Arizona Social Vulnerability Index

Technical Documentation

ASU Knowledge Enterprise Arizona State University

ASU Knowledge Exchange for Resilience Arizona State University

ASU Library Arizona State University

ARIZONA DEPARTMENT OF HEALTH SERVICES

ASU Health Observatory Arizona State University

The University of Arizona Mel & Enid Zuckerman College of Public Health Center for Rural Health

Acknowledgements

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Introduction

As part of the Arizona Health Improvement Plan (AZHIP), Arizona State University (ASU) provided technical assistance to the Arizona Department of Health Services (ADHS) Data Advisory Committee (DAC) to create a modified social vulnerability index (SVI) that tailors to the health, environment, socioeconomics, and demographics of Arizona, the “AZSVI”. The basis for the AZSVI is the “CDC/ATSDR SVI”[1], developed by the Centers for Disease Control and Prevention (CDC) Agency for Toxic Substances and Disease Registry (ATSDR). The CDC index uses 16 metrics from the US Census American Community Survey (ACS) to calculate a vulnerability score or index for each state, county, and census tract[2].

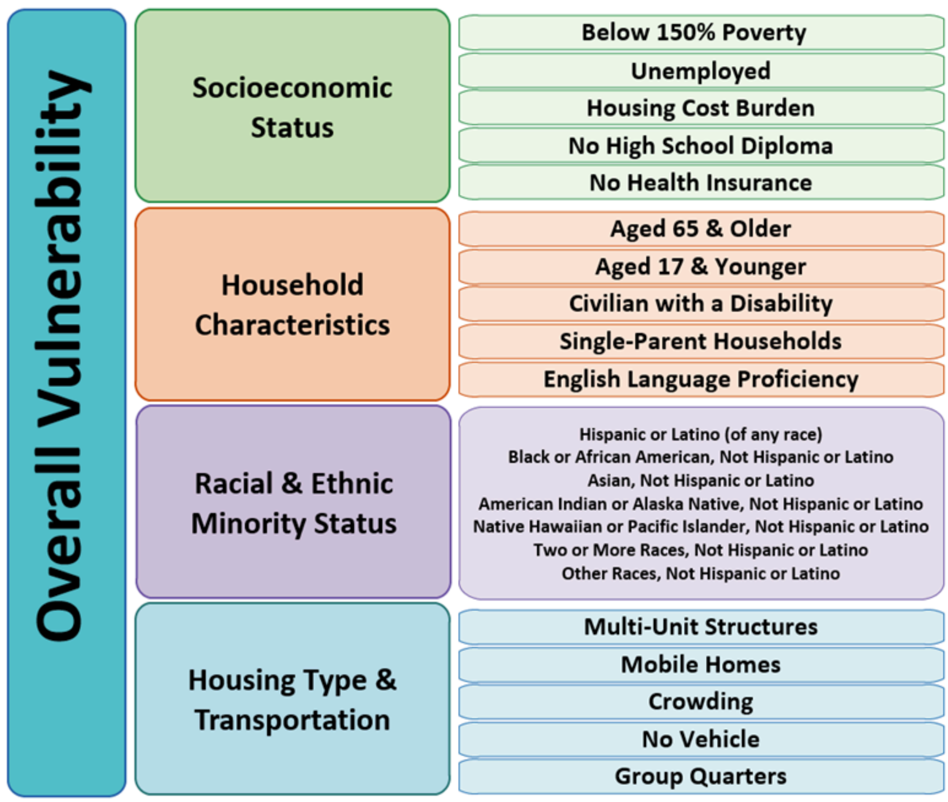


Figure 1: The most recent CDC Social Vulnerability Index is calculated from four themes with multiple metrics for each theme. This version makes use of ACS data from 2016-2020 and is referred to as the 2020 CDC/ATSDR SVI.

[1] CDC/ATSDR Social Vulnerability Index. https://www.atsdr.cdc.gov/placeandhealth/svi/index.html
[2] CDC/ATSDR Social Vulnerability Index. https://www.atsdr.cdc.gov/placeandhealth/svi/interactive_map.html

The CDC SVI was originally formulated by Flanagan et al. as a planning tool for disaster management that explicitly seeks to identify communities that would be disproportionately affected by hazard events[3]. CDC describes social vulnerability as the factors that may weaken a community's ability to prevent human suffering and financial loss in a disaster including poverty, lack of access to transportation, and crowded housing (see Figure 1)[4].

The CDC formulation of social vulnerability and specifically the index has some notable characteristics:

1. The definition of vulnerability is *not specific to individual hazards* for instance, hurricanes, heat-waves, or floods. It describes the underlying vulnerability to a generic set of potential but unidentified events.
2. Vulnerability is a *latent* construct that cannot be measured directly. It can only be estimated based on other socioeconomic and demographic variables. In other words, the SVI is an attempt to predict how a community would fare in the face of a disaster based on assumptions about underlying socioeconomic factors.
3. The SVI is a *single metric* calculated from aggregating other metrics organized into themes. It does not have a precise definition other than the formula used to calculate it.
4. The evaluation of any geographic area (county, census tract, etc.) is *relative, not absolute*. For example if a census tract has a vulnerability metric of 0.78, this does not mean that 78% of the subpopulation will be impacted severely or that the impacts will be 78% more severe. It only means that the area has a higher vulnerability score than a different area with an SVI score of 0.75, for example.
5. The CDC SVI makes use of both *"rankings" and "flags."* Rankings are the statistical percentile ranking of each unit area based on each of the individual indicators and for each of the themes. Flags are issued for each unit area that has an indicator ranking of greater than 90%. Flags can be interpreted as the number of metrics with very-high vulnerability (highest 10%). The CDC SVI can be represented as either rankings or flags at the levels of indicators, themes, and overall. It is important to note which metrics are being used in numerical scores and visualizations.
6. The CDC SVI is a measure of individual and household vulnerability averaged across a geographic area, not aggregate vulnerability or risk. In other words, very large areas with sparse or zero population can have high scores for vulnerability on a per-capita or per-household basis, but distort aggregate risk for resource allocation requirements. Areas with higher vulnerability and higher population concurrently will have higher resource needs. Resource allocation decisions may look at derived metrics for '*aggregate vulnerability*' or '*vulnerability density = aggregate vulnerability per square mile.*'

[3] Flanagan, B., Gregory, E., Hallisey, E., Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency management, 8*(1). DOI: 10.2202/1547-7355.1792l
[4] CDC/ATSDR Social Vulnerability Index Fact Sheet https://www.atsdr.cdc.gov/placeandhealth/svi/fact_sheet/fact_sheet.html

ASU followed the CDC conventions, definitions, and calculations throughout this work. This means that rankings may change for different areas from national rankings.

The scope of this work was to identify additional metrics that could be used to develop a fifth theme for an AZ-specific SVI that more appropriately represents the full range of hazards and disasters that could occur in the state, and the geographically specific socioeconomic factors that better predict vulnerability in local communities (see Figure 2). ASU has also produced a geographic information system (GIS) that is capable of creating maps of the individual layers, themes, and overall AZSVI index. This work was conducted iteratively with the ADHS Health Equity program staff and the DAC to evaluate and confirm the individual measures. ASU provided ".shp files" (shapefiles) with the final metrics in ESRI compatible file formats for ADHS that is included in their dashboard and "storymap" found on the ADHS website.

With the aim of capturing the unique characteristics of local community and state-wide Arizona-specific realities, the ideal approach to the choice of data involves crafting metrics and components rooted in local or state data sources, to differentiate from the SVI's reliance on Census data. Specifically, the CDC SVI is based entirely on data from the US Census American Community Survey (ACS). The ACS provides data at the county level on an annual basis, and at the level of census tracts on a 5-year rolling basis. Currently, the most recent ACS tract-level data was collected between 2017 and 2021. ACS data is subject to significant limitations; specifically, it is dated, may not be fully representative of underlying populations, and is slow to pick up changes in shorter than five year intervals.

In order to improve social vulnerability measurements, the ideal metrics would be local, recent, and fully representative. This concept inherently resonates with the notion that to truly understand and address the needs and dynamics of the Southwest region, we must draw from the most relevant and contextually rich information available, and closest to the source. However, when navigating the landscape of available data resources, it becomes evident that ACS data remains the best (and in many cases the only), comprehensive source spanning diverse geographies and scales for the state as a whole. Its far-reaching scope offers an unparalleled vantage point to describe the social, demographic, and economic dimensions across Arizona's diverse communities.

A number of key challenges complicate one's ability to use locally-sourced data; namely, the availability, level of quality, comprehensiveness, accessibility, and openness in locally-sourced data have precluded ASU's use of alternative sources in many cases. The need to procure accurate and representative information is of higher priority, and takes precedence when conceptually better data sources are found, but whose use is hindered by factors such as data gaps, inconsistencies in collection methodologies across local entities, and concerns surrounding accuracy or representativeness. In this trade-off between ideal and pragmatic, the ASU team strived to incorporate local or state-level data wherever feasible. Where such barriers prohibit their use, ASU recommended the Census data option, but listed some considered alternatives that might be useful in the long-term to develop an improved AZSVI.

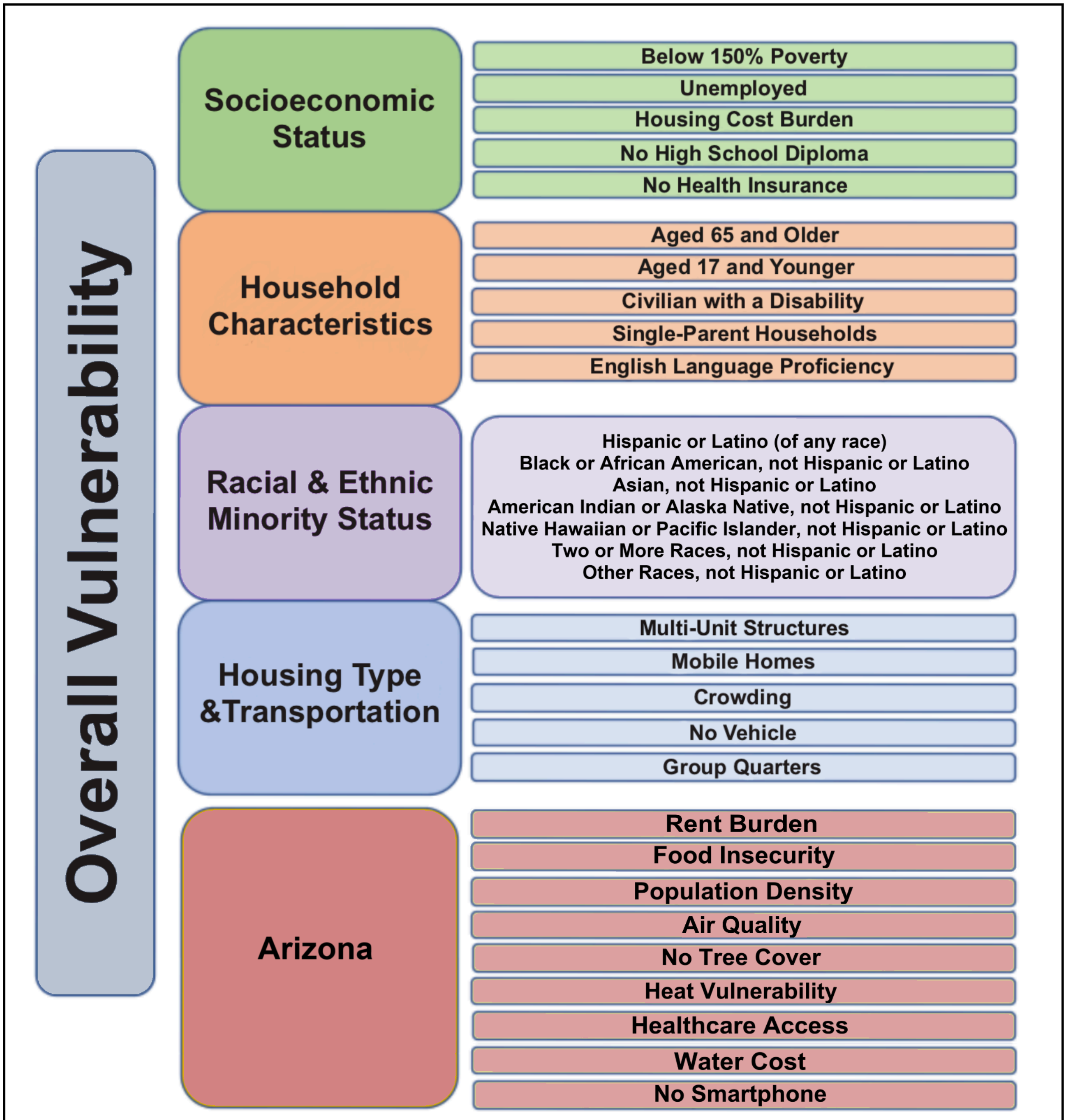


Figure 2: Illustration of the AZSVI with the addition of an Arizona specific theme. The AZSVI follows the same conventions as the CDC SVI with additional metrics.

Methods

Review and Selection of Indicators

The ADHS DAC conducted an online poll of its members in early 2023 to identify potential indicators that could be used in a new theme for an AZSVI. The results of that survey produced the following ten concepts/constructs:

1. Housing affordability/rent burden (added in CDC's 2020 update)
2. Distance/access to healthcare
3. Extreme weather (e.g. heat, cold, flooding)
4. Food insecurity
5. Broadband access
6. Water access and quality
7. Electricity accessibility
8. Substance abuse/trauma
9. Arrest/crime data
10. Fire risk.

ASU conducted an online search of resources that attempt to define and measure vulnerability or the similar constructs of resilience, risk, social cohesion, preparedness, and health equity. Over 15 similar resources were found and scanned for metrics that could inform the concepts/constructs identified by the DAC. ASU also conducted a thorough search of US Census ACS data sets for appropriate indicators.

Next, commonly used indicators were identified and ASU developed a master metric/indicator catalog from the sources that had the highest quality methodology for indicator/index development:

1. The CDC SVI
2. The FEMA Community Resilience Indicator (FEMA CRI) Analysis[5]
3. The Composite of Post-Event Well-being (COPEWELL) model[6]
4. The US Census Community Resilience Estimates (Census CRE)[7].

Relevant indicators were included that were identified by the ASU team from areas of subject matter expertise and prior projects.

On April 21, 2023, ASU hosted an in-person all-hands session with the full project teams and ADHS representation to review and select specific indicators based on the 10 DAC recommendations. The master catalog was used to identify appropriate metrics/indicators for concept/construct identified by the DAC.

Figure 3 shows an example of the process of “down-selection” from the information provided by the DAC and the specific data values to use from the ACS or other sources. Specifically, it is worth noting that the CDC SVI provides the concepts/constructs to include in the SVI, but

[5] FEMA.(2022). Community Resilience Indicator Analysis. Commonly used indicators from peer-reviewed research: Updated for Research published 2003-2021. https://www.fema.gov/sites/default/files/documents/fema_2022-community-resilience-indicator-analysis.pdf

[6] Copewell model (n.d.) The composite of post-even well-being. What if you could predict community resilience? https://www.copewellmodel.org/

[7] United States Census Bureau (n.d.). Community resilience estimates. ttps://www.census.gov/programs-surveys/community-resilience-estimates.html

requires exploration of the specific data tables and fields in the ACS to reproduce the index. Without exploration of the technical documentation, it would be nearly impossible to reproduce the CDC SVI. The explicit selection of the data elements is a critical step in ensuring that the AZSVI data elements are appropriate.

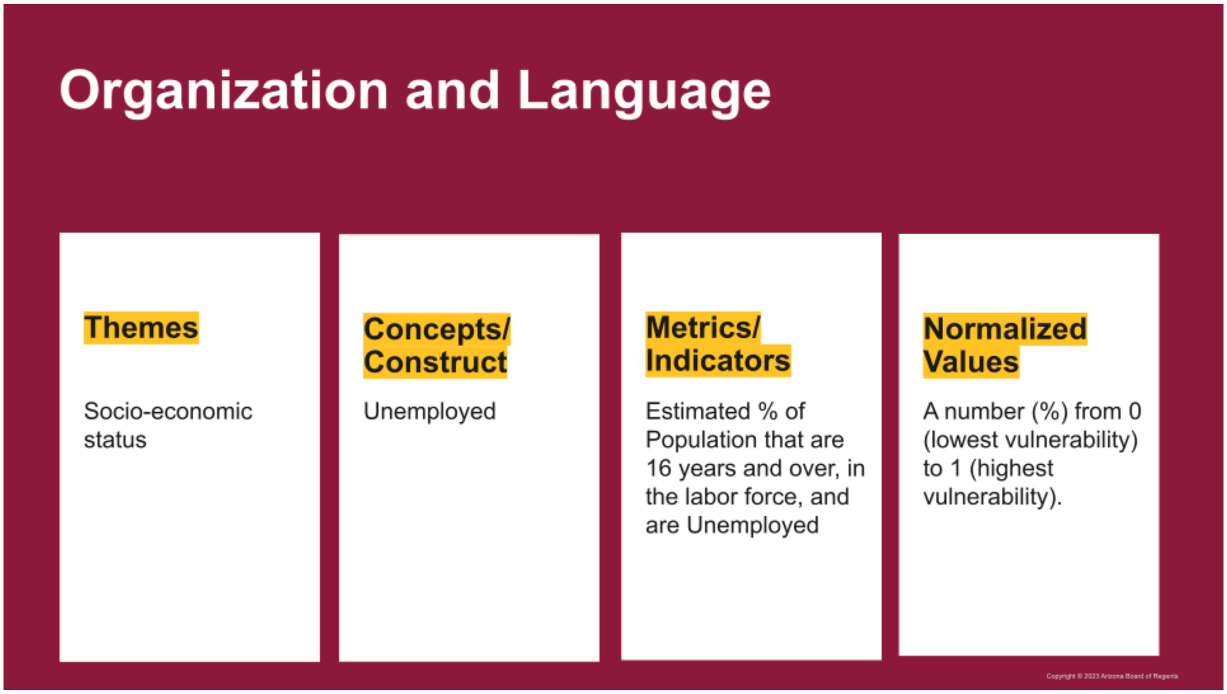


Figure 3: Organization of SVI in terms of themes, concepts/constructs, metrics/indicators, and normalized values. Specific metrics/indicators needed to be identified in order to select the specific data values and their source for use in the index.

Data Evaluation Criteria

For each of the data sources ASU evaluated proposed metrics against formal criteria for inclusion/exclusion in the AZSVI. Many of these criteria, such as existence, internal validity, and external validity, are useful as pre-screening criteria. Other evaluation criteria, such as collinearity, require additional analysis and a pool of candidate measures that need to be evaluated collectively. ASU aims to conduct future studies to validate the AZSVI, including future iterations that are beyond the current scope.

1. Existence: Has the data been collected through validated instruments?
2. Internal Validity: Examines whether the study design, conduct, and analysis answer the research questions without bias (e.g. mental health metrics are difficult to measure due to biases).
3. External Validity: Examines whether the study findings can be generalized to other contexts. Does the metric represent vulnerability in an index for Arizona?
4. Representative sampling: Does the data collected represent the demographics and

experience of the population being sampled?

5. Small populations: Do the error margins of small population sizes lead to spurious conclusions? If the confidence interval of a vulnerability metric is from 0.3 to 1.0, what is the correct conclusion: vulnerable or not?
6. Timeliness of data: Does the data collected from a 5 year census average (e.g. 2016-2020 or 2017-2021) represent current realities (e.g. housing burden, pandemic recovery)?
7. Reproducibility: Can the data be reproduced by ADHS in future years, or does it require dedicated data collection and proprietary algorithms?
8. Scale and precision: Is the data available at a uniform geographic unit (e.g. census tracts)? Where local / state data alternatives for Arizona are recommended, do they exist in a high-quality, consistent format, in a comprehensive manner across the state?
9. Collinearity: Does the data add new features that aren't already present in other data?

Upon review of the indicators, down-selection was used to attain the following seven topical areas (with an original goal of having around five) and distributed work across subject matter experts (SMEs) to recommend at least one meaningful indicator to use in the AZSVI for each:

1. Rent burden
2. Social services/food insecurity
3. Population density
4. Environmental (water, heat exposure, heat resilience)
5. Distance/access to healthcare
6. Price of Water
7. Broadband/telecommunications.

Two of the DAC recommendations were down-selected: substance abuse/trauma and arrest/crime data. The construct for substance abuse/trauma was identified as unattainable because there are no readily available indicators that would represent vulnerability without significant bias and omitted data. For example, the ACS does not have a question about substance abuse or trauma, and it is perceived as unlikely that respondents would self-report accurately. Alternative metrics such as the presence of substance abuse treatment centers or trauma recovery programs do not possess internal validity. In other words, they do not represent an underlying vulnerable population at the census tract level, but rather represent the availability of services for those who need (and can afford) to seek treatment.

Similarly, arrest/crime data have severe challenges with data accessibility and internal validity. It is debatable whether arrest incidence would lead to higher vulnerability, or if it is indicative of other structural socioeconomic factors and demographics including unequal police presence in neighborhoods, unequal enforcement, and whether arrests lead to convictions. In short, no metrics were available with a consistent interpretation at the census tract level for arrest/crime data that can be interpreted within the context of an SVI.

These recommendations are not intended to minimize the importance of substance abuse, trauma, criminal activity, and police arrests in the vulnerabilities that communities and their members face. Rather, these are the result of complex social dynamics within Arizona communities that government programs and services are established to address that would require more complex inquiry and research to properly formulate meaningful metrics. ASU's recommendation is that the AZSVI is not the appropriate instrument to incorporate these data elements.

The Environmental indicators in item 4 resulted in four metrics that were deemed internally consistent with resilience metrics: price of water, the Heat CRE from the US Census (developed by ASU), and the US Census Tree Cover metric based on remote sensing data from NOAA/NASA (with additional processing from ASU). These metrics are all proposed as new metrics to include based on subject matter opinions that represent novel, significant factors that will lead to an improved index, subject to future validation.

Novel AZSVI Indicators

Rent burden

Housing burden has been included in the CDC SVI since 2020, consisting of all housing types, including both rented and owned residential units. However, in Arizona, the need to account for vulnerabilities among renters is clear. In recent years, housing prices rose significantly in Arizona, exacerbating affordability problems among different income groups. Because of this trend, many Arizonans in lower to middle incomes have become more reliant on renting. Furthermore, the dramatic increase in rental prices after the pandemic has also made them unaffordable. According to the Pew Research Center, metropolitan areas were already seeing rent hikes before the COVID-19 outbreak, whereby in 10 urban areas, the median monthly rent increased 10% or more. Riverside, California and Phoenix, Arizona saw the largest increases during that time (18%)[8].

Renting households face higher financial vulnerability than homeowners, which motivates the inclusion of a metric that focuses on rent burden as a separate metric from housing burden. Several factors make renting households more financially vulnerable compared to homeowners. For instance, homeowners with fixed mortgage rates have stable mortgage payments, long-term stability, and the option to refinance or sell their homes to reduce costs. In contrast, renters have less control over rent increases; thus, significantly impacting their budget. It can lead to the possibility of frequent moves due to rental agreements, landlord decisions, or other circumstances. Frequent moves can disrupt their social networks, education, and employment opportunities leading to additional financial stress. On the other hand, homeownership is associated with wealth accumulation over time as homeowners build property equity. At the same time, renting households often have lower incomes and

[8] Leppert, R. (2022). 10 facts about U.S. renters during the pandemic. Pew Research Center. https://www.pewresearch.org/short-reads/2022/12/19/10-facts-about-u-s-renters-during-the-pandemic/

fewer financial assets. They do not benefit from this type of wealth-building, and their rental payments do not contribute to building equity or assets.

Moreover, renters are more susceptible to inflation and rental market fluctuations than homeowners. When inflation rises, the cost of living, including rent, tends to increase. Suppose renters income does not keep up with the rising costs. In that case, they will face financial strain, be forced to move to more affordable areas, forgo other expenses like air conditioning or medicine, or may face the risk of eviction, especially in areas with limited tenant protections. Arizona is currently 8th in the nation for the rate of rent increase, and Phoenix is the 7th city by share of renters paying more than $1,500 monthly[9]. ASU's tracking of evictions shows that the eviction rate in 2023 is the highest it has been since the 2008 housing crisis[10]. In fact, one alternative local/state data source that the team considered as an important metric is either people experiencing homelessness and/or eviction rates. However, as noted above data sources are sporadic, inconsistent, or non-comprehensive across the entire state. The Point-In-Time (PIT) count is a reasonable quality data source for understanding homelessness, but is not ubiquitous across Arizona, and does not adequately address housing precarity risks, being a count of persons already without housing. Another alternative considered was eviction rates from the various county court systems. However, gathering data from each county, ensuring a standard framework in a timely way presents significant challenges that make this conceptually sound metric, pragmatically impossible within the current data availability context. Perhaps in the future, there will be an opportunity for statewide evictions data collection for input into this metric. For now, ASU recommended using a less nuanced metric from the US Census that merits ongoing consideration locally.

ASU includes in the AZSVI the percentage of occupied units where rent burden is 35.0 percent or more of household income. This percentage represents the proportion of households that are spending 35.0% or more of their income on rent. This metric uses the Census ACS 2017-2021 data that provides insights into various socio-economic factors, including housing affordability. However, given the timeframe, it unfortunately does not capture trends after the pandemic.

This metric will help those who use the index to assess the affordability for renter income groups. A high rent burden percentage indicates that households are spending a significant portion of their income towards rent, leaving them less money to cover other essential expenses, including food, healthcare, education, energy, and transportation. High rent burdens may link to financial stress, housing instability, and even homelessness in extreme cases. For seniors on fixed incomes, unemployed households, or other groups, staying housed is critical. Understanding this will allow policymakers and social advocates to address these challenges and advocate for policies that promote housing affordability and stability among

[9] United States Census Bureau (n.d.). Household pulse survey data tables. https://www.census.gov/programs-surveys/household-pulse-survey/data.html
[10] Knowledge Exchange for Resilience (n.d.). Maricopa County: Eviction dashboard. https://resilience.asu.edu/evictions-dashboard

the population that needs this attention most - renters, not all homeowners as the general CDC metric presents.

In summary, rent burden is a crucial metric for understanding housing affordability and its impact on households and communities in Arizona. By focusing on this metric, policymakers and stakeholders can work towards creating more equitable and sustainable housing solutions and reducing vulnerability more generally.

Data source: U.S. Census Bureau, American Community Survey 5-Year Estimates (2017-2021)

Methods: Used the estimated percentage provided by the ACS, which represents occupied housing units where the rent amounts to 35% or more of the total household income.

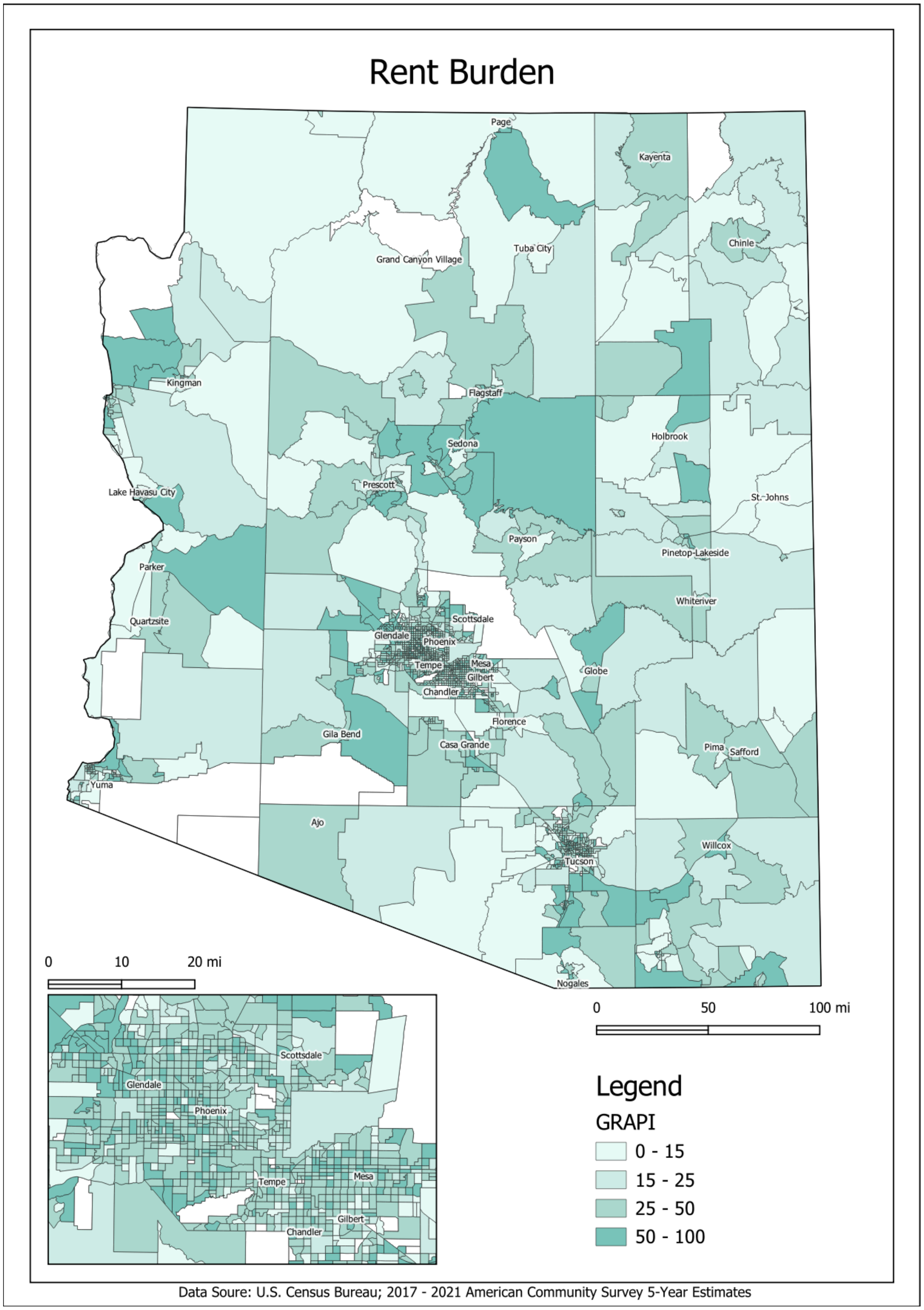


Figure 4: Percentage of occupied housing units experiencing financial burden with rent comprising 35% or more of total household income. (GRAPI - Gross Rent As a Percentage of Income).

Social services/food insecurity

The Supplemental Nutrition Assistance Program (SNAP) is the primary federal assistance program for low income individuals and families to receive subsidies for food. There is a complex relationship between SNAP and health outcomes, food security, and poverty levels. About 10% of Arizonans struggle with hunger, which can lead to poor effects like malnutrition and chronic health conditions such as diabetes, obesity, heart disease, mental health disorders and other diseases[11]. It is estimated that 42% of food insecure households (low +very low food security) participate in the SNAP program[12]. Participation in the SNAP program is strongly correlated with lower income levels, especially below 150% of poverty, which is part of the criteria for enrolling in SNAP. There are many individuals and families who may have food insecurity due to a lack of access to nutritious and affordable food; and many who may be participants in social services other than SNAP. Food security comes from the ACS 5-year (2017-2021) metric for percent participation in SNAP found in Subject table 2201: Food stamps/supplemental nutrition assistance program (SNAP)[13]. Therefore, the recommended metric to use is of percent households receiving SNAP assistance to measure vulnerability as it can give insight to its connection with food insecurity and negative health outcomes.

Data source: U.S. Census Bureau, American Community Survey 5-Year Estimates (2017-2021).

Methods: Used an estimated percentage obtained from the ACS, which indicated households receiving SNAP benefits.

[11] NIH (n.d.). Food accessibility, insecurity, and health outcomes https://www.nimhd.nih.gov/resources/understanding-health-disparities/food-accessibility-insecurity-and-health-outcomes.html

[12] Coleman-Jensen, A., Rabbit, M., Gregory, C., & Singh, A. (2022). Household food security in the United States in 2021. https://www.ers.usda.gov/webdocs/publications/104656/err-309.pdf?v=1367.6

[13] Food stamps/supplemental nutrition assistance program. ACS 2201_c04_001e.

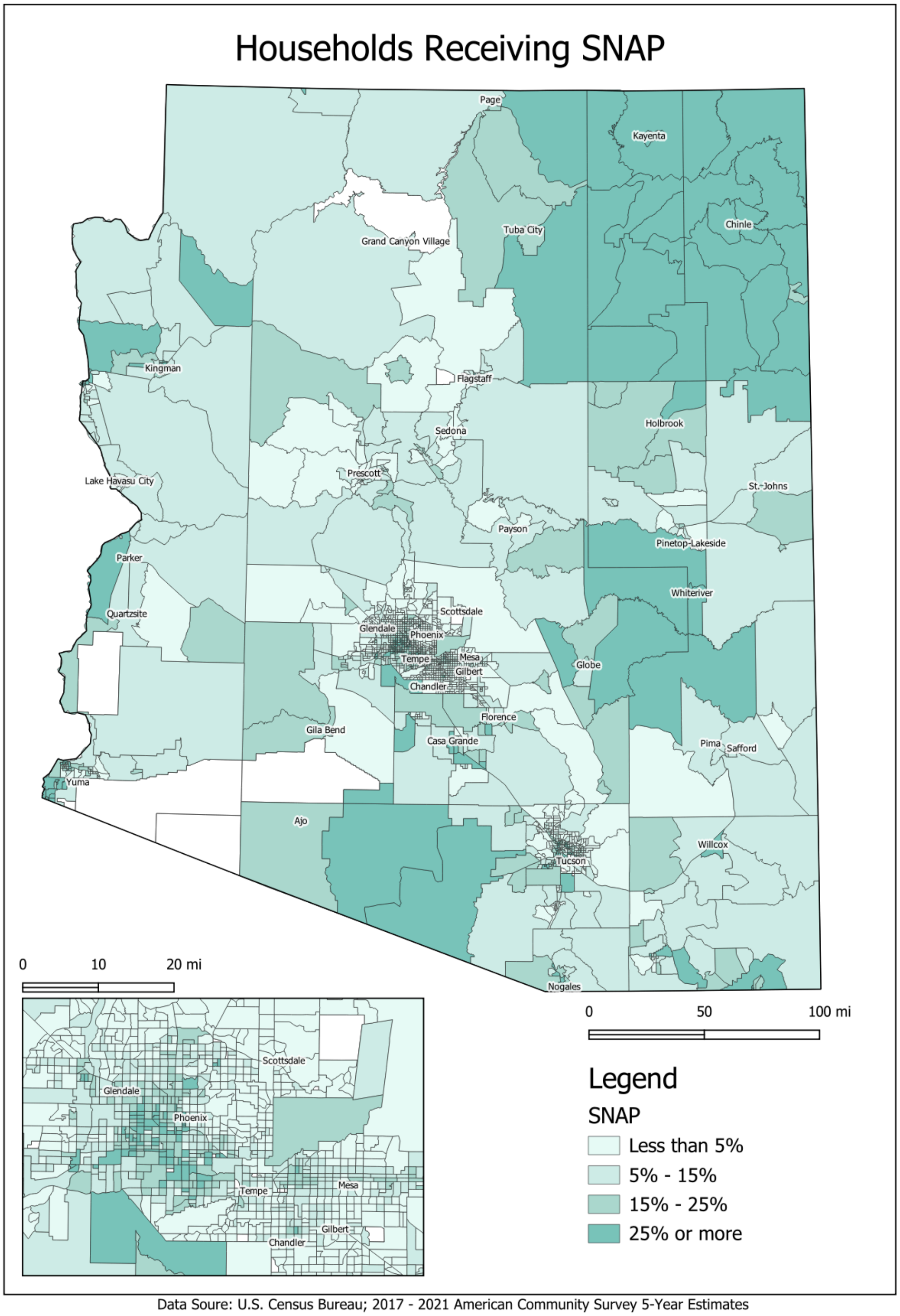


Figure 5: Percentage of households receiving SNAP benefits. Eligibility for SNAP is based on income below the Federal Poverty Level to reduce food insecurity risk.

Population density

Population density is not a part of the CDC SVI. “Rural” areas, as defined by the US Census, are those areas encompassing all population, housing, and territory not included within any urban area. In the 2020 Census definitions, urban areas must have a minimum of 2,000 housing units and 5,000 population. Based on these definitions, 89.3% of Arizona’s population is considered urban[14]. According to the CDC, rural Americans are at greater risk for poor health outcomes[15]. Among the reasons cited are long travel distances to specialty and emergency care, exposures to specific environmental hazards, and less access to healthcare.

Very few states, if any, have as much geographic variability in population density as Arizona. One of the reasons that the SVI has limited applicability to Arizona is that it is based on states with significantly denser populations, especially at the county level. Population density can be measured in many different ways that depend not only on geographic units like census tracts and counties that have complicated boundaries, but also in terms of travel times and distances to resources like healthcare and social services.

Population density is estimated as a ratio of population to area based on US Census data (in persons per square mile). Throughout the analysis, there are several important datasets that rely on data that are flagged by the US Census as impossible/difficult to compute, having a high bias, and having a small sample size. Population density is positively correlated with other metrics including access to healthcare, environmental features, and broadband/mobile services.

Data source: U.S. Census Bureau, American Community Survey 5-Year Estimates (2017-2021).

Methods: Divided the ACS total population estimates by the area in square miles for each census tract.

[14] United States Census Bureau (n.d.). Urban and Rural.
https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html
[15] CDC (n.d.). About rural health. https://www.cdc.gov/ruralhealth/about.html

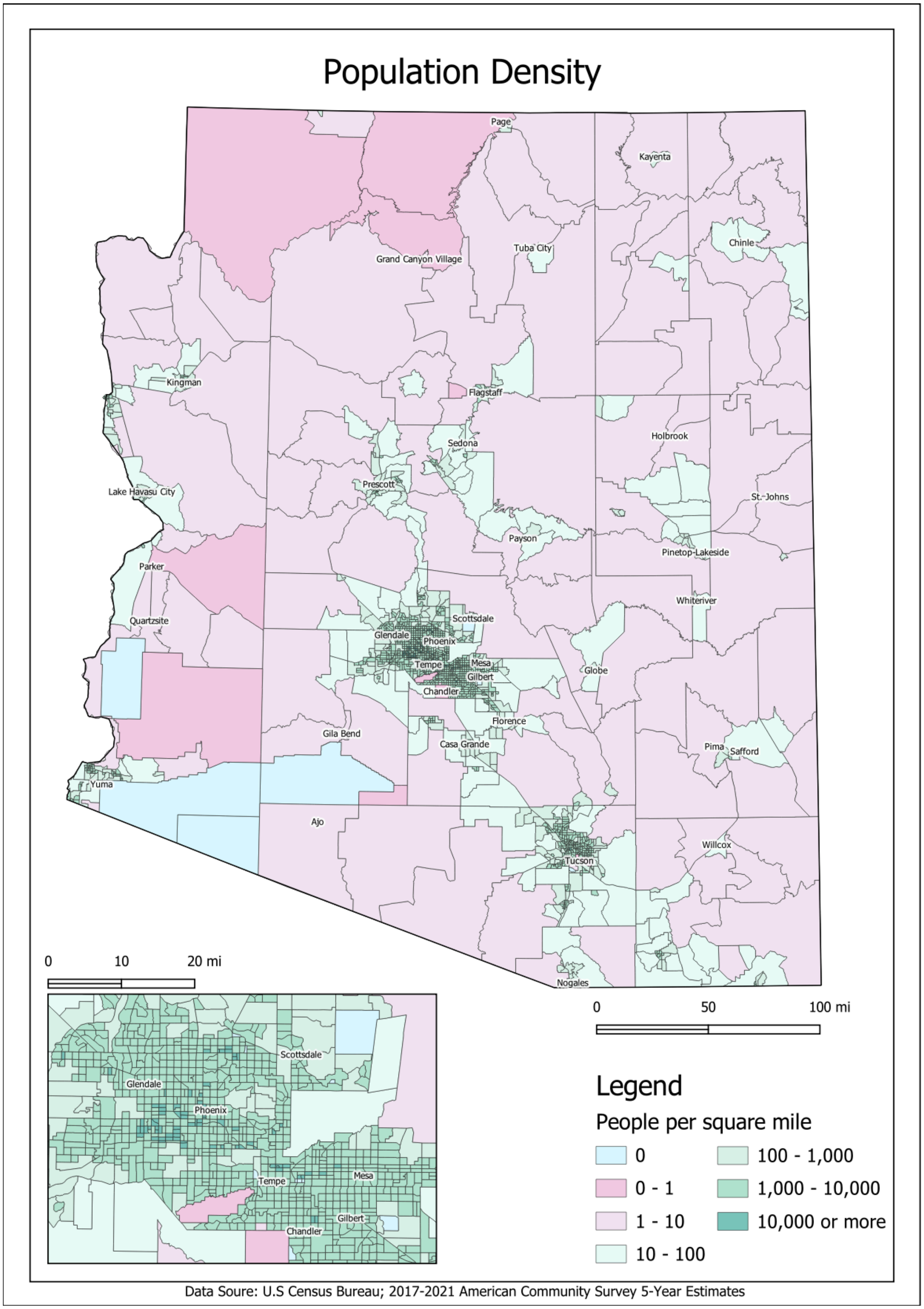


Figure 6: Population density in Arizona is predominantly rural (pink colors), with a concentration of residents around major cities such as Phoenix and Tucson (green).

Environmental Features

Given Arizona's unique geographic location and environmental characteristics, it is important to include a metric that captures the risk that these features present to the general population. In Arizona, two of the major environmental factors that affect health are heat and air quality. ASU recommended this metric in three components.

Heat

ADHS reports that more than 3,200 deaths from exposure to excessive natural heat have occurred in Arizona from 2012 to 2022. This number is rising year to year, whereby Maricopa County alone registered an historic 425 fatalities in 2022. Given that extreme heat is also the nation's most dangerous natural hazard, any set of metrics that is Arizona-specific must include consideration of vulnerabilities to heat.

The US Census recently published a new information product, Community Resilience Estimates (CRE) for Heat[16]. This product was developed and informed through a collaborative program between the US Census Bureau and the ASU Knowledge Exchange for Resilience at ASU. The primary focus of Community Resilience Estimates for Heat (CRE) is to assess a community's comprehensive resilience, encompassing its preparedness and response capabilities during extreme heat events, as well as its capacity to recover and adapt after facing such events. The CRE attempts to provide an estimate of resilience to a specific event, such that of extreme heat, that disproportionately affects Arizona. This is an interesting development in the utilization of United States Government (USG) data sources, since FEMA is responsible for supporting individual states in the creation of their hazard plans; Arizona, specifically the City of Phoenix, have been in discussions about federal declared emergencies for extreme heat[17].

Even though the CRE is built from similar factors as the SVI, the CRE risk factors are aggregated from *microdata*, focusing on individual and household level risk factors based upon aggregate or averaged rates across a geography. This is significant because, where the ACS components of the SVI describe risk-factor prevalence at an aggregated level (e.g. census tract), which are then summed, microdata describes the risk factors faced at the person (or household) level. Thus, provides a more accurate measure of that person's vulnerability. The risk factors are binary components that add up to 10 possible risks using data from ACS. The outcome is an index that generates small-area estimates at the aggregate level (e.g. tract, county, and state). It provides an estimation of the population count exposed to a certain number of risks. Although the methodology on the CRE for Heat is the same as the standard CRE files, there are some slight differences in risk indicators used to create the CRE for Heat index on the basis of ASU research. Three of the 10 risk indicators are somewhat modified

[16] United States Census Bureau (2023). Community resilience estimates (CRE) for heat. https://www.census.gov/data/experimental-data-products/cre-heat.html#

[17] City of Phoenix (n.d.). Office of heat response & mitigation. https://www.phoenix.gov/heat

from the standard CRE in order to account for vulnerability to heat *exposure* related to housing, energy and transportation. First, with respect to exposure that is a function of housing, whereas the CRE simply had a unit level crowding measure (>= 0.75 persons per room), CRE for Heat has a housing quality exposure indicator that also accounts for structure type (e.g. lives in mobile home, boat, RV, Van, or other). Second, in terms of energy burden, whereas the CRE simply had a poverty indicator (income-to-poverty ratio<130), the CRE for Heat's financial hardship indicator also includes whether the household's housing costs are greater than 50% so that electricity bills are represented. Finally, in terms of exposure due to mode of transportation, the original CRE has an indicator for no vehicle in the household, but the CRE for Heat's transportation exposure indicator also contains commute type (i.e. commuters that use public transportation, walking, biking, or other non-personal vehicle method). There are current plans for continuous improvement of the CRE for Heat with ongoing collaborations across the ASU KER team, Census, NOAA, NWS, FEMA, and NASA. Future plans include incorporating tree cover, as well as temperature data that triggers extreme heat warnings.

Data source: U.S.Census Bureau, Community Resilience Estimates (CRE) for Heat (2019-2020).

Methods: A spatial imputation using polygon centroids was conducted by ASU originally using the corresponded data to the 2019 census tract boundaries; then aligned the 2020 census tract boundaries with the remaining dataset. Population estimates were in three categories: zero risk factors, one-two risk factors, and three plus risk factors; those estimates with three plus risk factors were identified as an indicator of vulnerability. This process ensured consistency across the data despite the boundary changes between the two census years. The metric was scored and flagged at the 90th percentile, similar to other indicators, as part of the ranking process.

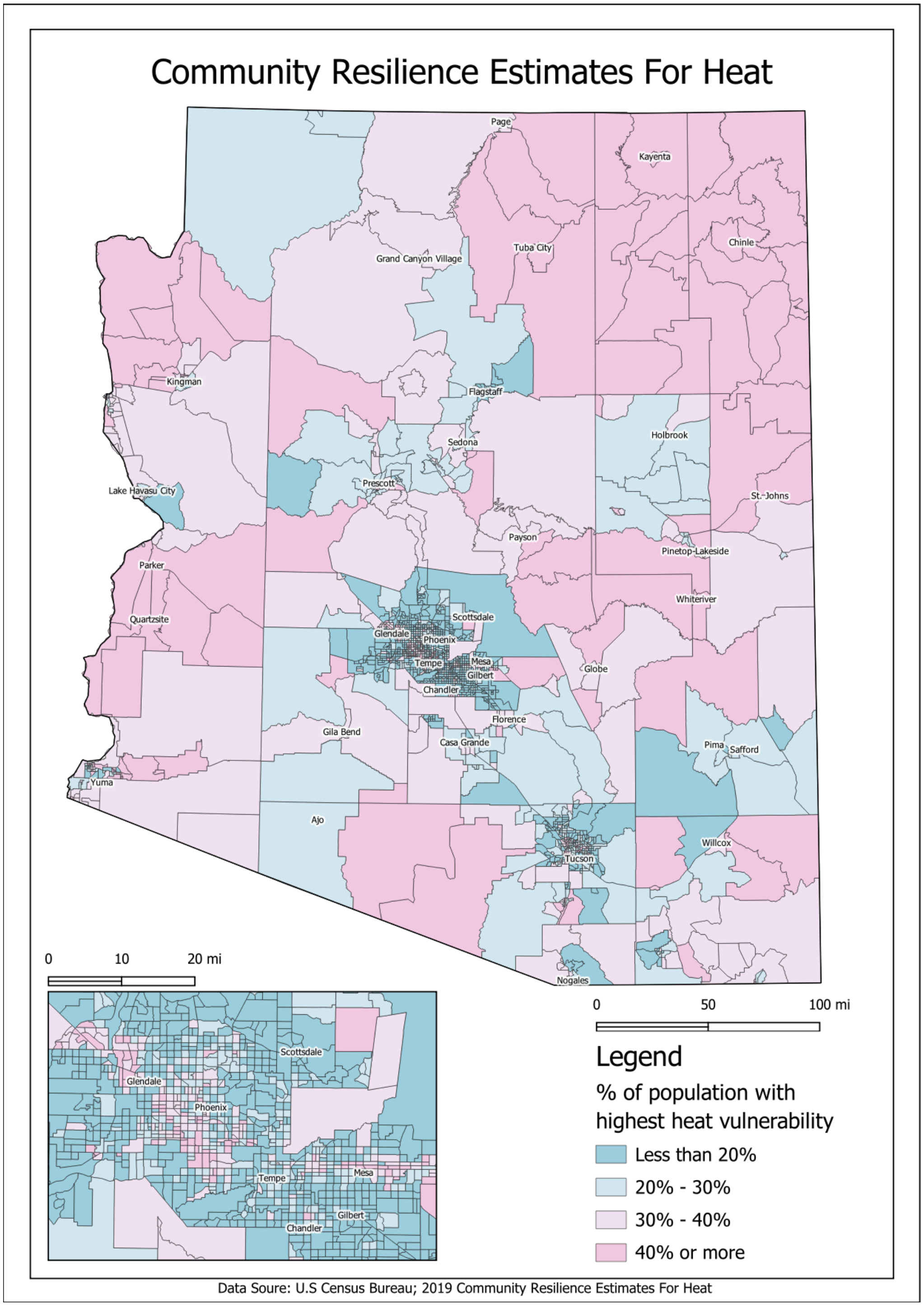


Figure 7: Percentage of population with three or more risk factors of vulnerability to heat. Heat vulnerability is based on multiple factors that reflect the population's geographic, socioeconomic, and health conditions.

Air quality

Data from the Environmental Protection Agency derived from satellite data from NASA and NOAA satellite programs was used to create air quality data for census tracts[18]. ASU examined three separate air quality measures: PM 2.5, PM 10, and Ozone. ASU selected PM 2.5 (particulate matter with size of 2.5 microns and below) as the preferred metric due to harmful impacts on health from inhaled combustion particles, organic compounds, metals, and smoke. ASU averaged the PM 2.5 values for the 2022 calendar year.

A key challenge for associating air quality measures is the sparse placement of calibrated air quality sensors across the state. There are a large proportion of census tracts having no air quality data associated with them. In order to provide approximate data for each census tract, a combination of centroid calculations around the locations of each sensor was used, as well as clustering analysis to create associations among areas to be represented by a given sensor.

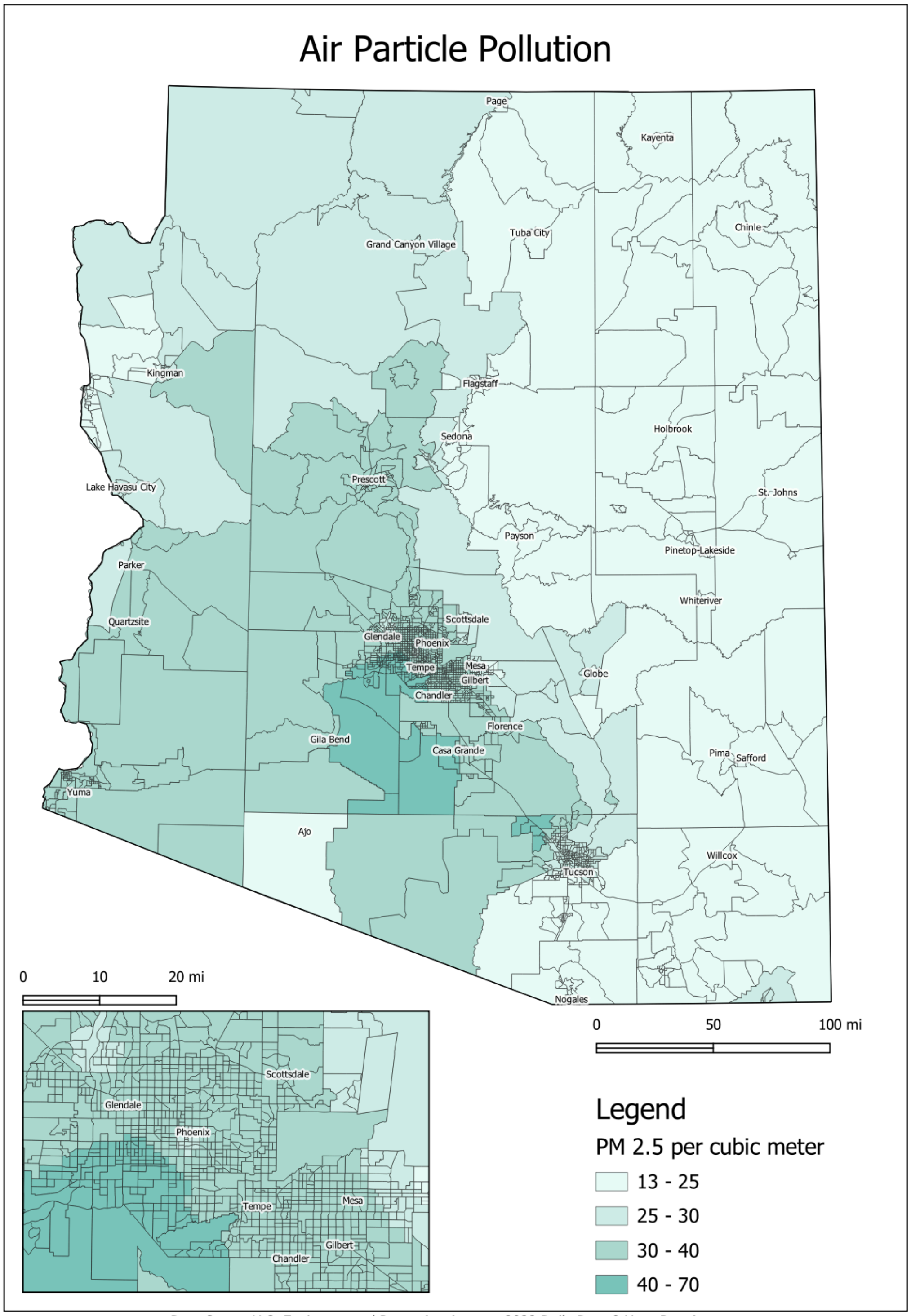
ASU first determined the centroid of each polygon using centroid calculation of the x and y coordinates. The centroids were then extracted and stored in separate columns in a DataFrame; and the coordinates were used as the basis for identifying the missing values using K-nearest neighbors (KNN) imputation. For a missing value, KNN imputation looks at its k-nearest neighbors and averages (or the weighted average) of the values. This average is then used to fill in the missing values. Weights were assigned as the inverse of the squared distance between each neighbor, which ensured that neighbors closer to the target entry had a larger impact on the final imputed value.

Data source*:* United States Environmental Protection Agency, Annual Summary Data (2022).

Methods*:* Used centroid calculation to locate the geometric center of each polygon of the limited air quality sensors in the state . The x and y centroid coordinates were extracted and stored in separate columns in a DataFrame. These coordinates were then used as the basis to identify missing values using k-nearest neighbors (KNN) imputation, a method used in data analysis and machine learning.

This approach attempts to surpass limitations posed by sensor availability, but it is only an estimation that does not account for a myriad of variables that contribute to the flow of particles and substances associated with air quality.

[18] United States Environmental Protection Agency (n.d.). epa.gov



Data Soure: U.S. Environmental Protection Agency, 2022 Daily Data 8 Hour Run Average

Figure 8: Levels of PM 2.5, the most harmful type of air pollution due to its small size (< 2.5 microns in diameter).

Tree cover

Data from the Multi-Resolution Land Characteristics (MRLC) Consortium's[19] satellite imagery analysis derived from NASA's Landsat data was used as its cutting-edge technology discerns and quantifies the extent of tree cover, employing a meticulous approach that ensures the accuracy and reliability of the dataset. It delves into the nuanced landscape of the United States, breaking down tree cover percentages at the granular level of census tracts. Each entry reflects the proportion of land covered by trees within these defined geographic units. By providing a comprehensive view of greenery distribution, this data aims to shed light on the environmental health of local communities and contribute to informed decision-making.

The dataset allowed for an assessment of the heat mitigation potential of tree canopy cover in different areas. High tree cover percentages can contribute significantly to shading and cooling effects, reducing the overall temperature in urban environments.

By cross-referencing tree canopy cover with demographic and socio-economic data, one can identify areas that are both heat-prone and socially vulnerable. This information is critical for targeting interventions and resources to enhance heat resilience in communities that may be more susceptible to heat-related health risks.

The data is planned to be added to future releases of the Us Census CRE for HEAT tool as mentioned earlier.

Data source: Multi-Resolution Land Characteristic Consortium, NLCD 2016 USFS Tree Canopy Cover (CONUS) (2021).

Methods: Tree canopy 30 meter resolution raster dataset was transformed into a polygon shapefile using the ArcGIS toolkit. For the purpose of percentile ranking and flagging, the proportion of land area covered by the tree canopy was deducted from the total land area. This deduction yielded the percentage of land without tree cover for each census tract. This particular metric was flagged at the 50th percentile to effectively identify all areas devoid of natural protection against extreme heat.

[19] Multi-resolution land characteristics consortium (n.d). https://www.mrlc.gov/

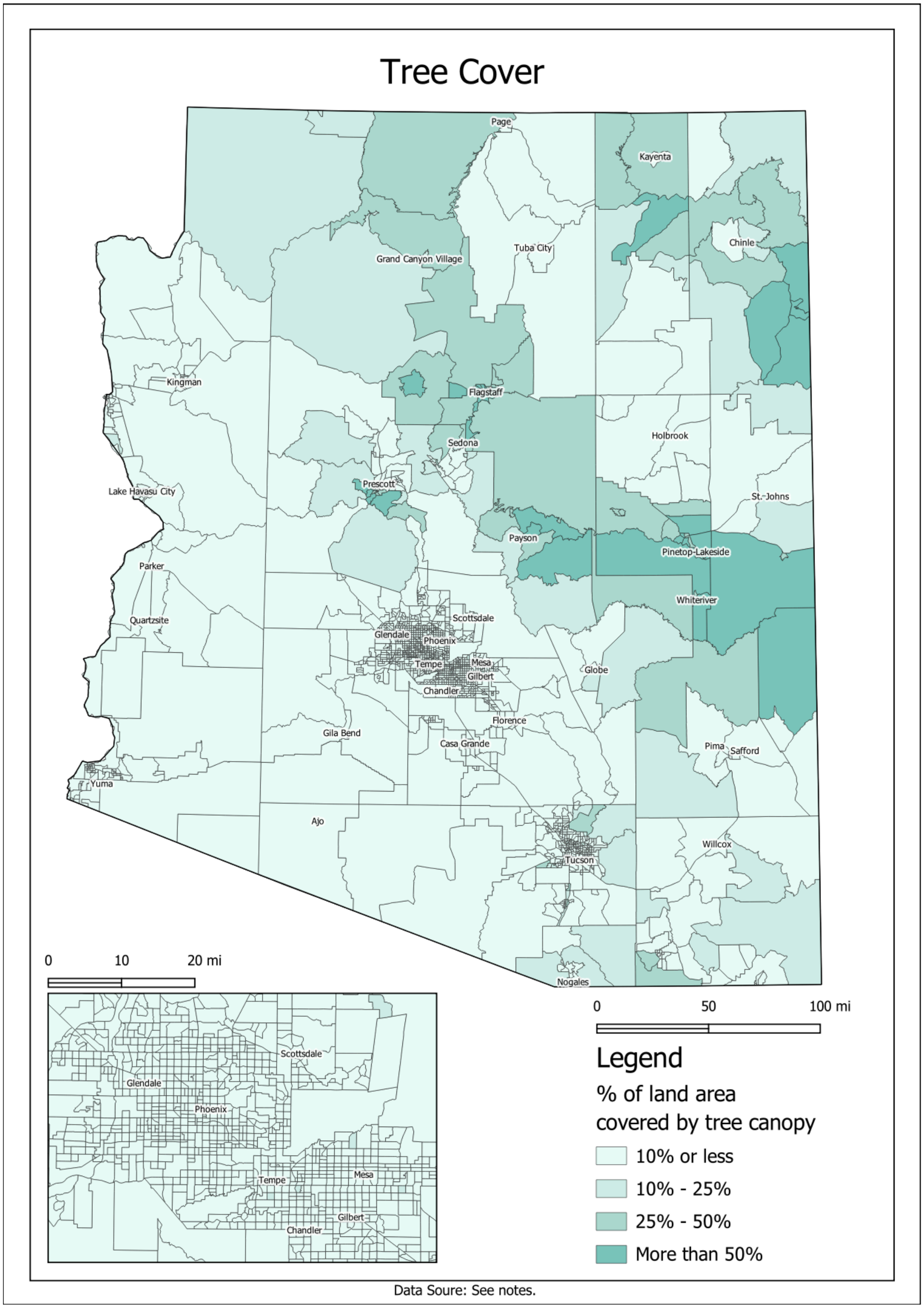


Figure 9: Percentage of land covered by tree canopy. Arizona's desert environment limits natural tree cover, contributing to the urban heat island effect. Tree canopy plays a vital role in mitigating extreme heat.

Distance/access to healthcare

Distance to healthcare can be a determining factor in obtaining the best health outcomes for conditions ranging from chronic to acute. People with chronic health issues who live far from health facilities can suffer negative outcomes due to their inability to access the routine treatment that chronic conditions require. For example, people who require routine treatments (e.g. dialysis) may suffer poor outcomes if distances affect their capacity to receive care. People who suffer acute medical emergencies often have short time windows to obtain life-saving care and treatment. The “golden hour” refers to the sixty-minute time window during which people who suffer a traumatic injury must receive medical care to ensure the highest likelihood of survival.[20] Arizona is a large state in which most of the population, and many of the services, are concentrated in urban areas. A 2022 report indicated that 82 of Arizona's 126 Primary Care Areas (PCAs), were designated as Arizona Medically Underserved Areas (AzMUAs).[21] Most of these were located in rural and tribal areas. For people throughout Arizona, and particularly those in medically underserved areas, it is important to measure and monitor the relationship between distance/access to healthcare and vulnerability.

To measure access to healthcare, the authors selected a population-center-to-facility drive time approach. Access to care is defined as “the timely use of personal health services to achieve the best health outcomes," and includes four elements: coverage, services, timeliness, and workforce. Each of these four elements are supported by the intersection of facility type, geographic proximity, and other factors. While geographic proximity alone may not address all potential barriers to access to care (e.g., cost, eligibility, linguistic/cultural appropriate services) it is widely used as a general proxy[22]. Moreover, it is recommended to use drive-time over distance in order to better account for variation in travel conditions across the state (e.g. traveling 10 miles across metro Phoenix compared to 10 miles in rural Cochise county).

Routes are calculated from each census tract’s center of population[23]. Centers of Population coordinates are published by the Census Bureau and are calculated to represent the point at which a featureless surface representation of the area of the tract “would balance if weights of identical size were placed on it so that each weight represented the location of one person.”The end-point facilities selected for this analysis include Federally Qualified Health Centers (FQHCs)[24], Rural Health Clinics (RHCs)[25], and Indian Health Service, Tribal-operated,

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[20] Wikipedia (n.d.). https://en.wikipedia.org/wiki/Golden_hour_(medicine)#

[21] ADHS (2022). Arizona medically underserved areas.Biennial report. https://www.azdhs.gov/documents/prevention/health-systems-development/data-reports-maps/reports/azmua-biennial-report.pdf

[22] Agency for Healthcare Research and Quality (n.d.). Access to care. https://www.ahrq.gov/topics/access-care.html

[23] United States Census Bureau (n.d.). Centers of population. https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html

[24] Rural Health Information Hub (n.d.). Federally qualified health centers and the health center program. https://www.ruralhealthinfo.org/topics/federally-qualified-health-centers

[25] Rural Health Information Hub (n.d.). Rural health clinics. https://www.ruralhealthinfo.org/topics/rural-health-clinics

and Urban Indian health program clinics”[26]. These endpoints represent facilities that are specially and specifically supported by federal legislation to address underserved populations both urban and rural via location and basic service requirements, or meet the needs of a specific population; for instance, tribal members. The selected facilities focus primarily on primary and preventive health care services.

Data source: UA Center for Rural Health (2022).

Methods: ESRI ArcGIS drive-time tool was used to calculate the drive-time to the nearest facility from the tract centers of population using the “closest-facility solver” and rural driving time[27].

[26] Indian Health Services (n.d.). Office of urban health programs. https://www.ihs.gov/; https://www.ihs.gov/newsroom/factsheets/tribalselfgovernance/; https://www.ihs.gov/urban/

[27] Esri (n.d.). ArcGIS online.Create drive-time areas. https://doc.arcgis.com/en/arcgis-online/analyze/create-drive-time-areas.htm

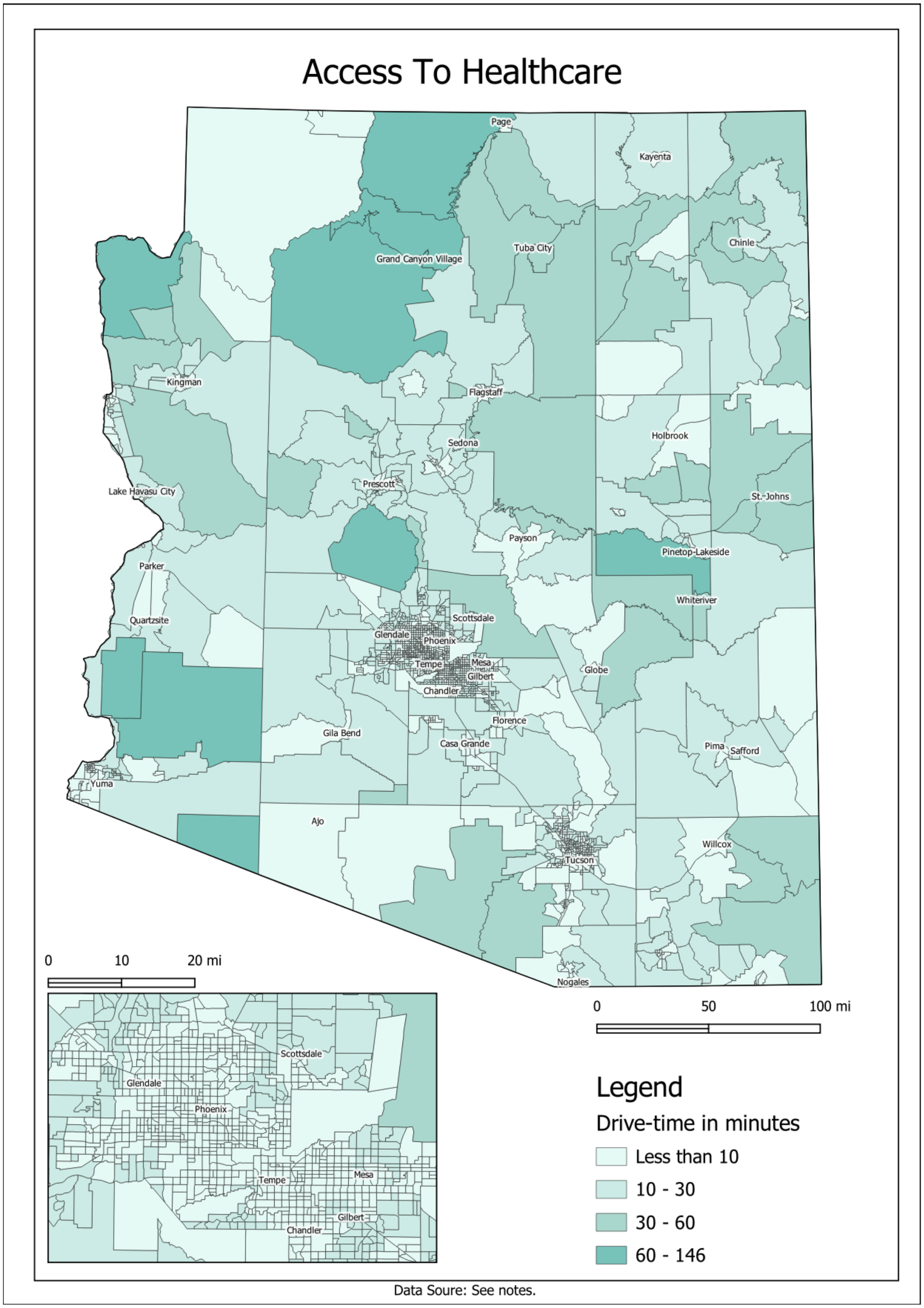

Figure 10: Drive time to the nearest healthcare facility. Longer travel times act as a barrier to timely and accessible care.

Price of Water

Arizona has an important history of rights to water and other natural resources that are economically scarce. Today, most of these natural resources are distributed through municipal and civic infrastructures. Prices of water, electricity, and other infrastructure services are not fully priced into the local and regional economy, yet they affect vulnerability in at least two ways: 1) individuals who face high utility costs are more likely to face hardship if income is lost, and 2) municipalities and companies who sell water as part of municipal infrastructure are likely to face higher risk and prices if their water supplies are less secure. These realities are assumed to be proxied in the cost of the water supplies, assuming that municipalities are appropriately charging economically fair prices and hedging/insuring risks. ASU chose to use water utility prices as a proxy for the vulnerability of reliance on infrastructure, while acknowledging infrastructure is a cumulative investment that favors ongoing investment.

Data Source: University of North Carolina (UNC) School of Government, Environmental Finance Center (2022)[28].

Methods: To calculate water price for each census tract, the average cost per 10,000 gallons was used from multiple utility companies in the service areas. A value of $1000 was given to tracts where there was no service (no water service) to reflect high-costs of hauling water. In the percentile ranking and flagging process, areas without water service were considered as most vulnerable, particularly in areas where the population is not zero. It's important to note that tracts with no population were entirely excluded from all calculations in this assessment.

[28] University of North Carolina (n.d.). AZ water and wastewater rates dashboard. https://dashboards.efc.sog.unc.edu/az

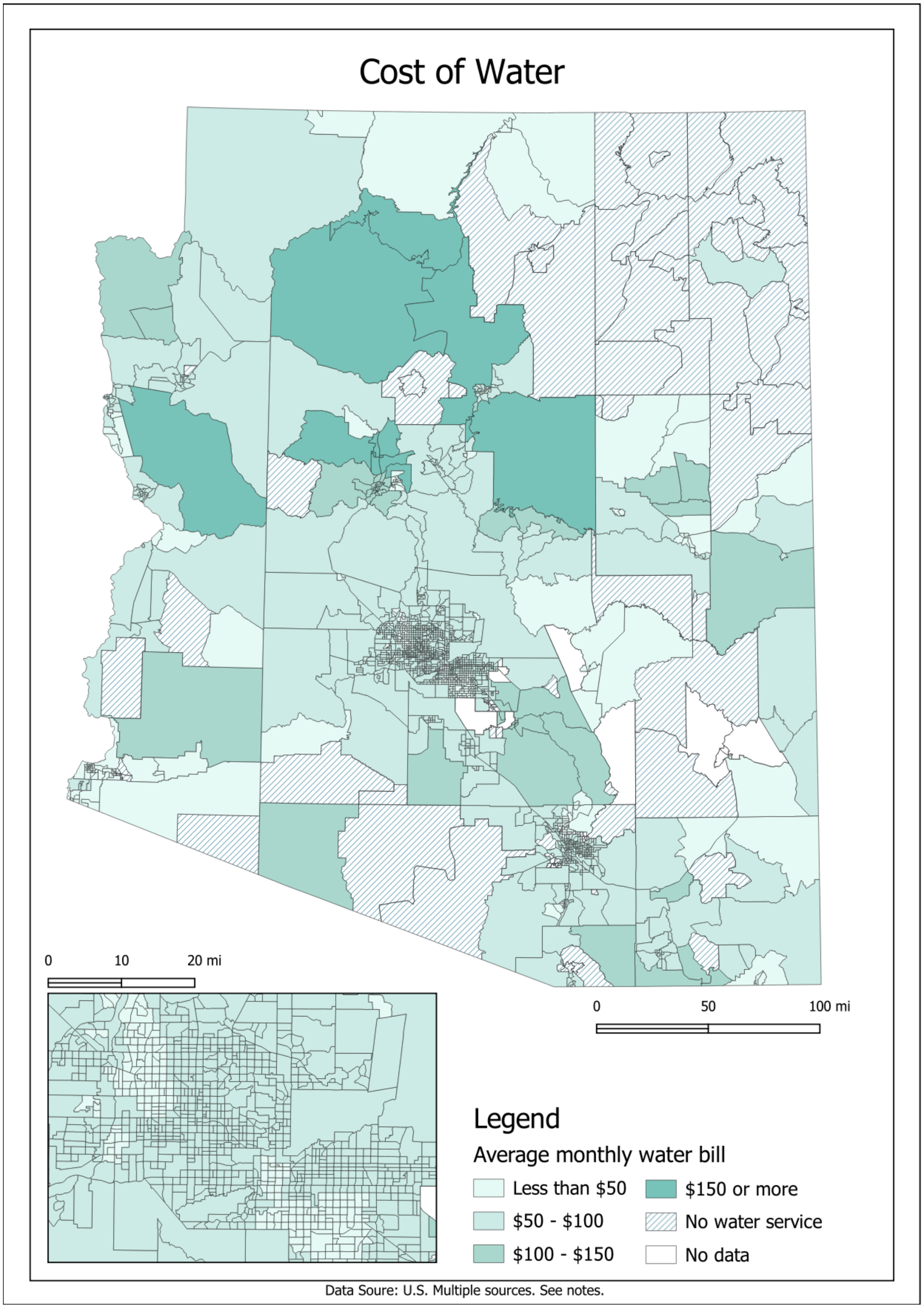

Figure 11: Average monthly water bill. High cost of drinking water puts an additional financial burden on households.

Broadband/telecommunications

Broadband and mobile infrastructure has impacts on health, education, economic development, emergency response, and many facets of life for all ages. Students need access to high-speed internet to participate in their educational programs. Adults need access to broadband internet for professional development and to execute remote work. All children and adults can benefit from telehealth services that connect doctors to patients in less time, for lower cost.

Based on the definition of social vulnerability, the implications of access to broadband and mobile phone services is significant. Cell phones with a reliable signal provide information about immediate hazards like heat waves, dust storms, flooding, and poor air quality, all of which can be mitigated through early warnings and forecasts.

ASU investigated three broadband metrics:

1. Owns a smartphone
2. Subscribes to any broadband services (faster than dial-up)
3. Subscribes to a broadband service that uses fiber, cable, or DSL.

The ability to communicate during acute events and the ability to access information and services online both decrease social vulnerability in different ways. ASU selected the metric for smartphone ownership because it has stronger face validity as a vulnerability metric. The other two metrics could have significant reporting errors if census respondents do not know which type of service they have.

Data source: U.S. Census Bureau, 2017-2021 American Community Survey 5-Year Estimates.

Methods: The ACS table offered an estimated percentage representing the population with smartphone devices. To determine the percentage of the population without a smartphone, the ACS estimated percentage was subtracted from 100%.

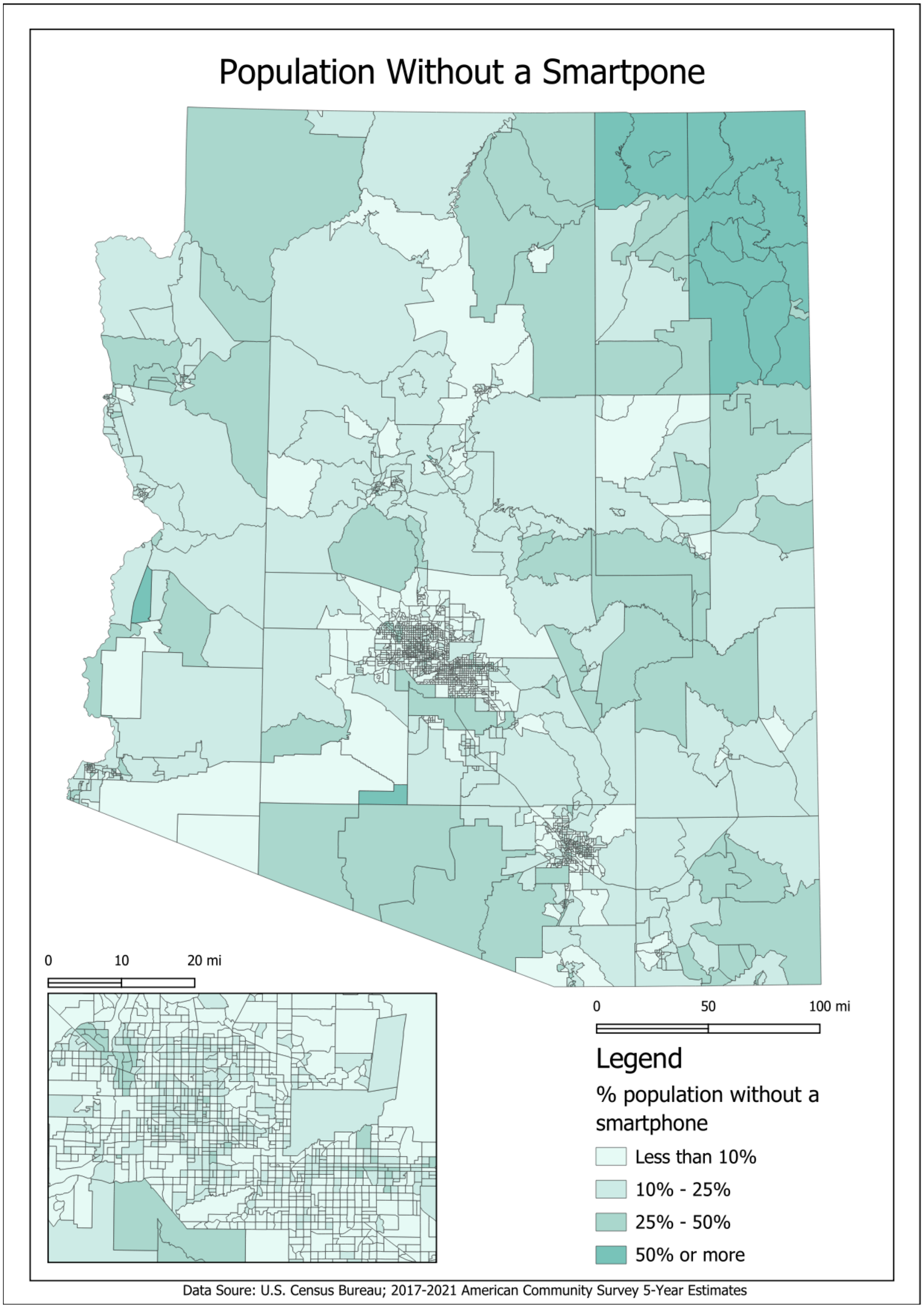

Figure 12: Percentage of population without a smartphone. Higher percentages of people without a smartphone are prevalent in rural areas.

Calculation of the Index

The CDC SVI is calculated as the "percentile rank among all tracts for 1) the 16 individual variables, 2) the four themes, and 3) its overall position."[29] The sums of the rank orders for each variable ***within each theme*** are rank-ordered a second time to produce the scores for each theme. The sums of the rank orders for each variable ***across all themes*** are rank ordered to produce the overall score. Note that the overall score treats each variable equally and does not make use of the themes. This is important because the themes do not all have the same number of variables and are therefore weighted disproportionately in the CDC SVI.

The AZSVI uses the identical method as the CDC SVI for consistency with one exception - the sums of each theme score are used to produce the overall score. This has the effect of weighting each theme equally in the AZSVI and not over- or under-weighting themes based on the number of variables within each theme.

First, ASU rank ordered the new, individual metrics across all census tracts within Arizona. Second, they summed each percentile ranking and ranked the aggregate score to produce the AZ-specific theme. Lastly, the AZ-specific score was added to the other four CDC theme scores to produce a sum of rankings, which is ranked a third time to produce the overall score.

ASU used the same notation for the AZSVI data as the CDC SVI in the data files. The rank order of an individual "metric" is denoted with the attribute name "epl_metric." These rank orders are calculated for each tract for which data is available. As described in the preceding paragraph, each epl_metric within a "theme" is then summed to produce "spl_theme" and rank ordered again to produce "rpl_theme." The process is repeated: the rpl_theme scores are summed to create an spl_themes score, which is rank-ordered to create the final score, rpl_themes.

The CDC SVI score is a relative score that is computed by comparing geographical units (either tracts or counties) to similar units. Any change to the index that includes or excludes additional counties or census tracts will change the final results numerically. For example, using the SVI algorithm to score census tracts in all of Maricopa County will produce different results than scoring every census tract in the state of Arizona and comparing to the Maricopa County specific results. It is not possible to calculate a score for a single tract or county. It is extremely important to identify which tracts or counties are included in the scoring algorithm.

Of the 1,765 census tracts in Arizona, there are 17 tracts that have an estimated population of 0 according to the US Census data. It is not feasible to calculate an SVI score for these tracts because several of the metrics are per-capita rates that cannot be calculated if there are no

[29] Agency for Toxic Substances and Disease Registry (ATSDR) (n.d.) CDC SVI documentation (2020). https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2020.html

inhabitants. The CDC excludes these tracts with zero population from the calculations. There are also 51 tracts that are missing one or more metrics. This can happen when there is not enough data to calculate a metric correctly from ACS data. The CDC removes these tracts as well, since they cannot have a fair comparison with tracts that have all metrics during the ranking process. ASU followed their methodology and replicated their process when preparing both Arizona-specific and combined datasets. The result is that 68 tracts (3.9% of the total) are ultimately excluded in the AZSVI as shown in Table 1. ASU created an additional dataset and a map layer with these 68 tracts as a convenient option of reviewing the available data and visualizing their features separately from the full dataset.

The CDC SVI and the AZSVI include one additional metric: the number of individual vulnerability indicators that are in the highest decile. Every ranked epl value that is above 90% receives a “flag” for that census tract. The number of flags are summed to produce an aggregate score for each tract that represents the number of vulnerabilities in the “highest” range for each tract.

Figure 13 demonstrates the stages of calculations that were used to appropriately exclude tracts that are missing data and calculate the overall AZSVI.

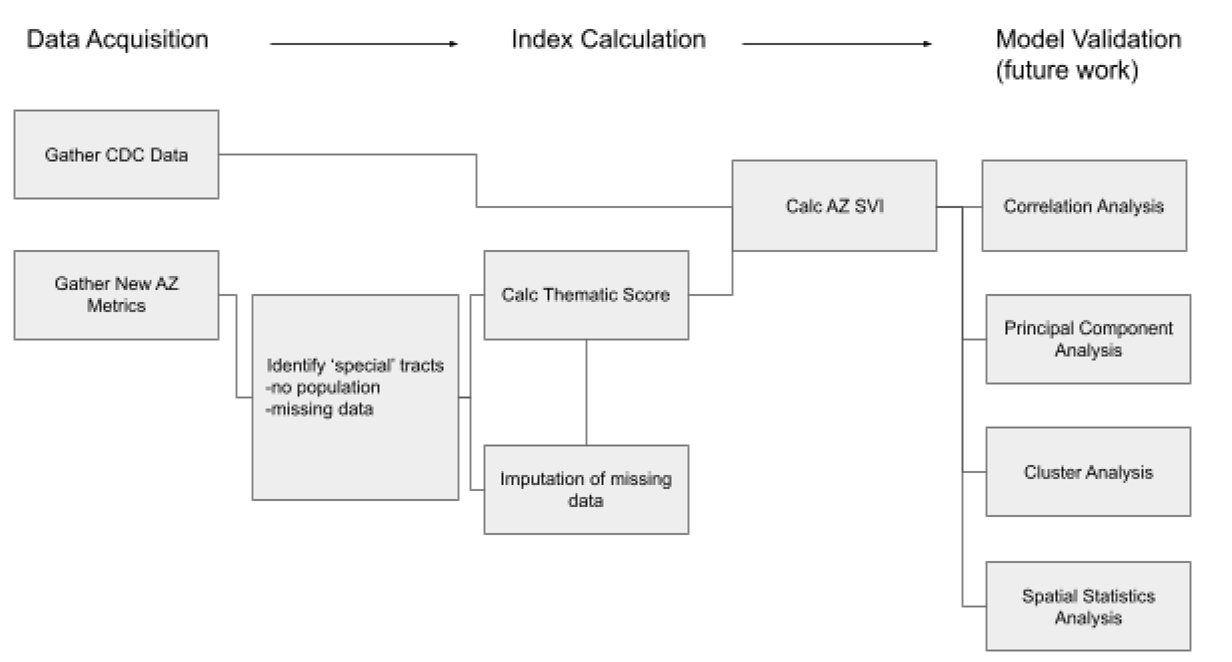

Figure 13: Flow chart of calculation of AZSVI with CDC SVI.

1. ASU removed census tracts where:
    a. Population estimate is zero.
    b. At least one indicator is not available (NULL) (*Table 1*).
2. Calculated EPL (ranked percentile) on each remaining tract.

3. Flagged tracts where EPL is in the 90th[30] percentile (Yes = 1, No = 0).
4. Summed EPL and Flags to calculate the rpl_theme5 (overall ranked percentile) and f_theme5 for each remaining tract.
5. Added back tracts with zero population and missing data.

Further, there were four metrics in total that contained null values. Population density was removed 17 times because the population is zero. GRAPI, which stands for gross rent as percentage of income, was removed 56 times because the denominator, number of rental units available, could not be computed within ACS. The price of water was not estimated for 12 tracts based on ASU's matching algorithm to census tract, which is an expected result since many areas do not have a municipal or private water provider. SNAP enrollment (food-stamps) was not estimated by ACS for 30 tracts because the denominator is households below a poverty threshold, which is not measurable in low-response areas. Note that the tracts that have no population also do not have data for GRAPI or SNAP.

Table 1: Exclusion criteria for tracts with zero population or missing data.

Exclusion Variable	Exclusion criteria	Data Evaluation Criteria	Count of tracts
Population Density	Population is zero.	1, 5	17
GRAPI	Data is not available (NULL)	1.	56
Price of Water	Data is not available (NULL)	5. 8.	12
SNAP	Data is not available (NULL)	1	30

[30] *Because a large portion of Arizona is an arid desert environment that can't support tree growth, the "no tree cover" indicator was flagged on the 50th percentile instead of the 90th.*

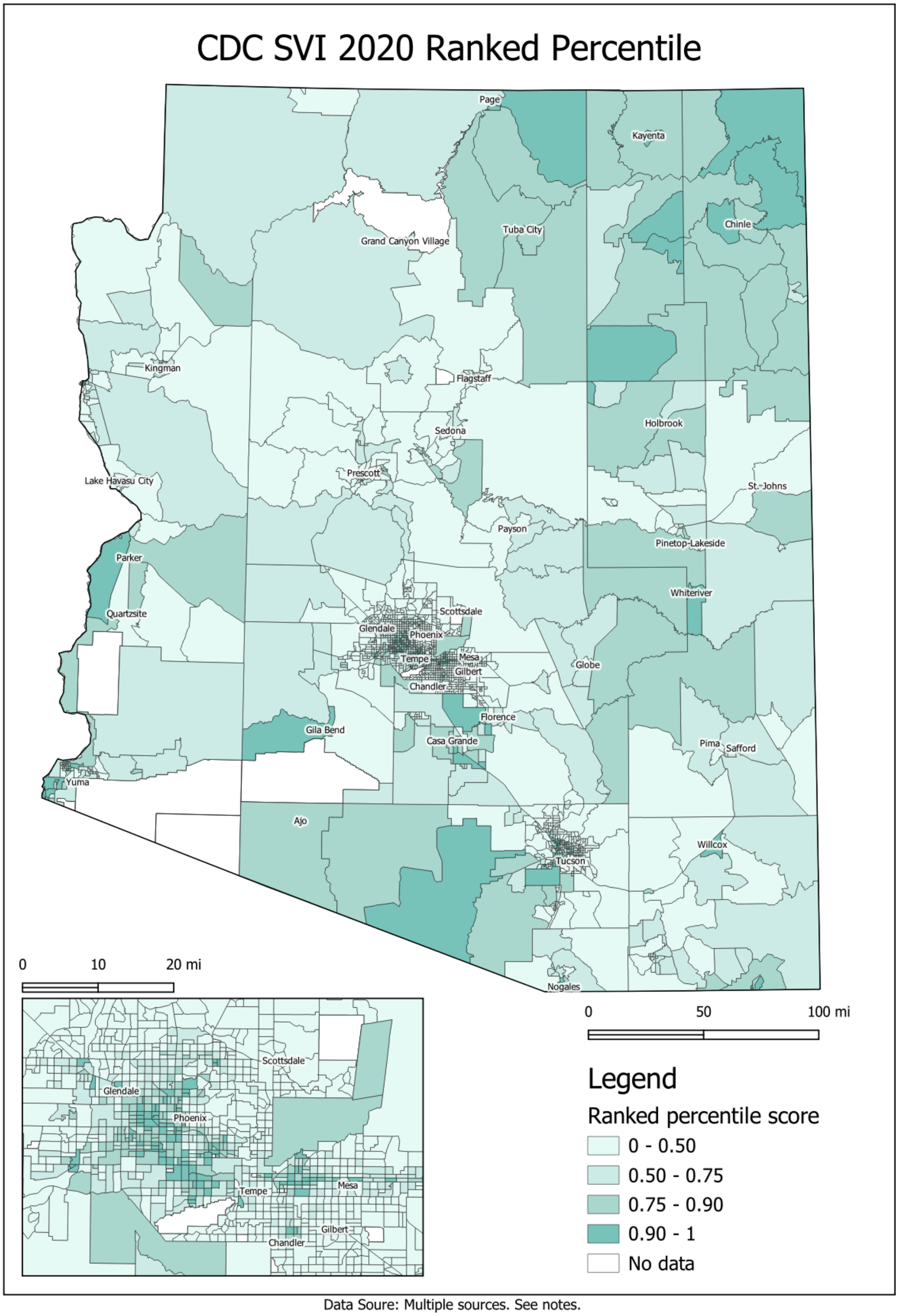

Figure 14: Ranked percentile score (Vulnerability Index), created by CDC. Higher score indicates higher vulnerability.

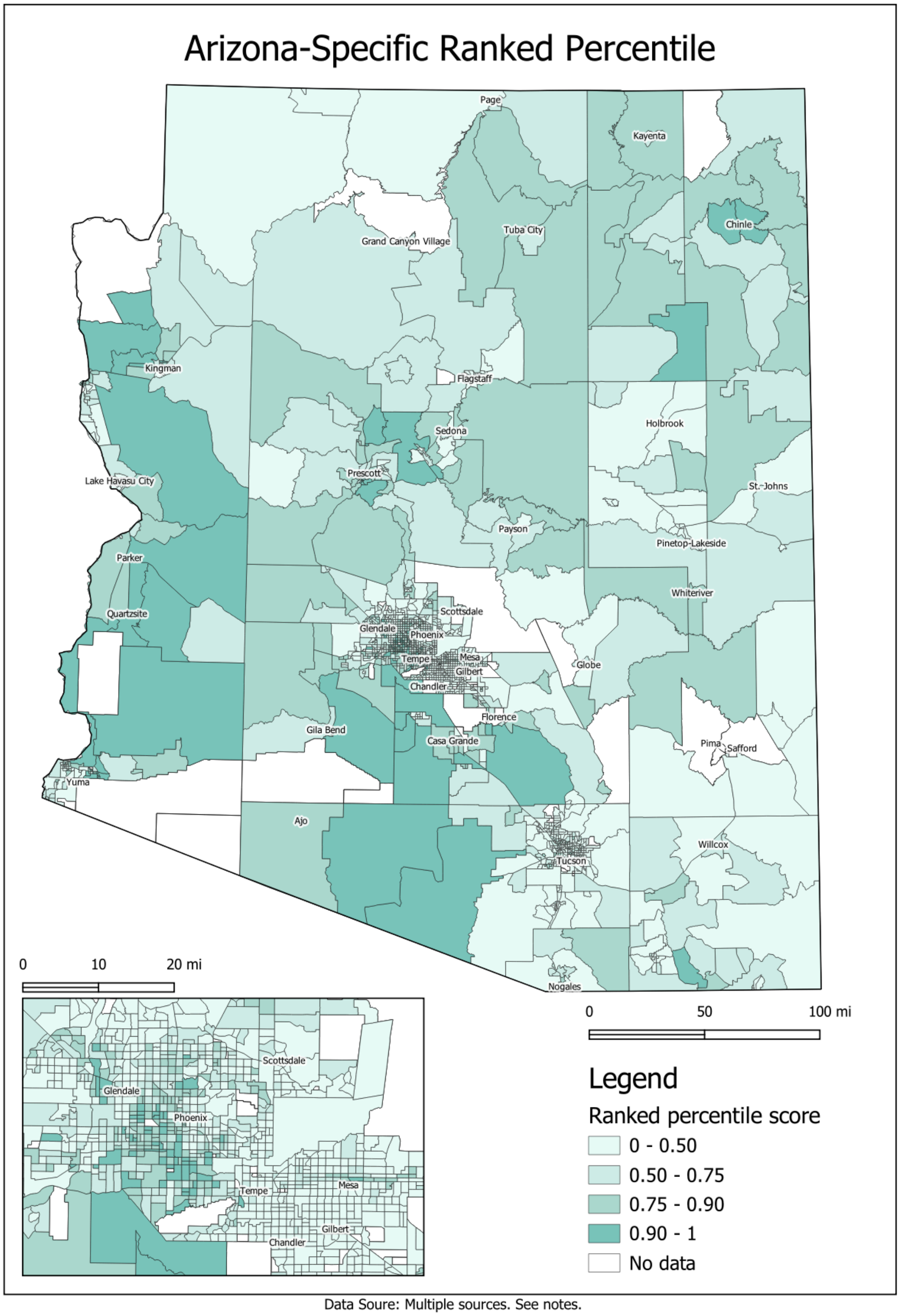

Figure 15: Ranked percentile score (Vulnerability Index) based on Arizona-specific indicators. Higher score indicates higher vulnerability.

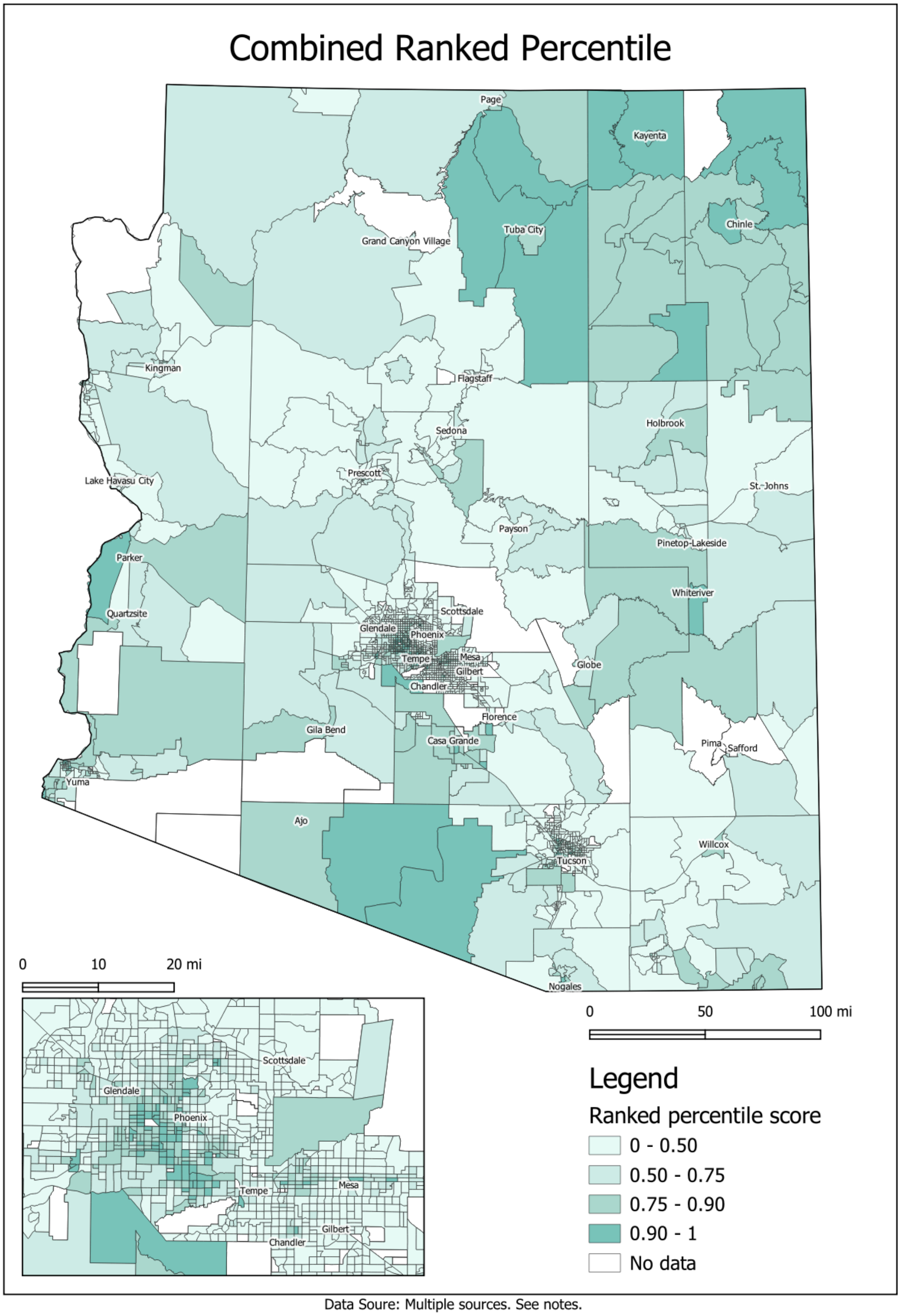

Figure 16: Ranked percentile score (Vulnerability Index) with both CDC and Arizona-specific indicators combined. Higher score indicates higher vulnerability.

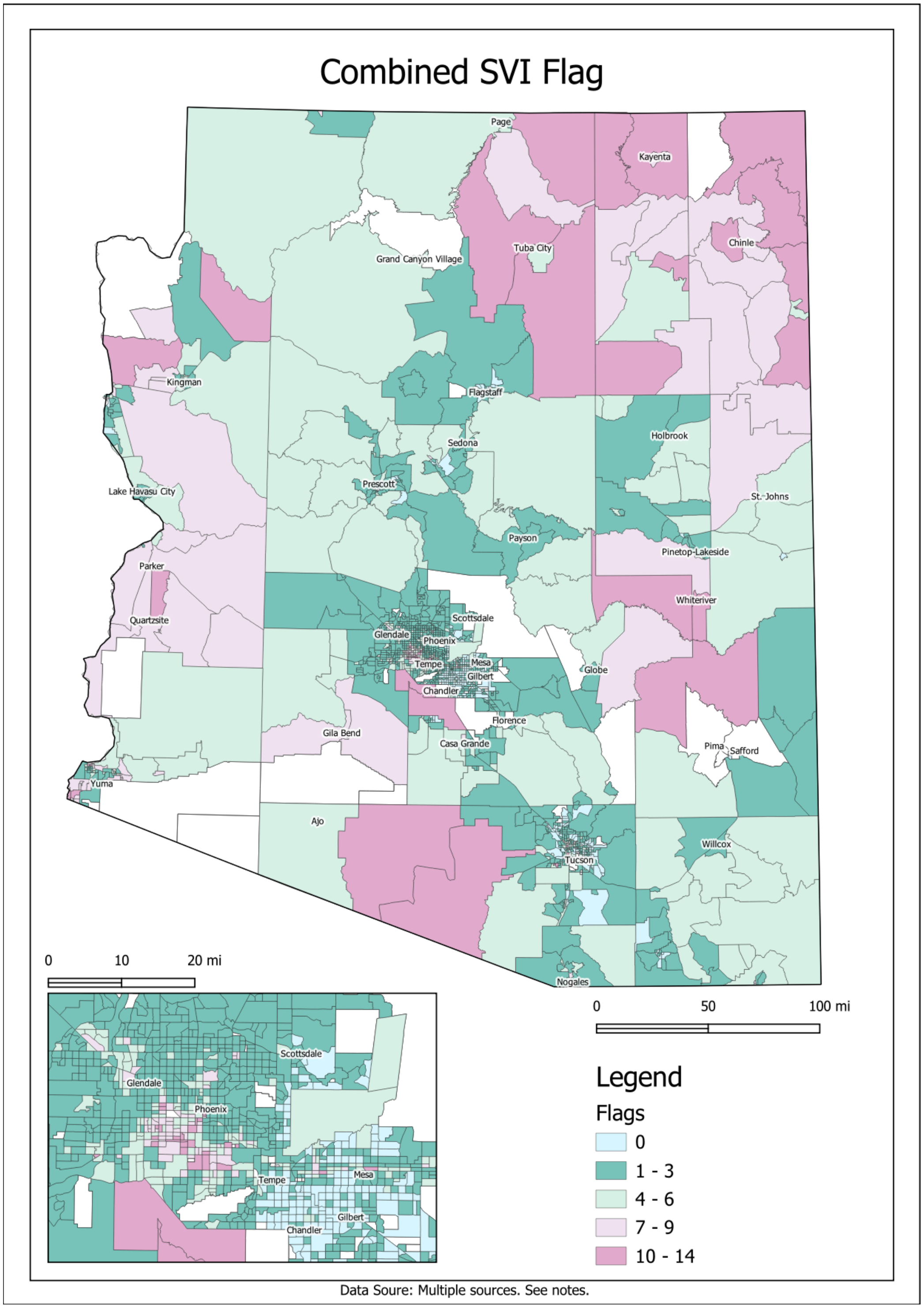

Figure 17: Flags. Census tracts where the theme's ranked percentile score is 0.9 or higher were flagged. Theme flags were summed to create a total flag count for combined cdc and Arizona-specific indicators. Higher flag count indicates higher vulnerability.

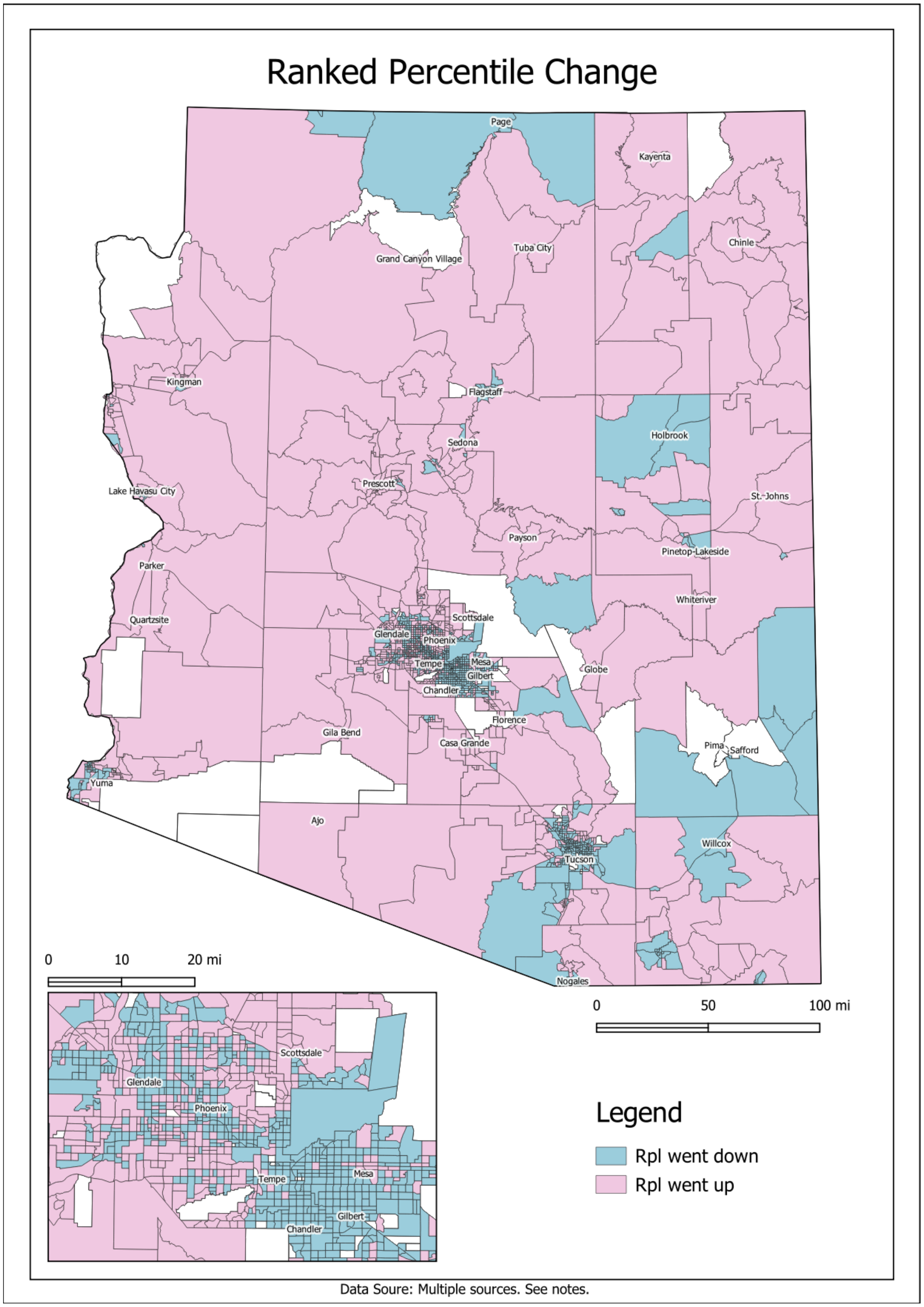

Figure 18: Post combination of CDC and Arizona-specific indicators, the recalculated Vulnerability Score (rpl) shows changed distributions. Vulnerability has increased (pink) in some areas and decreased (blue) in others.