', 'GEOID20']]]
svi_dff.replace(-999, np.nan, inplace=True)

#svi_dff.head()
#svi_dff.info()
#print(svi_dff.isna().sum())
```

... with this as the goal ...

| | | | |
|-------------|----------------------------|-----------------|--|
| AIR QUALITY | % with asthma | IDENTITY | Born citizens vs foreign-born |
| | Cancer risk per 1M | | % non-Hispanic, white |
| SOCIETY | PM2.5 Max | ECONOMIC ISSUES | Median household income |
| | % speaking limited English | | % housing units owned, rented, or vacant |
| | Avg education level | | % paying >30% for housing |
| | Crimes per 1K | | % unemployed or no health insurance |
| | GINI index | | % under the poverty line |
| | SVI percentile ranking | CIVIC | "Urban" areas and Walkability |

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RESULTS: VARIABLE DESCRIPTIONS

Dimensions of the DF: (716, 38)

| Variables | Descriptions |
|------------------------------|--|
| GEOID20 | Census tract identifier (2020) |
| ACS_PCT_CTZ_US_BORN | % of U.S.-born citizens |
| ACS_PCT_FOREIGN_BORN | % of foreign-born residents |
| ACS_PCT_WHITE | % identifying as white |
| ACS_PCT_NONHISP | % non-Hispanic |
| ACS_MEDIAN_HH_INC | Median household income |
| ACS_PCT_OWNER_HU | % owner-occupied housing units |
| ACS_PCT_OWNER_HU_COST_30PCT | % owners with housing costs > 30% of income |
| ACS_PCT_RENTER_HU | % renter-occupied housing units |
| ACS_PCT_RENTER_HU_COST_30PCT | % renters with housing costs > 30% of income |
| ACS_PCT_VACANT_HU | % vacant housing units |
| ACS_PCT_UNEMPLOY | % unemployed individuals |

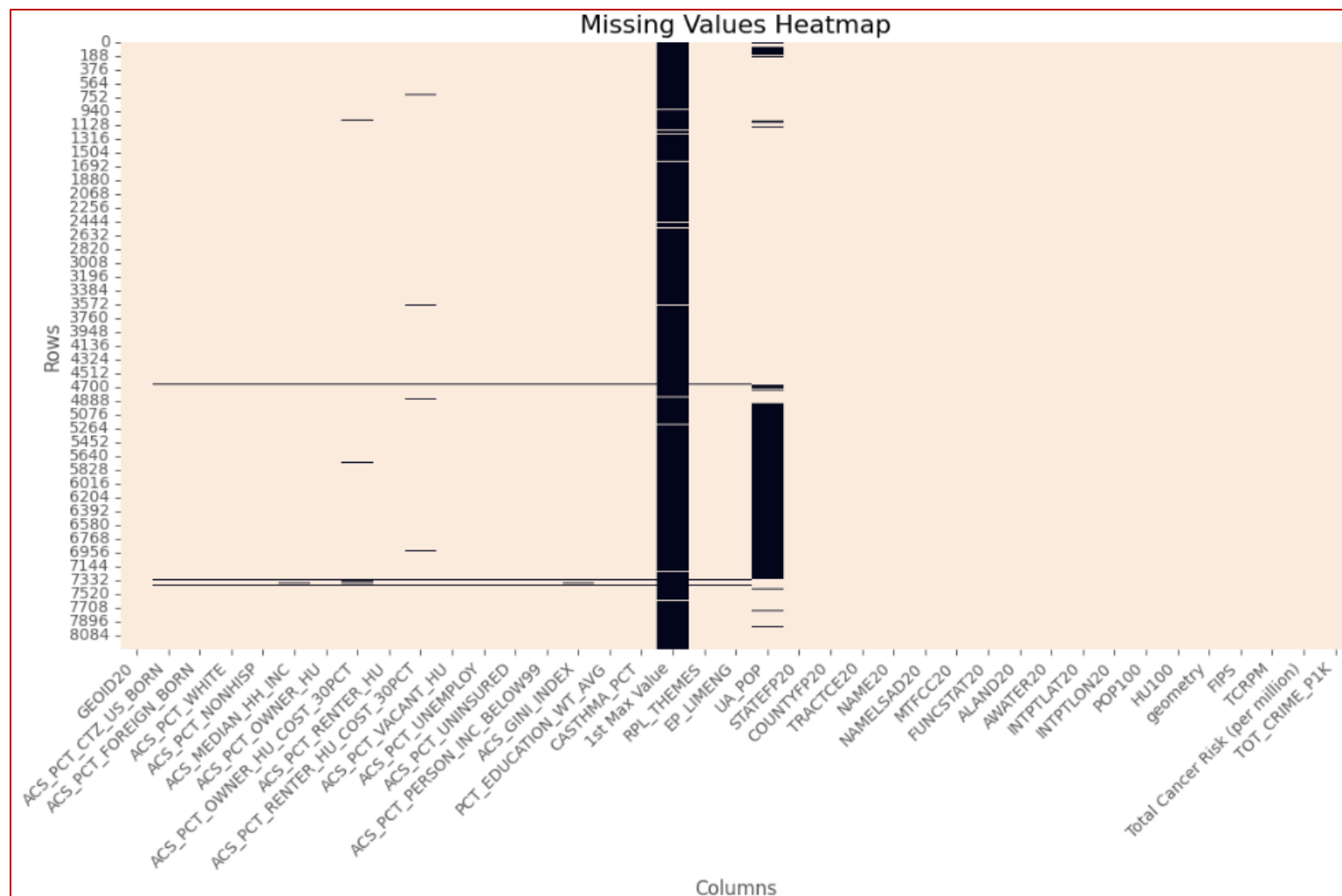
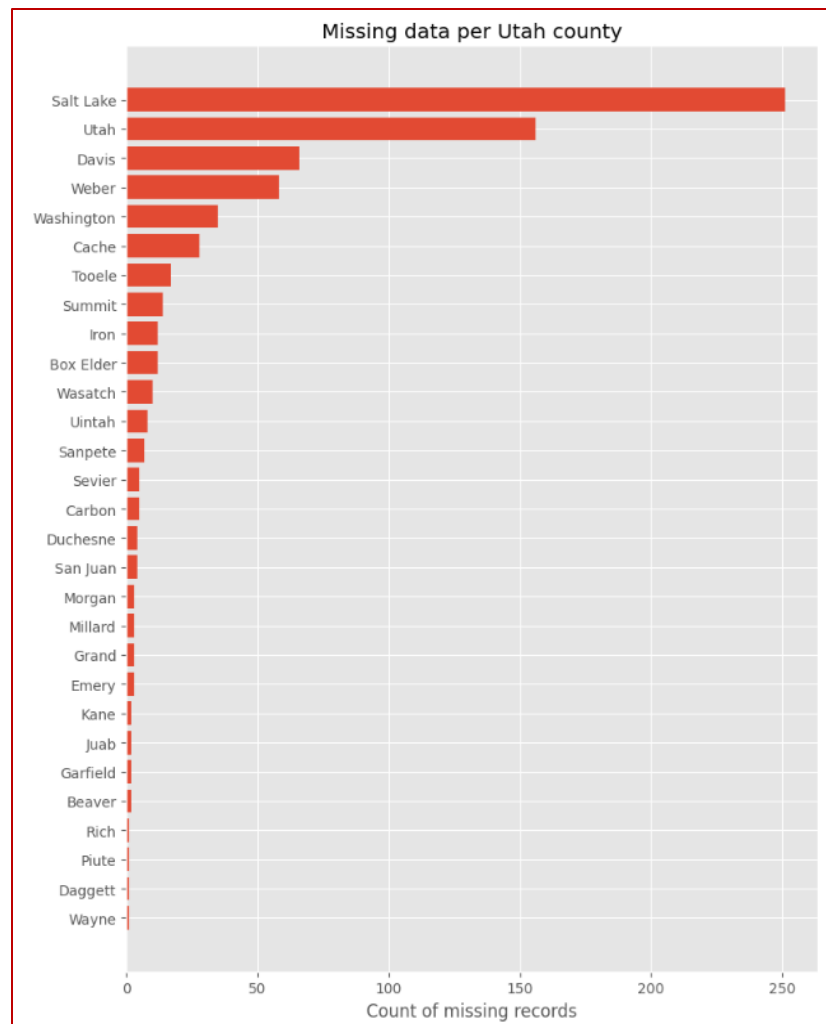
| Variables (continued) | Descriptions (continued) |
|----------------------------|--|
| ACS_PCT_UNINSURED | % of population without health insurance |
| ACS_PCT_PERSON_INC_BELOW99 | % of people with income below the poverty line |
| ACS_GINI_INDEX | Income inequality index |
| PCT_EDUCATION_WT_AVG | Weighted average of educational attainment |
| CASTHMA_PCT | % of population with asthma |
| RPL_THEMES | CDC Social Vulnerability Index score |
| EP_LIMENG | % of people with limited English proficiency |
| UA_POP | Population in Census-designated "Urban Areas" |
| ACS_PCT_WALK_2WORK | % of workers walking to work |
| 1st Max Value | PM25 highest $\mu\text{g}/\text{m}^3$ at monitoring site |
| TCPRM | Total cancer risk (per million) |
| TOT_CRIME_P1K | Total crimes (per 1000) |

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RESULTS: MISSING DATA



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RESULTS: EDA BY STATE LEVEL



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RESULTS: EDA BY COUNTY LEVEL



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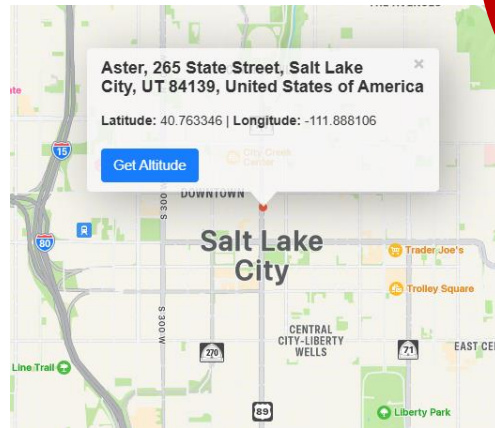
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DATA ANALYSIS

```
latitude_slc = 40.763346
longitude_slc = -111.888106

sdoh_result = get_sdoH_for_coordinates(latitude_slc, longitude_slc, sdoh_df=df)
print(sdoh_result)
```



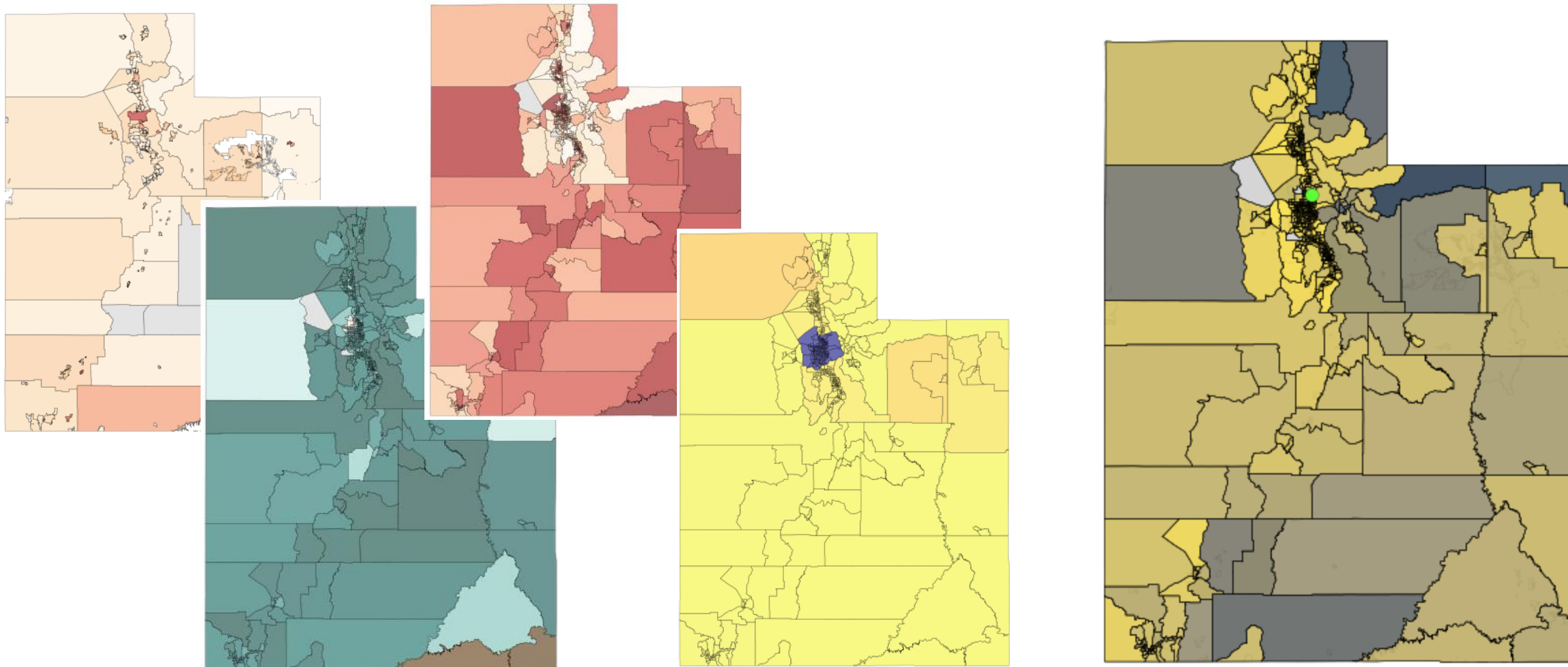
Inputting geographic coordinates within Utah allows us to identify the relevant census tract and retrieve the associated raw SDOH variables.

Here is an example for SLC

| | |
|---------------------------------|---|
| input_point | POINT (-111.888106 40.763346) |
| STATEFP20 | 49 |
| COUNTYFP20 | 035 |
| TRACTCE20 | 114000 |
| GEOID20 | 49035114000 |
| NAME20 | 1140 |
| NAMELSAD20 | Census Tract |
| MTFCC20 | G5020 |
| FUNCSTAT20 | S |
| ALAND20 | 3153173 |
| AWATER20 | 0 |
| INTPTLAT20 | +40.7575950 |
| INTPTLON20 | -111.8974571 |
| POP100 | 4344 |
| HU100 | 2929 |
| ACS_PCT_CTZ_US_BORN | 85 |
| ACS_PCT_FOREIGN_BORN | 15 |
| ACS_PCT_WHITE | 84 |
| ACS_PCT_NONHISP | 94 |
| ACS_MEDIAN_HH_INC | 61917 |
| ACS_PCT_OWNER_HU | 38 |
| ACS_PCT_OWNER_HU_COST_30PCT | 23 |
| ACS_PCT_RENTER_HU | 62 |
| ACS_PCT_RENTER_HU_COST_30PCT | 42 |
| ACS_PCT_VACANT_HU | 21 |
| ACS_PCT_UNEMPLOY | 6 |
| ACS_PCT_UNINSURED | 8 |
| ACS_PCT_PERSON_INC_BELOW99 | 11 |
| ACS_GINI_INDEX | 1 |
| PCT_EDUCATION_WT_AVG | 4 |
| CASTHMA_PCT | 0 |
| 1st Max Value | NaN |
| RPL_THEMES | 1 |
| EP_LIMENG | 1 |
| UA_POP | 4344 |
| geometry | POLYGON ((-111.91397866107363 40.7606410737250... |
| FIPS | 49035 |
| TCRPM | 700 |
| Total Cancer Risk (per million) | 700 |
| TOT_CRIME_P1K | 1010 |

MAPS

By putting geospatial shape files into GeoDataFrames as basemaps, then linking each variable mostly by GEOID20 and assigning colormaps to the range of values, we made HEATMAPS:



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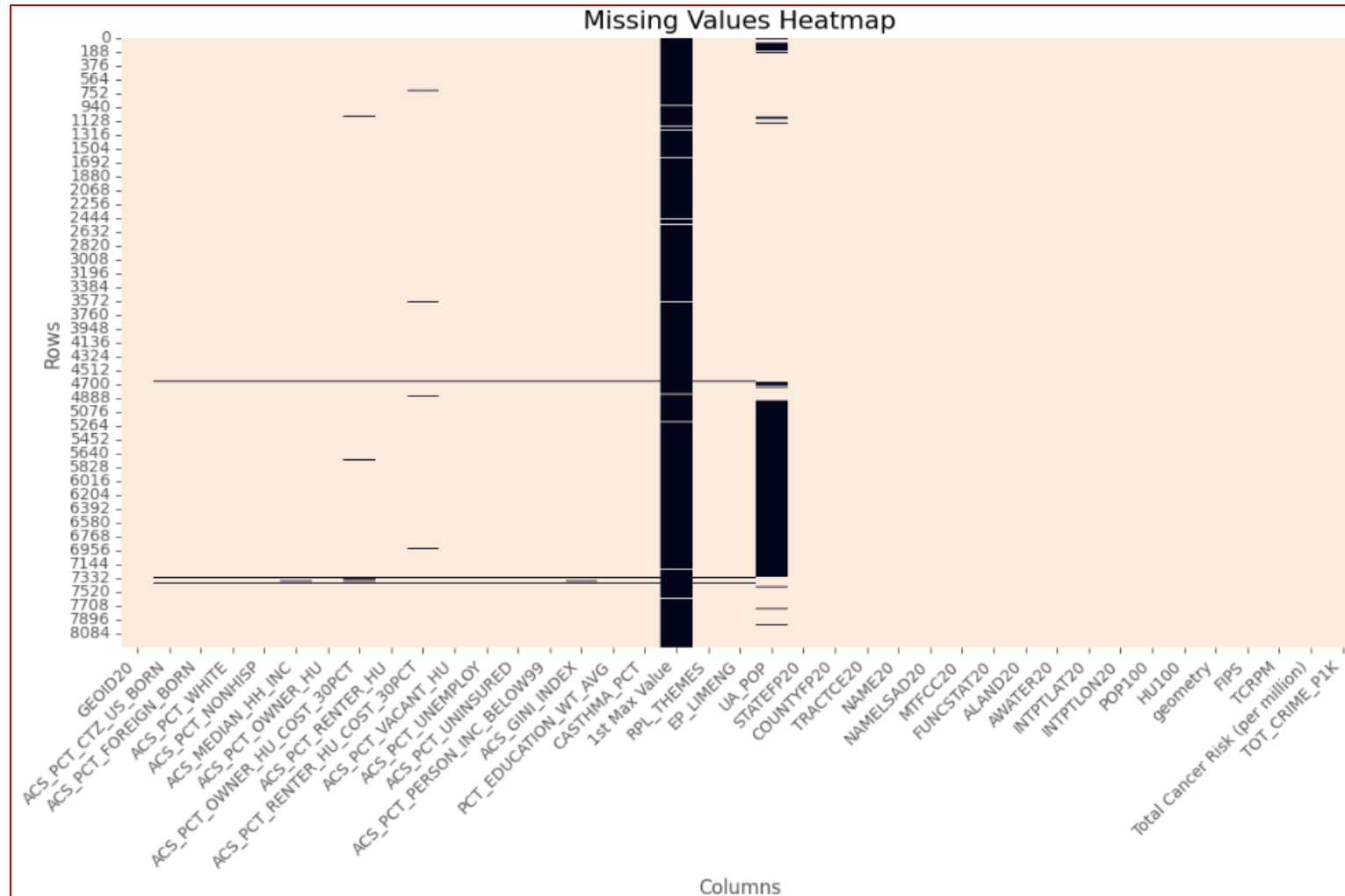
CONCLUSIONS

- Data is readily available from public sources, but it requires varying degrees of data wrangling to compile them into one source that facilitates interoperability.
 - Mapping datasets that were originally compiled at the city or county level into census tracts leaves artifacts in the data
- This unified dataset, created through data compilation and mapping, enables aggregate analysis, GIS visualization, and comparisons of individual factor impact on clinical outcomes.
- This CSV dataset represents a significant first move towards standardizing and compiling SDOH data in an open architecture. This will allow for a better understanding of a patient's situation and improve decision-making in care planning.

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POTHoles IN THE INFORMATION SUPERHIGHWAY: MISSING DATA



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