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SPATIAL INVESTIGATION OF TOXIC SITES AND WATER—A FOCUS ON RACIAL EQUITY

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Abstract

This study puts a spotlight on the relationships among toxic sites (i.e. Brownfields, Superfunds, and Toxic Release Inventories), income, race, and water features such as groundwater wells and streams, all within the Salt Lake county, Utah target area. There were two hypotheses to be tested, which asked the questions: are toxic sites disproportionately located in low-income and minority communities in SL, and do these site proximities to water bodies such as lakes and streams affect water quality assessments and groundwater wells? The analyses in this research were completed with literature reviews on toxic sites and water with an environmental justice perspective, as well as implementing geographic information systems (GIS) to create cartographic representations of this environmental issue—spatial pattern analyses were conducted, and Kernel Density Estimation (KDE) and Getis-Ord Gi* (GOG) were the geoprocessing tools used to identify any correlations among the toxic sites, demographics, and water features. From analyzing the figures, the findings reported within this study align with many of its similar predecessors: vulnerable communities such as people of color (POC) and low-income groups have a disproportionate number of toxic sitings near them, and these toxic sites are inversely correlated to the assessments on water quality.

Introduction

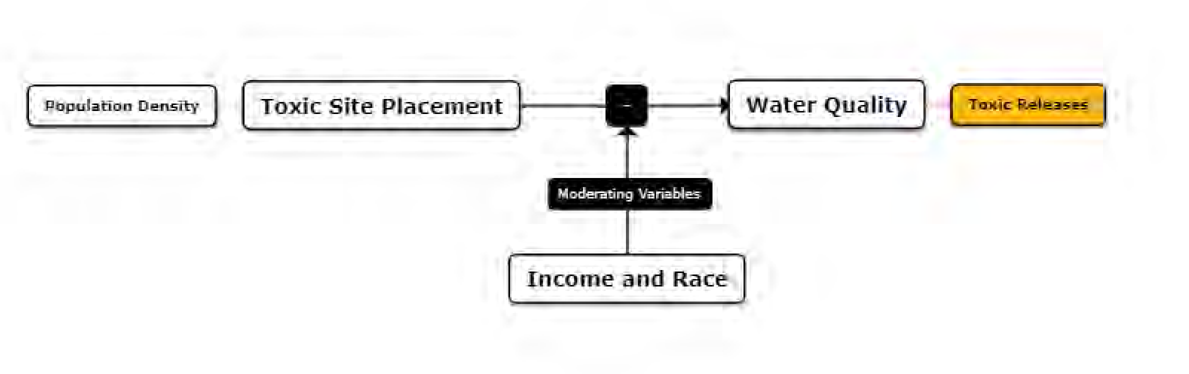
Waste is an increasing concern in urban environments, specifically toxic sites and the dangers they pose against water resources—toxic sites in this study's context mean Brownfields, Superfunds, and Toxic Release Inventories (TRIs), which are point sources of pollution. From an environmental justice perspective, these issues affect marginalized communities the most. Salt Lake (SL) county in Utah (UT) is one of the top three states in the nation that disposes the most toxic waste (EPA, 2021), which is the sample area in this research project (see figure 1) that investigates and provides further understanding of toxic site correlations with marginalized populations (low-income and race) as well as water bodies (groundwater wells and streams). Considering this, there are negative implications for SL's future health surrounding water, and unfortunately and unwillingly, minorities are the canary in the coal mine, their experiences serving as a warning for the future health dangers that could impact others—this is an issue happening now and will inevitably affect almost everyone in SL.

The environmental issues in the aforementioned paragraph concerning toxicity and water come with demographic disparities—the Black, Hispanic/Latino, then the Asian and Pacific Islander communities are the most polluted populations within the urban United States (US) in that order (Ash & Fetter, 2004, p. 459). There is a profound and significant possibility that SL exhibits similar trends, making it imperative that this study's discussions are conducted with an environmental justice (EJ) paradigm.

Research Questions and Framework

This study seeks answers to two questions: first, are toxic sites, that is Brownfields, Superfunds, and TRIs, disproportionately located in low-income and minority communities in SL? And second, do these site proximities to water bodies such as lakes and streams affect water quality assessments and groundwater wells? This research hypothesizes that, yes, toxic sites are disproportionately located in low-income and minority communities in SL, and that, yes, these site proximities to water bodies affect water quality assessments and groundwater wells.

Conceptual Model



In the conceptual model above there are three primary variables, which are:

Toxic Site Placement, which is the independent x variable that can be affected by Population Density, as well as the moderating variables Income and Race below the diagram.

Water Quality, which is the dependent y variable that can be affected by Toxic Releases, and while pollution can come from nonpoint sources, the focus lies on toxic site point sources.

Income, a moderating variable that has influence on Toxic Site Placement.

Race, another moderating variable that has influence on Toxic Site Placement.

The general purpose of this conceptual model is to visually explain the relationships among all of the above variables, and in this instance, it depicts that Toxic Site Placement has an inverse relationship with Water Quality as the negative sign placed between the two variables denotes—as the Toxic Site Placement increases, the lower the Water Quality becomes. However, it is important to note that the vice versa situation is more complex and cannot be simply applied to this situation, which is that as Toxic Site Placement decreases, the higher the Water Quality becomes—this previous statement is not necessarily true, which is discussed in-depth within the literature review section.

Literature Review

Toxic sites are home to dangerous chemical wastes dumped from a variety of land types, which include agricultural, commercial, and industrial areas, etc. The most recent data provided in 2019, according to the Environmental Protection Agency's (EPA) TRI, Utah ranked number five out of all fifty-six states and United States (US) territories nationwide based on total releases per square mile at 198.5 million pounds (lbs), or 90,038.1 metric tons (MT), from on-site and off-site releases combined (Environmental Protection Agency, 2021). Within the UT counties, SL disposed of 166.3 million lbs. (75,432.4 MT.) (Environmental Protection Agency, 2021), accounting for 83.8% of UT's removals in 2019.

According to Laura Briefer, the Director of Salt Lake City's Department of Public Utilities, "On average, 90% percent of Salt Lake City's water supply comes from [the] local Wasatch Mountain snowpack. About 10% of [the] water supply also comes from groundwater" (University of Utah, 2018). It is then stated that the water supply is qualified as safe, however, just in 2020 the Department of Environmental Quality (DEQ) found that ninety percent of Utah schools tested positive for lead contamination in their drinking water systems (Roe, 2020). The Wasatch Mountain snowpack is located outside of the study site, but the Utah Division of Water Rights recorded 173 groundwater wells throughout the Salt Lake Valley (Utah Division of Water Rights, n.d.) where massive amounts of toxic waste disposal persists with some water bodies assessed as "impaired" from nearby monitoring sites (Department of Environmental Quality, n.d.).

Therefore, adding to the water supply concern, water resource contamination is another major concern for SL as contaminants can contain hundreds of chemical compounds (Andrade et al., 2018) (Barnes et al., 2008) (Menció et al., 2016) and some industrial/factory sectors near water bodies like lakes and rivers often see heavy metal pollution, and the current technology is incapable of fully cleaning the intense concentrations (Dong et al., 2015) (Liu et al., 2020) (Marchant et al., 2011) (Pan & Li, 2016). Even if toxics are released on land only there potential still remains for the soil to absorb the chemicals and/or heavy metals as groundwater contamination from anthropogenic sources are likely surrounded by absorbent soils. This begs the question, how exactly can this toxicity be decontaminated? According to several studies on Brownfield and Superfund remediation, cleaning these sites are demanding, difficult, and expensive (Kaufman et al., 2003) (Lange & McNeil, 2004) (Saha et al., 2017) (Travis & Doty, 1990).

However, without active participation in cleaning contaminated soils and waters, a certain amount of remediation is not possible, and dirty water is near impossible, if not absolutely, to fully restore (Kaufman et al., 2003) (Travis & Doty, 1990). On a more optimistic note, new technologies and research are being done to alleviate groundwater contamination issues, such as developing assessments of heavy metals (Yang et al., 2012) with GIS (Neshat & Pradhan, 2015) and programming (Guo et al., 2019), sharing workflows to classify legacy pollution in groundwater (Weitzman et al., 2021) and help identify groundwater pollution sources (Ayvaz, 2016), as well as manage contaminants (Elshall et al., 2020), and testing sanitation systems (Pujari et al., 2011). However, solutions to effectively remediate sites are still lacking, and contaminated water is not the only danger that is posed, as there are also air-water chemical interactions to account for (Dueker et al., 2012).

As these environmental issues rise, so do concerns and events of water contamination, especially their damages against people of color (POC) in conjunction with environmental inequality. Historically, the trend is that POC suffered the brunt of environmental degradation and its lasting effects in their communities (Ash & Fetter, 2004) (Chakraborty et al., 2011) (Collins & Grineski, 2019) (Downey et al., 2008) (Downey & Hawkins, 2008) (Grant et al., 2010) (Jones, 2021) (Laurian, 2003) (Morello-Frosch et al., 2001) (Morello-Frosch et al., 2002) (Morello-Frosch & Lopez, 2006) (Morello-Frosch et al., 2011) (Pastor et al., 2001) as “race, as a social construct and mechanism of classification, historically defined and continues to shape the distribution of power, privilege, and economic resources in American society” (Morello-Frosch & Lopez, 2006). A study conducted on minority populations’ proximities to toxic facilities sought to investigate whether toxic facilities or minority move-in came first, and the research produced four important findings. First, disproportionate siting mattered more than minority move-in within the sample area. Second, less-educated, low-income, minorities, and renters suffered most from disproportionate siting. Third, areas undergoing ethnic churning/transition were as vulnerable to siting as areas with older or more established minority populations (Pastor et al., 2001). Lastly, at the time of the study, Blacks and then Hispanics/Latinos were closest (within one-fourth of a mile) to a toxic site, in that order, but the number of Black individuals decreased and the Hispanic/Latino individuals increased over the span of one or two decades in the sample area. This research is one of the foundations for many studies examining toxic sites and marginalized communities that came after it, many with similar results and more findings that demonstrated the threat POC and low-income groups were in concerning pollution and other forms of environmental degradation (Ash & Fetter, 2004) (Chakraborty et al., 2011) (Collins & Grineski, 2019) (Downey et al., 2008) (Downey & Hawkins, 2008) (Grant et al., 2010) (Jones, 2021) (Laurian, 2003) (Morello-Frosch et al., 2001) (Morello-Frosch et al., 2002) (Morello-Frosch & Lopez, 2006) (Morello-Frosch et al., 2011).

The literature review identified these negative relationships that marginalized individuals have with the environment as the result of three factors, which were cited at least once in all the readings. First, historical and contemporary racism. Second, biased policies and regulations. Third, discriminatory behavior and practices in the market. The factors are oversimplifications to the complex and complicated EJ topic and systemic problems, but are enough to explain that prejudices and racisms adapt, and that “past and present discrimination in the US are imprinted onto our urban landscape, as evidenced by the persistent spatial separation of diverse communities along racial/ethnic and, to a lesser extent, class lines” (Morello-Frosch & Lopez, 2006). The following paragraphs will explain that these factors are supported by, although not limited to, academic and scientific distrust (Cashman et al., 2008) (Corburn, 2003) (Laurian,

2003) (Messer et al., 2017) (Morello-Frosch & Lopez, 2006) (Morello-Frosch et al., 2011) as well as ecological gentrification (also known as environmental/green gentrification) and an imbalance in power and participation in green initiatives (Anguelovski, 2015)—these are main focuses in the majority of papers regarding EJ and are ones that take many aspects from the aforementioned three factors.

Distrust in science is not a new concept and is a certainty within the ecological sphere—in fact, distrust in environmental sciences is one of the major obstacles to achieving sustainability (Messer et al., 2017). There are three main reasons for this distrust: historical prejudices and gatekeeping in the scientific field that worsened relations with minorities, research findings that do not necessarily align with the target audience's priorities and lived experiences (i.e. conflicts of interests), and the way in which the climate and the environment are framed and communicated to people (Messer et al., 2017)—these reasons result in suspicions on the fidelity of scientific studies. A predominant example of scientific apprehension in the readings relates to an important EJ theme, participation—cooperating with the individuals who live, breathe, and sleep with the pollution festering in their neighborhoods (Cashman et al., 2008) (Corburn, 2003) (Laurian, 2003); these studies stress that academic jargon is a significant barrier that prevents individuals from fully understanding the depth and breadth of the situation that they are in, and that anecdotal and local knowledge help immensely with policy-making and analysis.

Environmental health movements are gradually adopting community cooperation into decision-making, with a study providing cases where local participation proved indispensable to the suggested solution; qualitative data collection in a tribal area proved more accurate when locals volunteered to distribute and interview individuals; significant trust developed when scientific and local individuals worked together to study Latino men's health; the locals surveyed the health of their POC urban community and found that certain buildings emitted dangerous volatile organic compounds (VOCs). The latter finding is important to pay attention to because it was found solely because of local knowledge and participation, if not, the researchers would have used census tracts or block groups, which are the smallest location aggregations that exist in databases. These mentioned examples also overlap with the other reason that contributes to the three factors, agency.

Lack of agency is something that minority communities contended with historically and contend with presently (Brown et al., 2004) (Corburn, 2003) (Laurian, 2003), their exclusion from their own ability to determine what they want and what is best for their community's environment has and still is often usurped by powerful and represented groups, both in the political and societal spheres (Anguelovski, 2015). According to Anguelovski's study, green politics, when implemented locally, is frequently beneficial to the environment, but damaging to minorities—the White and the wealthy's opinions have more precedence in governmental affairs regarding environmental remediation. The research highlighted that as degraded neighborhoods are cleaned up, private investors move in and gentrify the newly restored area, squeezing poor and long-term individuals out—this is the work of ecological gentrification, the modern color line that pushes vulnerable populations out of the historical color line and historical zoning practices that segregated them to toxic areas in the first place. This is an ongoing problem that these communities experience, and when they witness physical forms of sustainability such as green space or a Whole Foods grocer construction or other, they express worry—and per the study, they view these green amenities as a sign to "redevelop" the area, and their apprehension is not unfounded.

However, the gap that this paper fills pertains to race—there is extensive focus on Black and Hispanic/Latino populations (Downey & Hawkins, 2008) (Jones, 2021) (Pastor et al., 2001) or grouping POC into one category that could blur important relationships (Anguelovski, 2015)

(Grant et al., 2010) (Morello-Frosch et al., 2002), and observations between toxic sites and low-income, Asian, Native Indian, and Pacific Islander are less studied compared to those two demographics. Quantitative methods are also lacking when it comes to analyzing toxic site, minority, and water relationships with one another—from the literature reviewed for this study, there are primarily separated focuses like toxic-minority and toxic-water relationships.

Data and Methodology

Eleven datasets total were utilized for this research study and are listed below, and were also categorized into different sections, which are Boundaries, Demographics, Toxic Sites, and Water.

Boundaries

Census block group data were acquired from Social Explorer's open source Geodata database. The shapefile provides all census block groups throughout the United States accurate to the year 2019 (U.S. Census, 2019). This aggregation was chosen at a finer resolution to avoid ecological fallacy.

County boundaries data were acquired from the Utah Geospatial Resource Center (UGRC) open source database for the state of UT (UGRC, 2011).

Demographics

Comprehensive data on demographics such as income, population, population density, and race were acquired from Social Explorer, whose data is based off of the 2019 five-year estimate American Community Survey (ACS) (U.S. Census Bureau, 2015–2019).

Income data, or median household income data (U.S. Census Bureau, 2015–2019), is categorical and measured in dollars per year, and for the purposes of this study was grouped into five different classes: $20,000 to $50,000 (there was no record of a median household income below $20,000 in the survey), $50,000 to $75,000, $75,000 to $100,000, $100,000 to $140,000, and $140,000 to $250,000 (there was no record of a median household income above $250,000 in the survey).

Population data, or the number of individuals living in a census block group, is measured as the total number of individuals per census block group and was utilized for normalizing other datasets such as race (U.S. Census Bureau, 2015–2019).

Population density data (U.S. Census Bureau, 2015–2019), or the concentration of individuals in an area, is categorical and measured as individuals per square mile, and was grouped into five classes according to Natural Breaks (Jenks): 0 to 3,256 people per square mile, 3,256 to 5,896 people per square mile, 5,896 to 8,645 people per square mile, 8,645 to 13,548 people per square mile, and 13,548 to 37,971 people per square mile.

Race data, or the arbitrary categorization of people based on skin color, language, and/or origin, is categorical and grouped into six different classes according to the ACS: Asian, Black, Hispanic/Latino, Native Indian, Pacific Islander, and White (U.S. Census Bureau, 2015–2019). This study did not account for those who identified as some other race alone nor two or more races.

Toxic Sites

All toxic sites data on Brownfields, National Priority Lists (NPLs), Superfunds, and Toxic Release Inventories (TRIs) were acquired through the UGRC.

Both targeted Brownfields (UGRC, 2021b) and non-targeted Brownfields (UGRC, 2021a) data were downloaded, and are point/node data types. These sites "are real property, the expansion, redevelopment, or reuse of which may be complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant", and one dataset is targeted for cleanup while the other is not targeted for clean-up.

Both NPLs and Superfunds data were downloaded, and are point/node data types. The former is a "list of national priorities among the known releases or threatened releases of hazardous substances, pollutants, or contaminants throughout the United States" (UGRC, 2021c), and the latter are sites that "release or threaten release of hazardous substances that may endanger public health or the environment" (UGRC, 2021d).

The TRI data is a point/node data type and "is an EPA database containing data on disposal or release of toxic chemicals from U.S. facilities and information about how facilities manage those chemicals through recycling, energy recovery, and treatment" (UGRC, 2021a).

Water

Assessment data, last updated in 2021, were downloaded from the UT Department of Water Quality (DWQ), an extension of the UT Department of Environmental Quality (DEQ), which are polygon features that section off a number of UT's water bodies and are assessed, or rated, based on if the area passes impairment tests (Department of Environmental Quality, n.d.).

Streams data, last updated in 2016, were downloaded from the UGRC, which are line features that represent all rivers, streams, and tributaries found in UT (UGRC, 2016).

Groundwater data, last updated in 2016, were downloaded as a .csv file from the UT Division of Water Rights, an extension of the UT Division of Natural Resources (DNR) (Utah Division of Water Rights, n.d.).

Succinctly, all of these collections of data were cleaned and interpreted utilizing a data science application known as Exploratory, and a GIS application known as ArcGIS Pro, all to provide insightful cartographic mapping and analyses like kernel density estimation (KDE) and Getis-Ord Gi* (GOG) to better understand the critical issue of environmental inequities and dangers of toxins within proximity of water bodies. Below explains in much more detail the project's workflow.

Prior to implementation into ArcGIS Pro, all datasets were uploaded into the Exporatory application for data cleaning and management. Copies of the datasets were edited to remove fields that would not be used for the research project and while the demographic datasets had accompanying data dictionaries, the fields were renamed to avoid user error when creating maps and conducting spatial analyses tests in ArcGIS, as many fields were originally named alphanumerically. Seven new fields were added to the census block group dataset, which included all six racial categories normalized by the total population as well as the number of toxic sites found in each census block group, which were located manually in ArcGIS Pro.

After calculating all fields, all datasets were then joined by their unique 12-digit numerical codes representing their respective census block groups, referred to as their GEOIDs; for datasets that did not have census block group GEOIDs (i.e. groundwater and all toxic site data), a new field was created as a solution and the GEOIDs were located via ArcGIS and manually input into the new GEOID fields in Exploratory. Once all datasets were joined, the resulting duplicated fields were deleted and the data were refined again before being uploaded into a new ArcGIS project, which had the geographic coordinate system (GCS) set as the World Geodetic System 1984 Web Mercator (auxiliary sphere) (WGS 84). Then the XY Table to Point data management tool was used to create features of groundwater well points.

All datasets were projected into a projected coordinate system (PCS) known as North American Datum 1983 (NAD 1983) Universal Transverse Mercator Zone 12N (UTM 12N) as specified for the state of UT. The previous step was an integral precondition to utilize the built-in

Add Geometry Attributes geoprocessing tool in order to calculate the real area in square miles of the census block groups, because population, income, and race data needed to be normalized by real-life area and should not rely on the feature's virtual polygon area.

Once all aforementioned processes were completed, it resulted in a total of fifteen new fields: area in square miles, toxic site counts, toxic site counts normalized by area, race normalized by total population (6), and race normalized by area (6). Afterward, the county layer only showed SL county using the Definition Query and all other data were clipped, restricted to the SL county layer's extent. The Buffer geoprocessing tool was then used on the groundwater and toxic site data, specified with a one-mile radius. Finally, maps were created of the study area, population density, the race normalized by the population to show the number of individuals per 1,000 people, median household income, water bodies and groundwater wells, toxic sites, as well as the KDE and GOG spatial analyses maps with color-blind symbologies and all divided into five classes using Jenks.

The KDE geoprocessing tool was specified with a 5,000 mile search radius, Densities as the output cell values, and Planar as the method. The GOG geoprocessing tool, or hotspot analysis, was specified with the Zone of Indifference for the conceptualization of spatial relationships and Euclidean as the distance method. To note, the Zone of Indifference is a combination of Fixed Distance Band and Inverse Distance, and states that features within the critical distance, which was automatically calculated by the tool, of the target feature receives a weight of one, influencing computations—when that critical distance is exceeded, the weights diminish with distance (ESRI, n.d.-b). This conceptualization of spatial relationships was chosen compared to other options due to the nature of the project and toxic sites, of which its potential contamination threat may have a "fuzzy" reach.

Results

Figure 2 shows the population density in SL, where the highest concentrations of people lie towards the north, west, and the urban center. It is also important to note that the middle road is the Interstate 15 (I15) highway and there is a significant drop in population density throughout the freeway's entire segment in SL, likely due to the business/commercial and industrial zones within its vicinity on either side; there is also a similar, although not as prominent, pattern with the Interstate 215 (I215) and Belt Route highways.

Figure 3 shows the White population per 1,000 people put into five classes: 134 to 528, 528 to 711, 711 to 834, 834 to 922, and 922 to 1,000. The number of White individuals has a dominant presence almost opposite to figure 2 in the northeast, east, southwest, and south. Figure 4 shows the Black population per 1,000 people put into five classes: 0 to 12, 12 to 37, 37 to 78, 78 to 143, 143 to 264. The densest areas are in the West Valley City area and just north of the county's center, with very few individuals located outside. Figure 5 shows the Hispanic/Latino population per 1,000 people put into five classes: 0 to 82, 82, to 184, 184 to 312, 312 to 471, and 471 to 817. There is a significant presence in the northwest section of SL county and a significant lack elsewhere. Figure 6 shows the Native Indian population per 1,000 people put into five classes: 0 to 9, 9 to 31, 31 to 71, 71 to 151, and 151 to 297. This demographic is much more sparsely distributed compared to the clustered appearances of figures 3 thru 5, with some denser blocks in the west and towards the urban center as well as the southeast area near the Lone Peak Wilderness. Figure 7 shows the Pacific Islander population per 1,000 people put into five classes: 0 to 12, 12 to 42, 42 to 86, 86 to 155, and 155 to 265. This demographic is somewhat sparsely distributed, but a clustered pattern can be noted in the west and northwest. Figure 8 shows the Asian population per 1,000 people put into five classes: 0 to 22, 22 to 53, 53, to 101, 101 to 181, and 181 to 313. This demographic is distributed throughout SL county, with darker census block groups in the northwest and northeast.

Figure 9 shows median household income measured in dollars per year, and from observation, the high-income areas above $100,000 show a similar pattern to figure 3, which represents the White population, but it is important to note that perceived correlation does not equate to causation. Figure 10 shows assessment areas, groundwater wells, and streams in SL county. The assessments were categorized into five classes where 1 supports all designated uses, 2 supports all assessed uses, 3 has insufficient data and is in the process of further collection, 4 is considered impaired and a total maximum daily load (TMDL) requirement is greenlit, and 5 is considered significantly impaired to require a TMDL as well as being added to the 303(d) list, which is according to the EPA, “a state’s list of impaired and threatened waters (e.g. stream/river segments, lakes)” (EPA, n.d.). The map shows that 23 out of 41 (56%), which is over half of the regions, are rated as a 5 and are mostly located in the southwest and east, and according to figure 12, many of these high rated regions have at least one toxic site in its area or within a one-mile radius vicinity. Figure 11 shows both the toxic sites and groundwater wells, the latter of which has a one-mile radius buffer; from analyzing the map, it can be seen that the vast majority of groundwater wells have at least one toxic site within their buffers.

Figure 13 is the hotspot analysis of the toxic sites in SL, and the hotspots are predominantly clustered in the urban core, reaching towards the center and touching part of West Valley. The cold spots are predominantly located in the southeast area of SL county, located within the vicinities of Draper, Riverton, and Sandy as well as the west below Magna. Figure 14 shows the KDE as well as the groundwater wells, much of the concentration in the northwest area, encompassing Rose Park, which has a large Hispanic/Latino population, and some concentration along I15. Figures 15 through 22 show the comparisons between the demographic maps with the KDE map; from analyzing all figures, it can be observed that there is significant overlay over the POC demographics, and strongly on the Hispanic/Latino, Black, and low-income populations, while being more inversely related to the White and high-income populations.

Discussion

To reiterate, figure 2 shows population density and the highest concentrations of people lie towards the north, west, and the urban center. According to anecdotal evidence, these are areas (e.g. West Valley City in the west, Rose Park in the northwest, and Salt Lake City as the core) more known to have POC and low-income residents, especially looking at figures 4 (Black), 5 (Hispanic/Latino), 7 (Islander), and 8 (Asian). However, it is also interesting to note that figures 6 (Native Indian), 7, and 8 are the most sparsely distributed when compared to the more clustered figures 4 and 5. There are a few possible reasons that produced these results that are more explainable for figures 7 and 8; the Latter Day Saint (LDS or Mormon) church is extremely wealthy and its followers’ class, income, and opportunities benefit from membership, and the church has a significant presence with the Islander populations in Utah as well as overseas (Collins & Grineski, 2019) (Fletcher, 2017); there is palpable economic divide as income inequality is the worst, and continues to grow, with the Asian population (Kochhar & Cilluffo, 2020). As for the spatial pattern in figure 6 that represents the Native Indian population, there was no reason found during the length of this study and should be investigated in the future.

In figure 3, it shows the number of White residents, which again, have a dominant presence almost opposite to figure 2 in the northeast, east, southwest, and south. According to more anecdotal evidence, these are areas (e.g. Greater Avenues in the northeast, Holladay in the east, Daybreak in the southwest, and Riverton in the south) predominantly known to have White and high-income residents. Figure 13 of the hotspot analysis, shows a significant cluster of hotspots throughout the Salt Lake City area, expanding outward, which encompasses a large section of the I15 highway that has more industrial activity compared to the length of the freeway past the Murray area. Figure 15 is an inset map comparing the population density with the KDE map, and it is easy to observe that the KDE extent does not dominate over concentrated census block groups, but figure 22 shows that the KDE extent gravitates towards low-income census block groups while in figure 16 it generally avoids the higher-concentrated areas of White individuals

However, the spatial pattern is different when analyzing figures 17 (Black) and 18 (Hispanic/Latino) as the KDE extent significantly overlaps high-concentrated areas of these minorities, especially the latter—this aligns with many previous studies discussed in the literature review that toxic sites are in closest proximity with the Hispanic/Latino community and then the Black community (Ash & Fetter, 2004) (Pastor et al., 2001). From all figures it can be inferred that toxic sites may have especially the strongest relationships with the Hispanic/Latino communities as well as the low-income communities.

Looking at figure 11 towards the north, especially the urban core as well as Rose Park (known to have many Black and Hispanic/Latino residents), there is alarming overlap between toxic sites and groundwater wells. Although these close proximities do not guarantee contamination, the threat of potential toxicity is high especially due to improper disposal of waste and human error that could cause contamination (Chaudhuri & Ale, 2014) (Santucci et al., 2018). Something that did not align with this research's findings are the locations of the rank 4 or 5 water assessments—while it is often stated minorities have close proximity to the dangers of environmental degradation and legacy pollution (Ash & Fetter, 2004) (Laurian, 2003) (Morello-Frosch et al., 2001) (Morello-Frosch et al., 2002) (Morello-Frosch & Lopez, 2006) (Morello-Frosch et al., 2011), these impaired areas were in the southern and eastern areas of SL, predominantly White and wealthy, and this should be investigated in the future.

As the research continued, several weaknesses were encountered and noted. First, this quantitative study is an exploration of cross-sectional data, which were acquired and recorded at different times and in different databases. Upon closely inspecting the figures, they suggest that many of the studies mentioned in the literature review have veracity—however, it is only a suggestion as correlation does not always mean that there is causation. Second, a manual distance band was not input for the hotspot analysis and was automatically calculated by the system, and this study assumed positive spatial autocorrelation and did not utilize the Global Moran's I geoprocessing tool to calculate the proper distance band—it would have been beneficial to execute the tool at 100 mile to 500 mile intervals up to 10,000 miles and graphing the z-score, where the number before the drop or negative slope would indicate the ideal distance band. Third, there is no geographically weighted regression (GWR) analysis to statistically describe the toxic sites' and race data's relationships with one another—this was omitted because the toxic site points did "not [have] enough variation for at least one local neighborhood" (ESRI, n.d.). Fourth, the water assessments did not cover the entirety of SL, only parts of it, and these waters being assessed are not all designated for drinking usage, which would have to adhere to much stricter regulations—this means that regions assessed at a 2 rating could still have toxins, but are passed because they are not for drinking.

Conclusion

To repeat, this study wanted to find out if toxic sites (i.e. Brownfields, Superfunds, and TRIs) were disproportionately located in low-income and minority communities in SL and if these site proximities to water bodies such as lakes and streams affect water quality assessments and groundwater wells. The hypotheses, from observing cross-sectional data, was affirmed, much like previous research on toxic sites and marginalized groups and water contamination (Ash & Fetter, 2004) (Chakraborty et al., 2011) (Collins & Grineski, 2019) (Downey et al., 2008) (Downey & Hawkins, 2008) (Grant et al., 2010) (Jones, 2021) (Laurian, 2003) (Morello-Frosch et al., 2001) (Morello-Frosch et al., 2002) (Morello-Frosch & Lopez, 2006) (Morello-Frosch et al., 2011) (Pastor et al., 2001).

There are two key takeaways from this: Hispanics/Latinos and then Blacks as well as low-income individuals are closest to toxic sites and could possibly be the most affected now and into the future by them, and all impaired water assessments had at least one or more toxic sites within their regions. However, these key takeaways as well as other findings require further investigations; a qualitative assessment on an affected population and their experiences with toxic site proximity is an opportunity to dive into the depth of EJ in SL for the Hispanic/Latino community much like the study from Cashman et al. (2008), and researching into the water assessment data's spatial pattern is notable as they are located nearer to the White and high-income populations. Also, studying the contaminated air-water interactions in SL could reveal spatial patterns not seen in the area before, and other future directions could include the use of a GWR analysis.

Figure 1: Study Area in SL

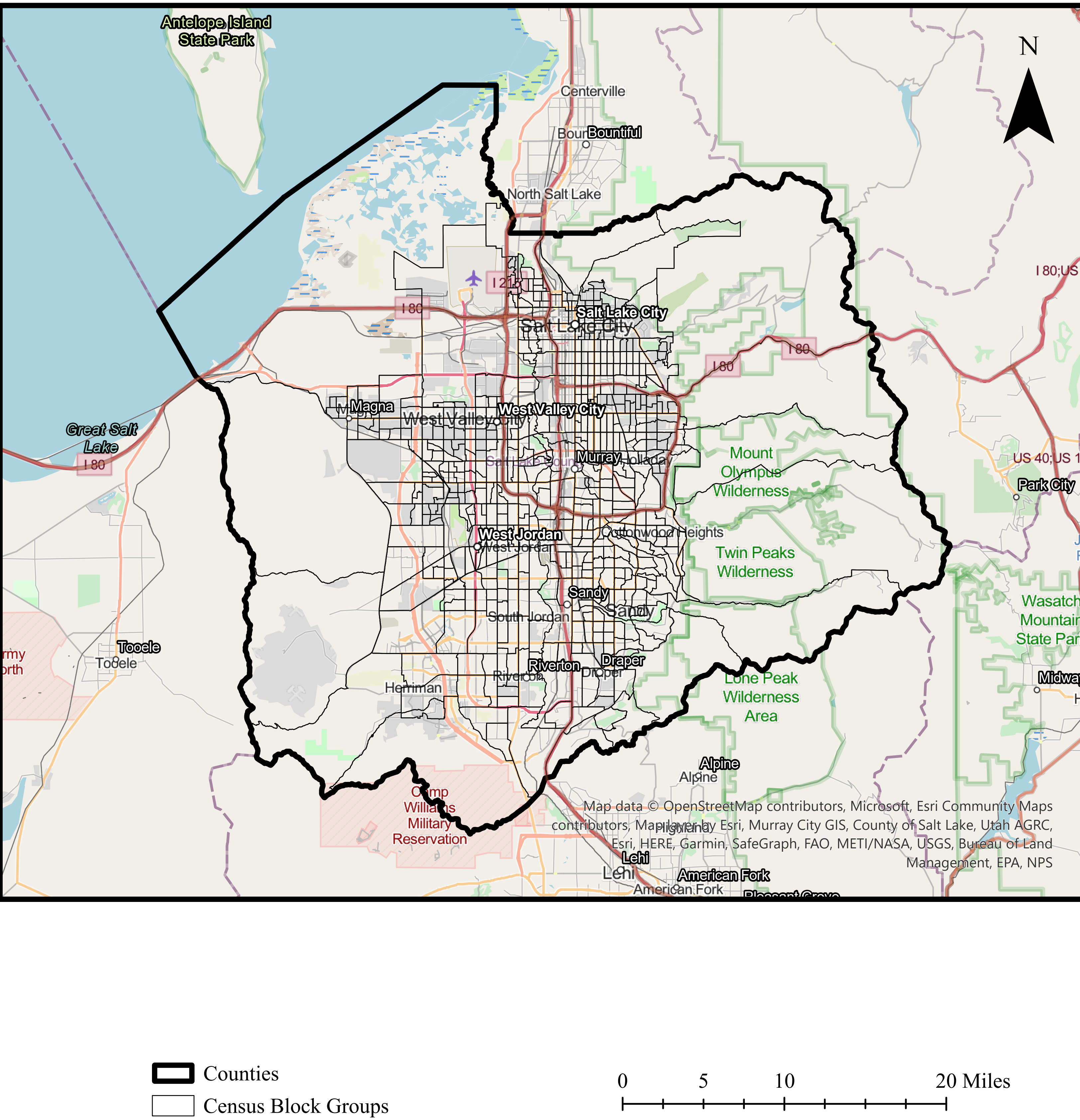


Figure 2: Population Density in SL

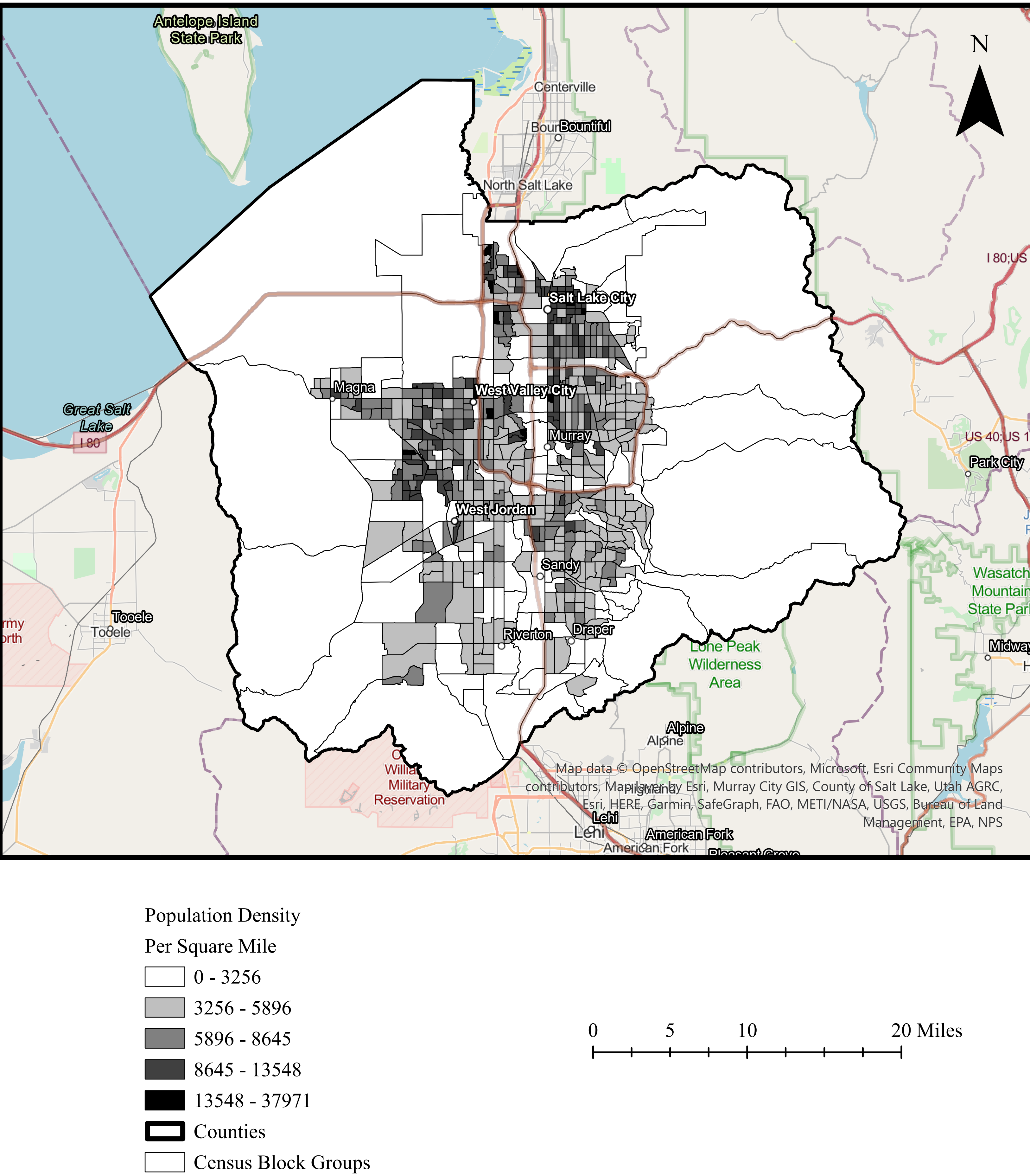


Figure 3: White Population in SL

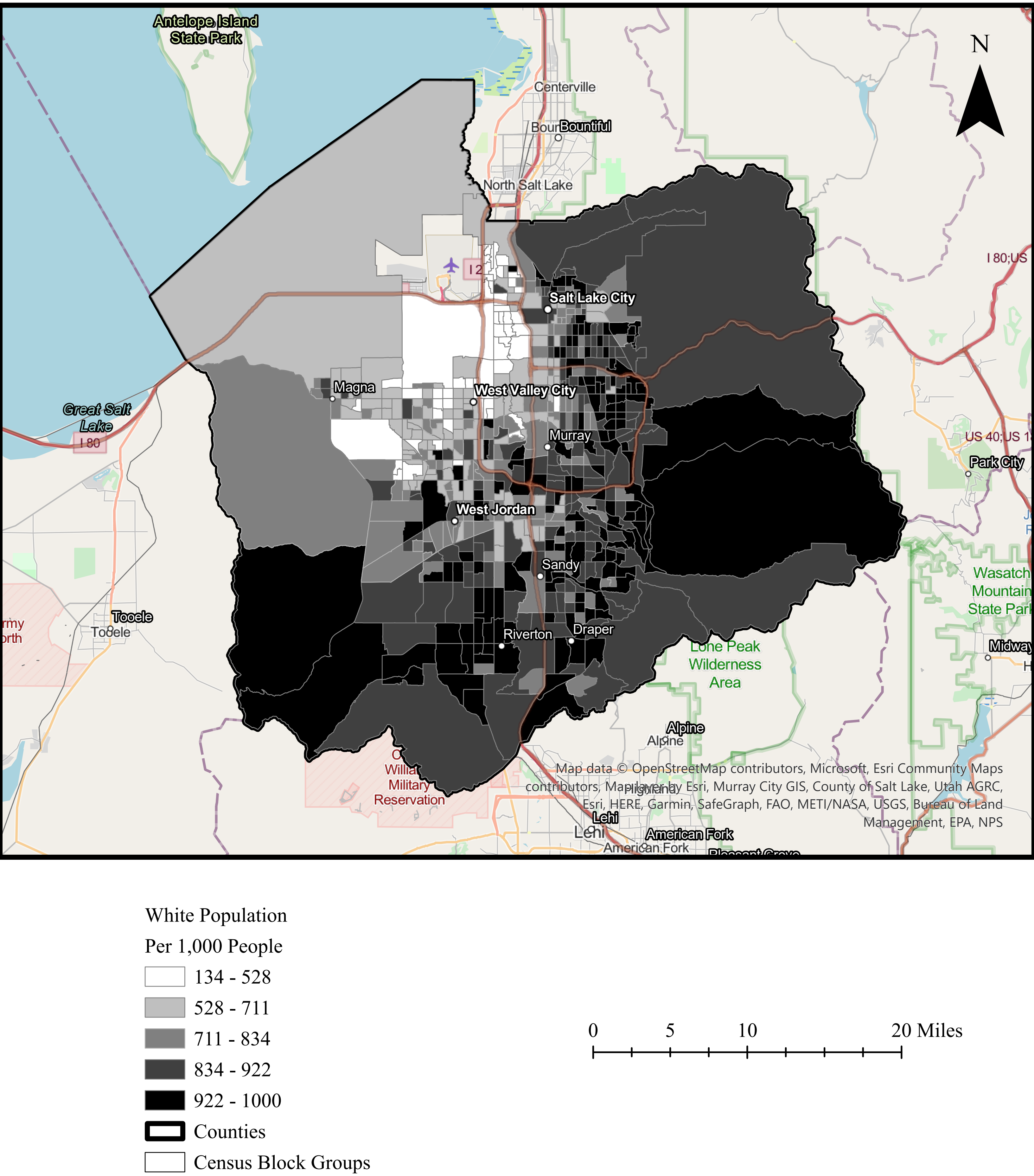


Figure 4: Black Population in SL

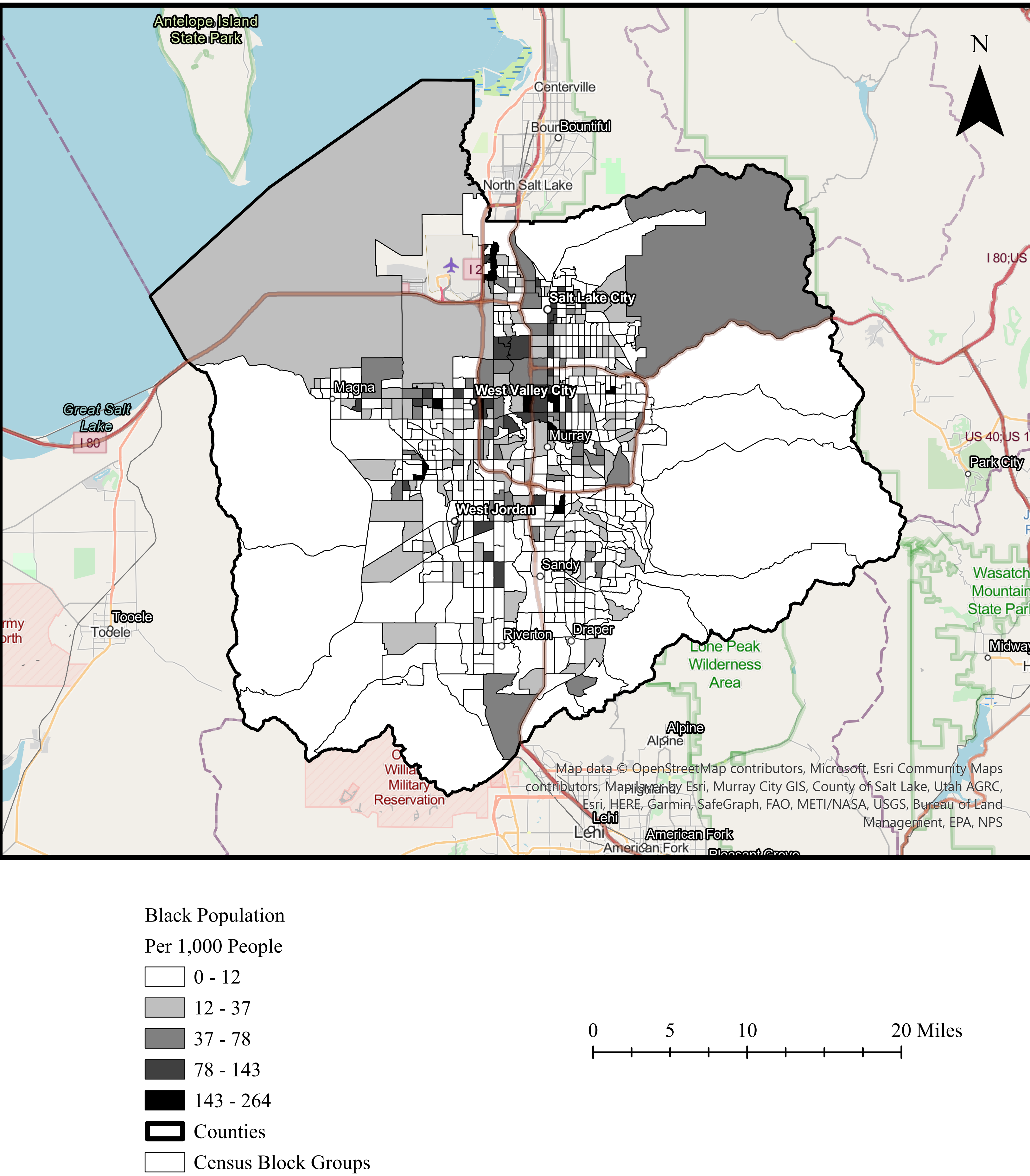


Figure 5: Hispanic/Latino Population in SL

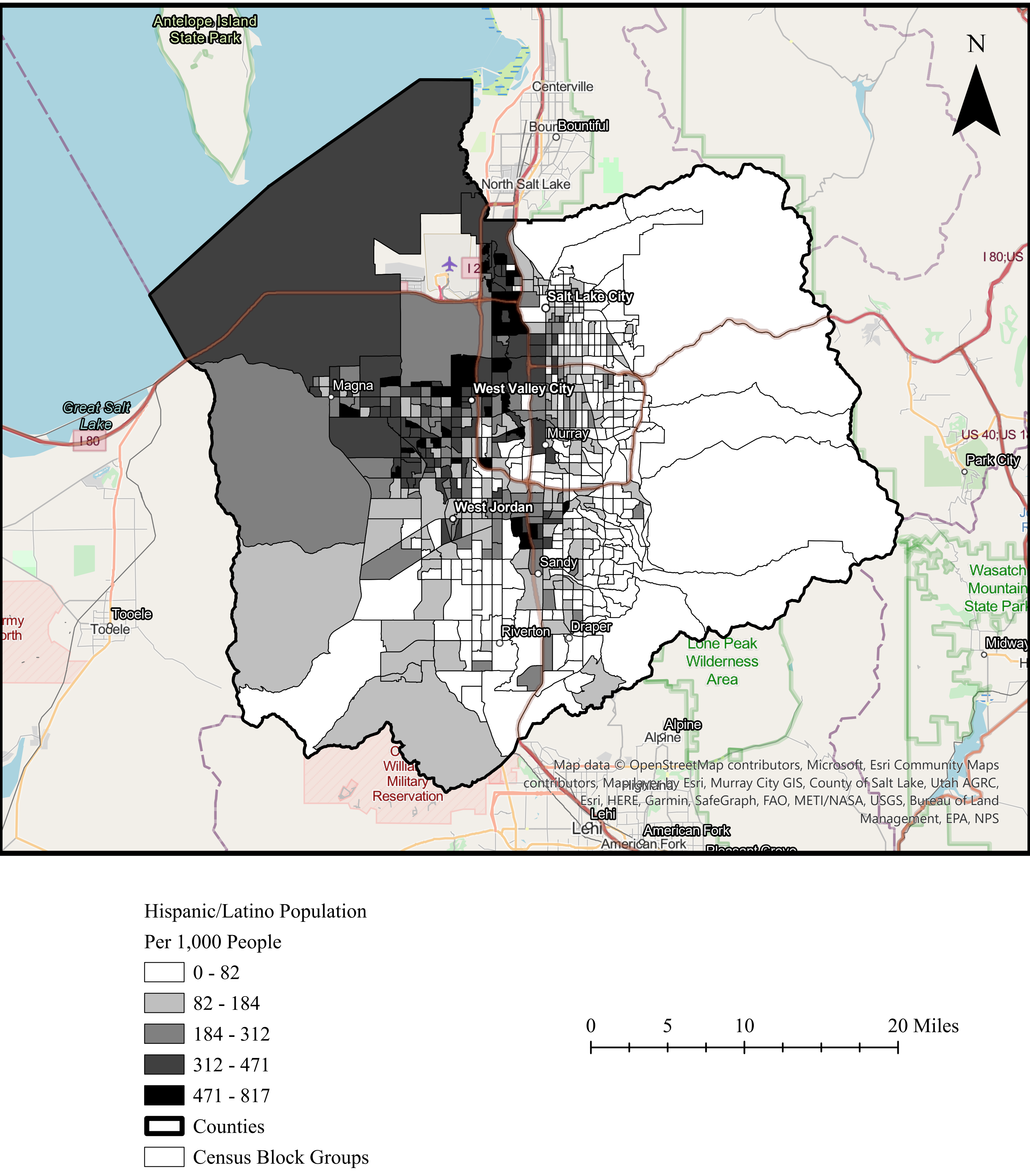


Figure 6: Native Indian Population in SL

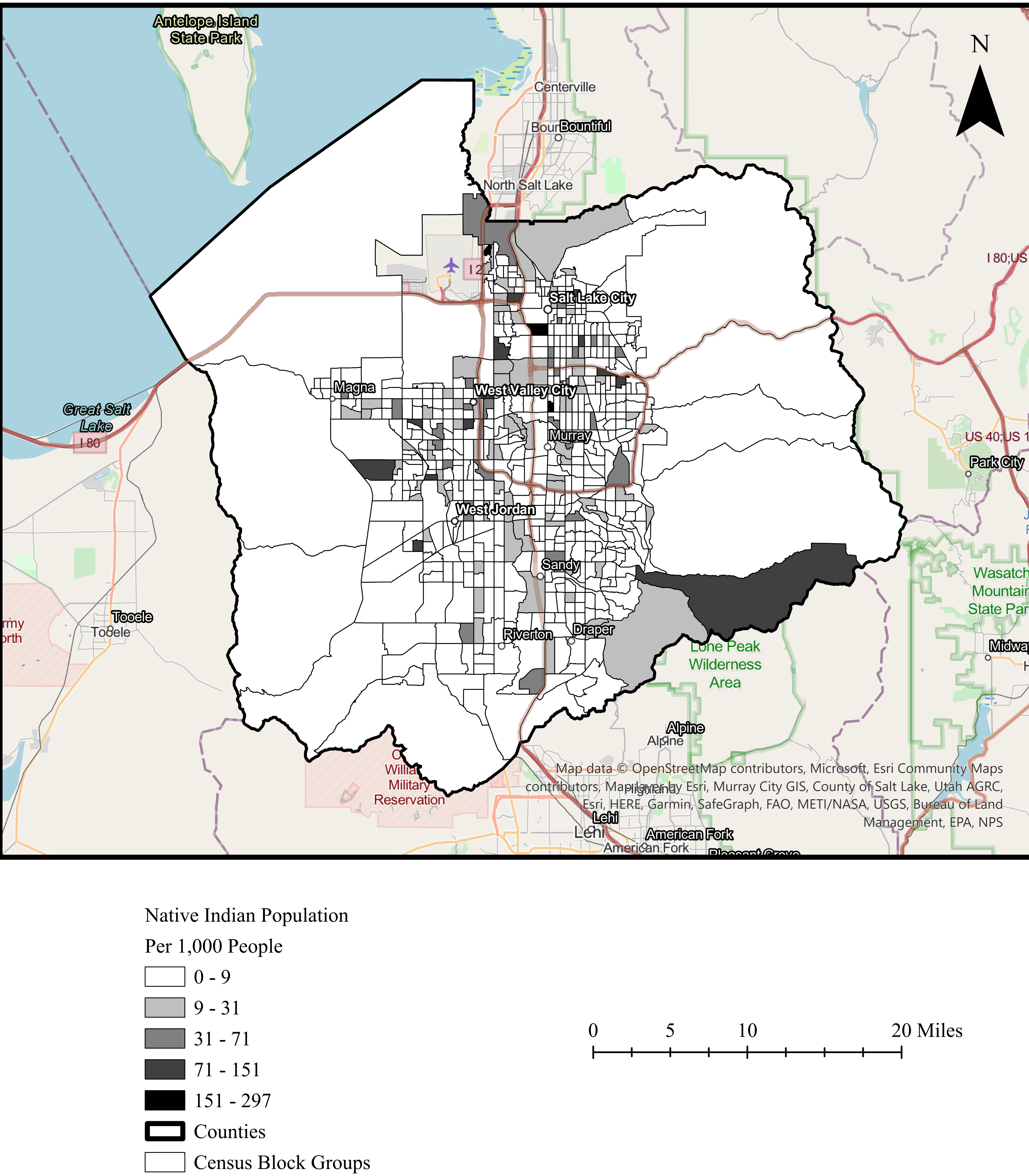


Figure 7: Islander Population in SL

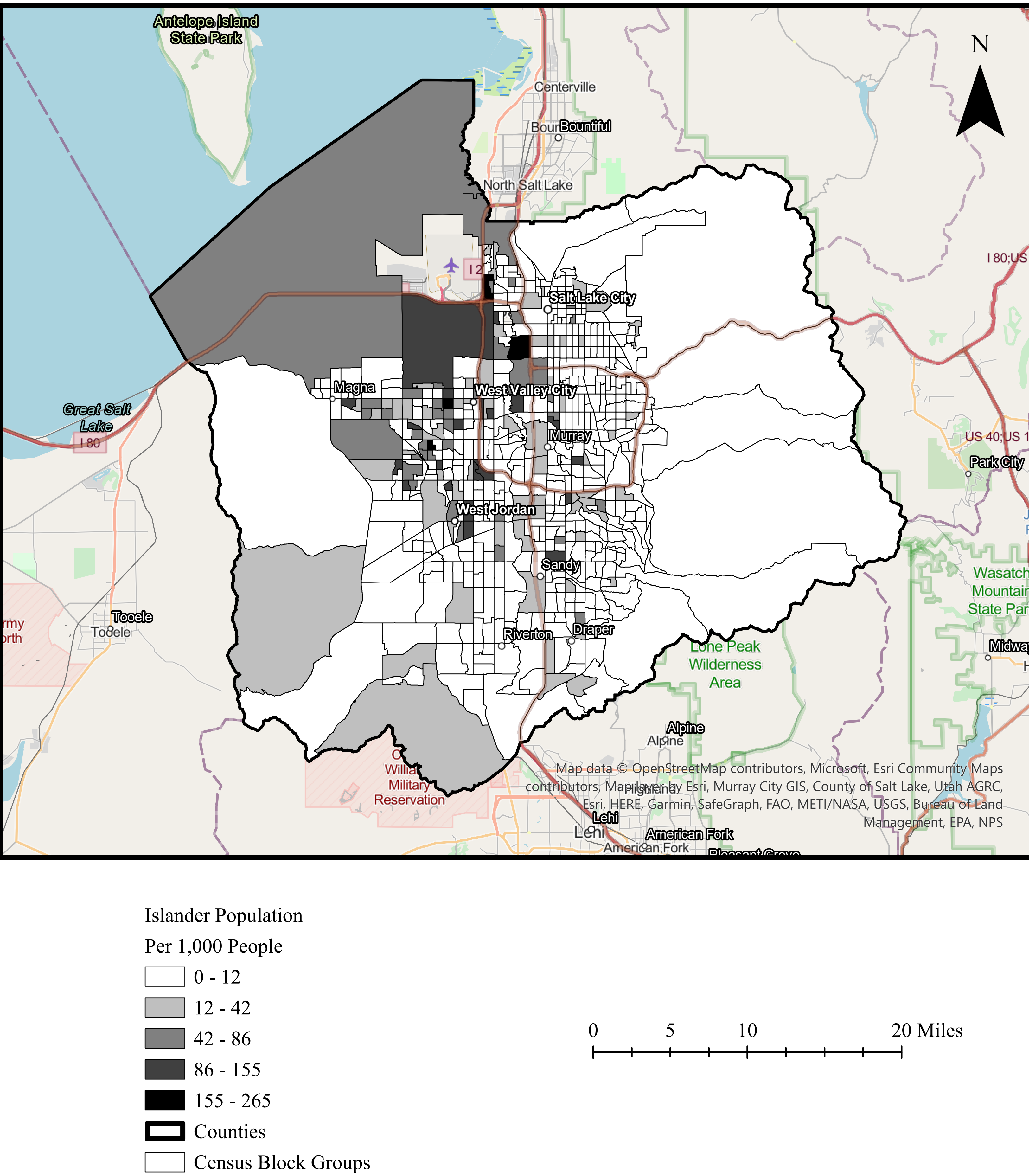


Figure 8: Asian Population in SL

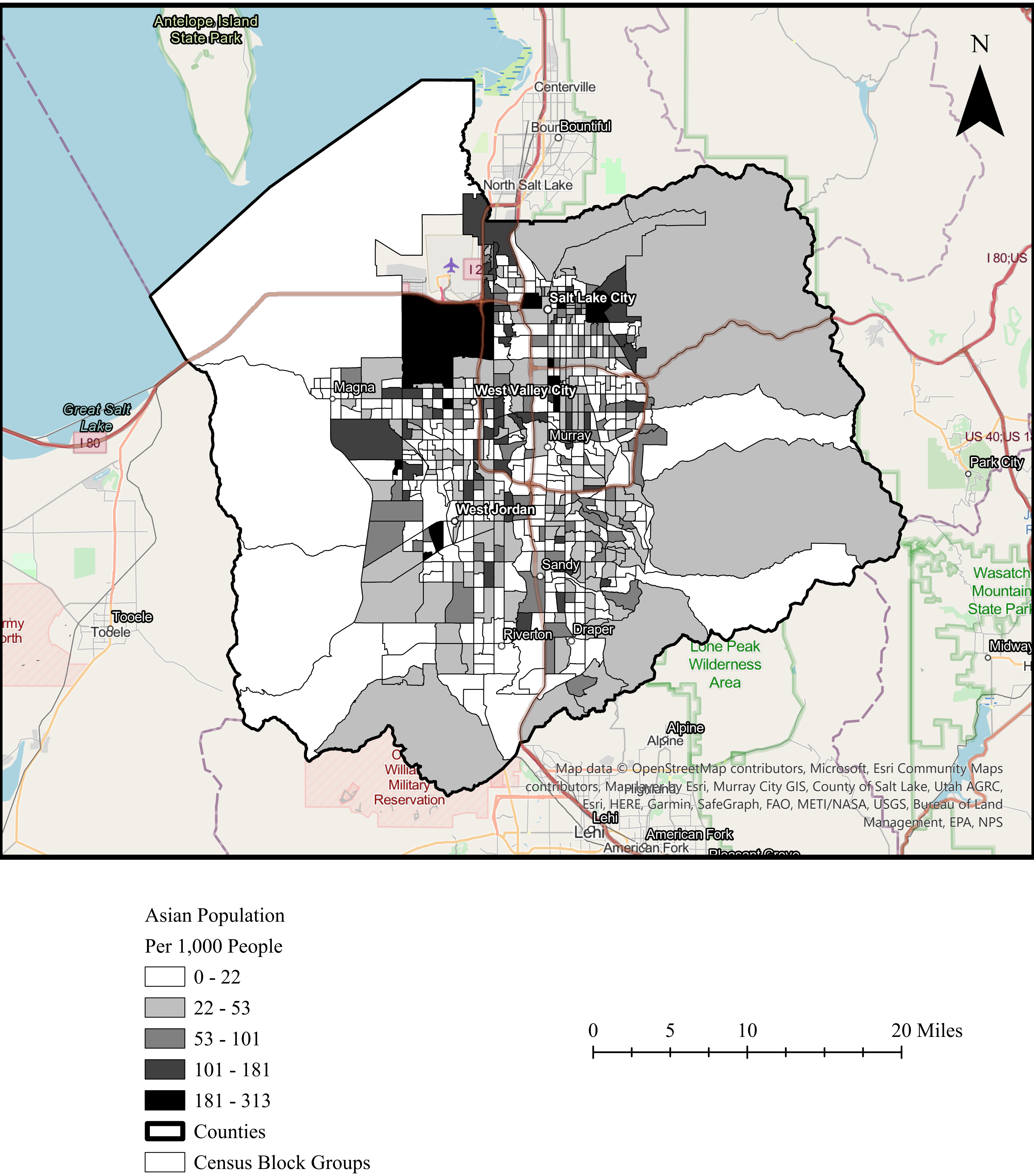


Figure 9: Median Household Income in SL

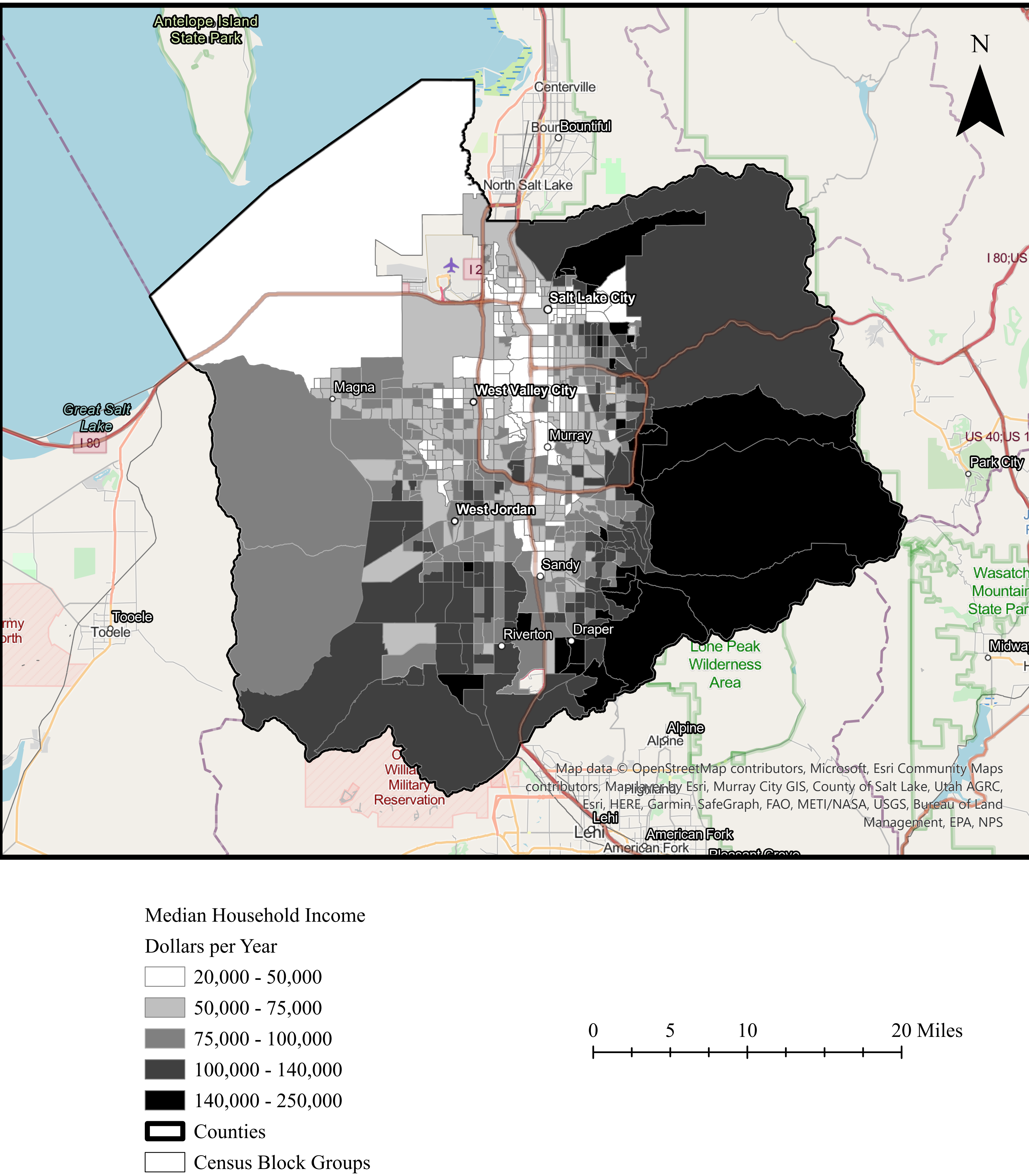


Figure 10: Assessment, Groundwater, and Streams in SL

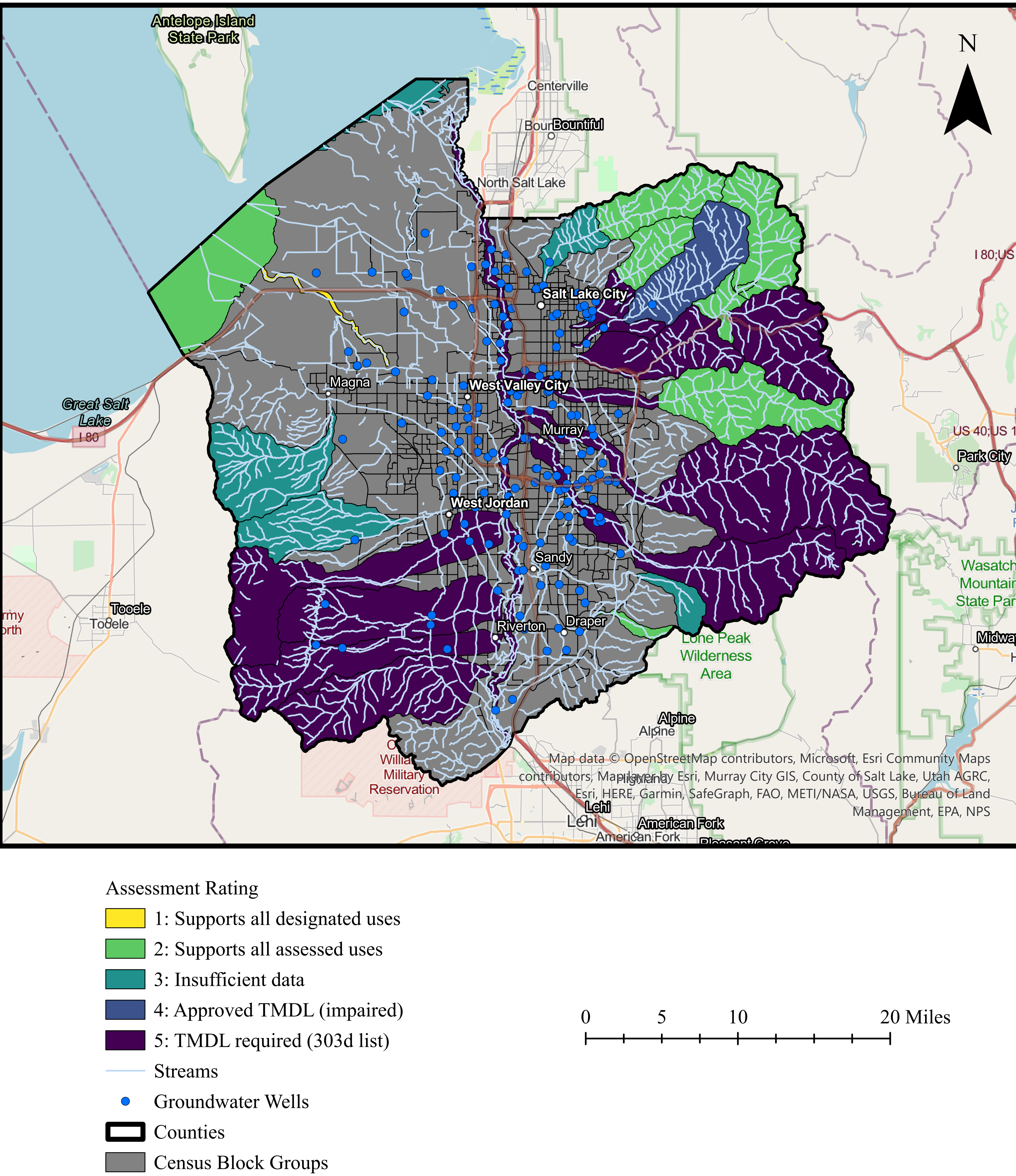
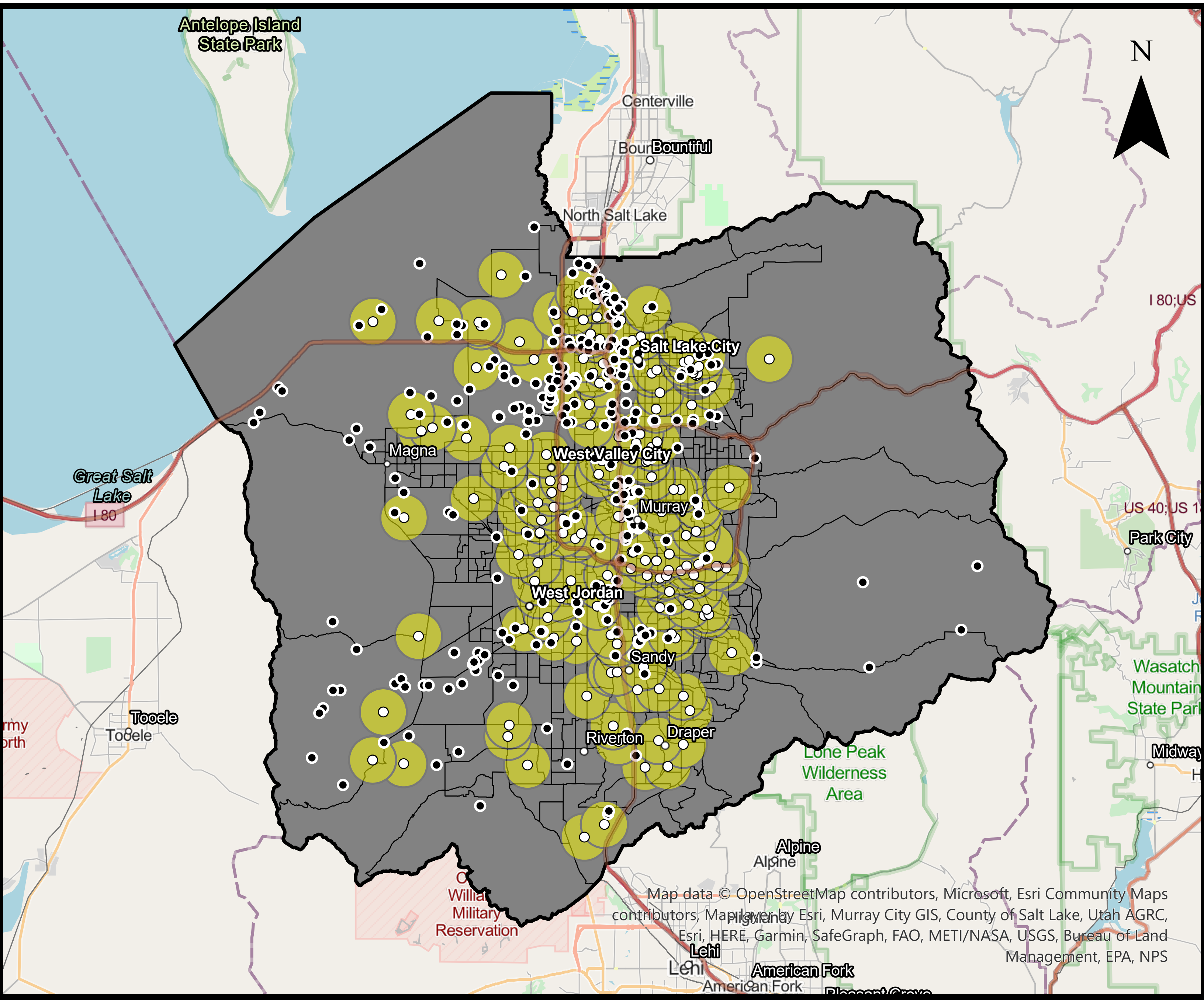


Figure 11: Groundwater and Toxic Sites in SL



- Toxic Sites
- Groundwater Wells
- Groundwater Buffer (1 mi.)
- Counties
- Census Block Groups

0 5 10 20 Miles

Figure 12: Assessment, Streams, and Toxic Sites in SL

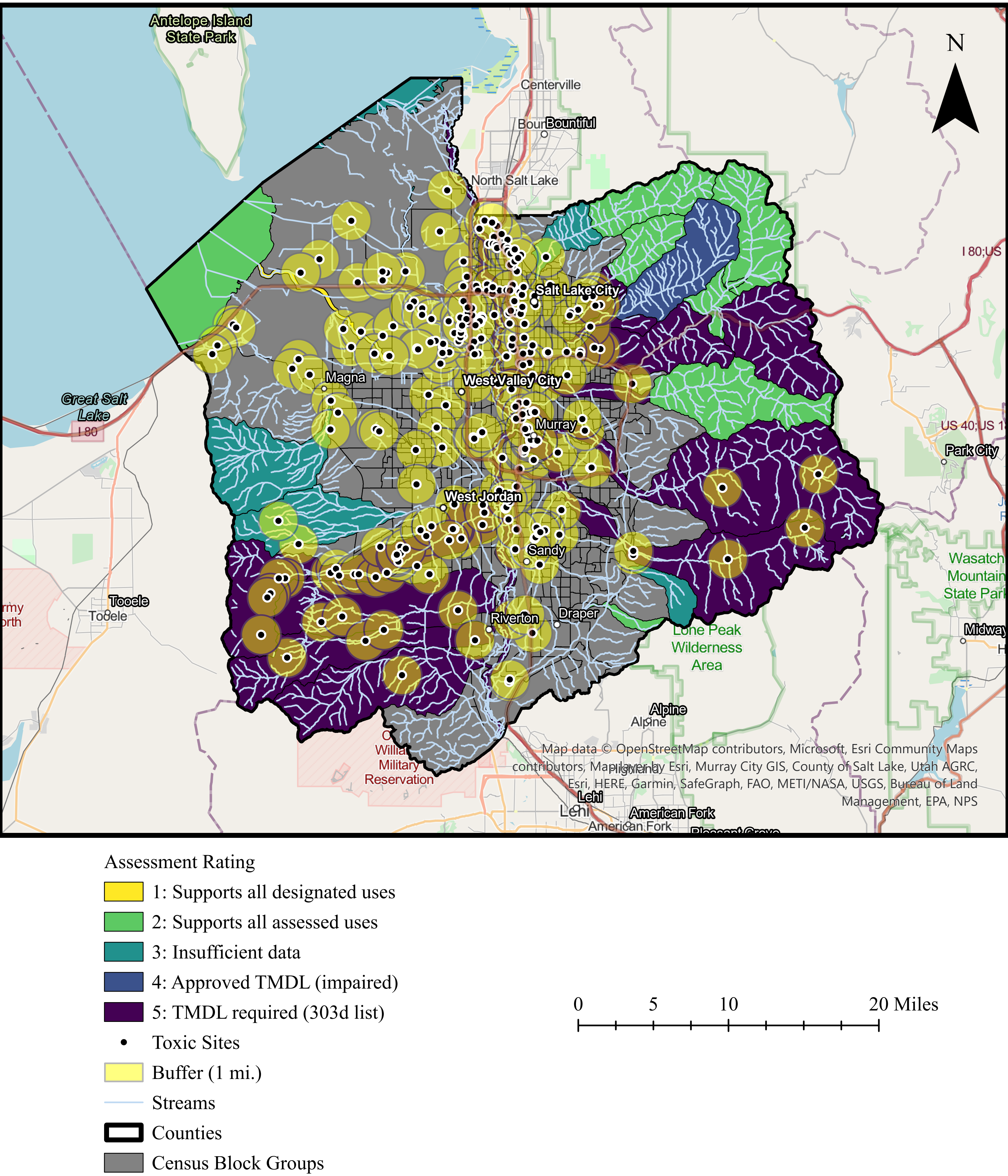


Figure 13: Getis-Ord Gi* Hotspot Analysis of Toxic Sites in SL

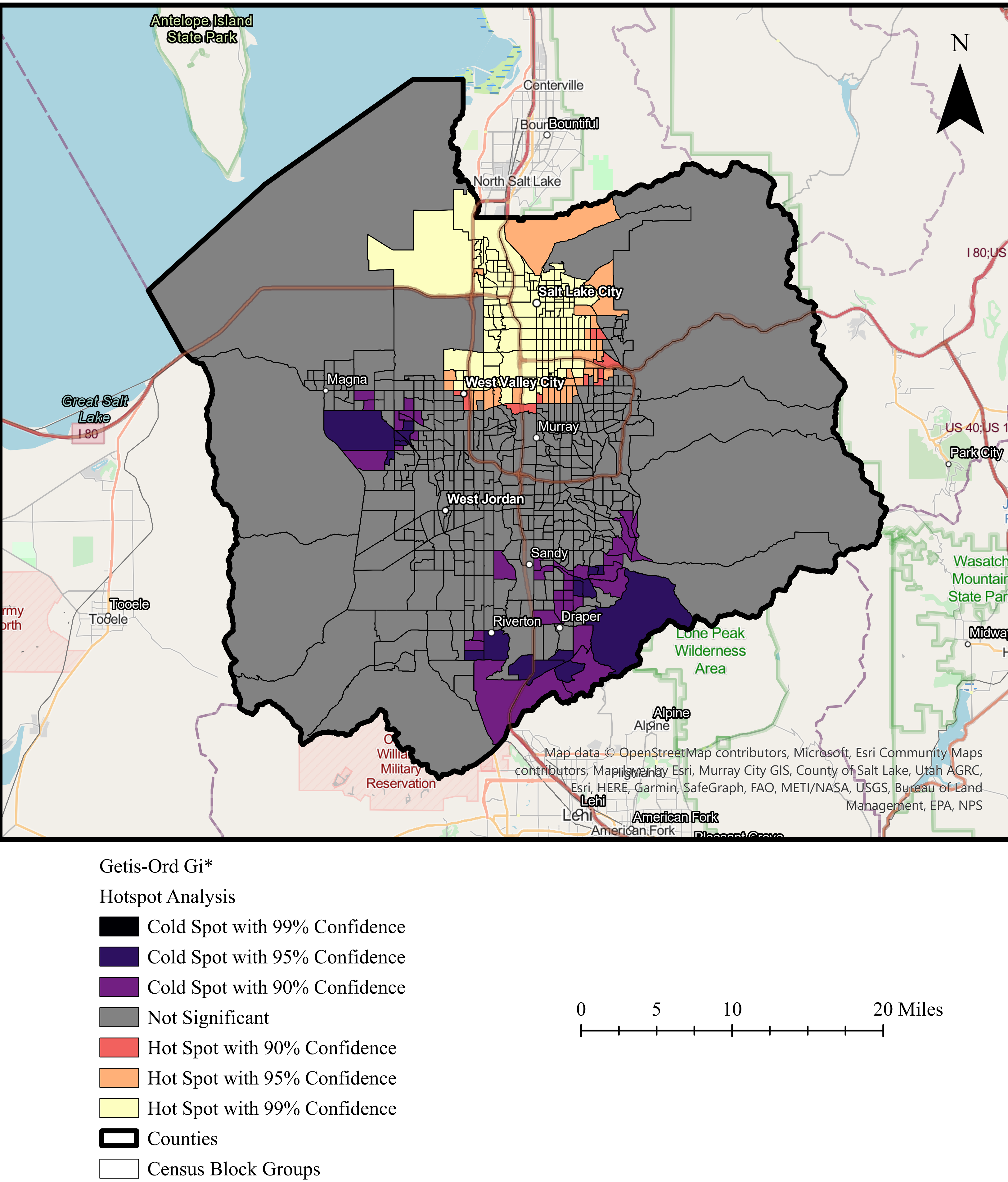


Figure 14: Kernel Density Estimation of Toxic Sites in SL

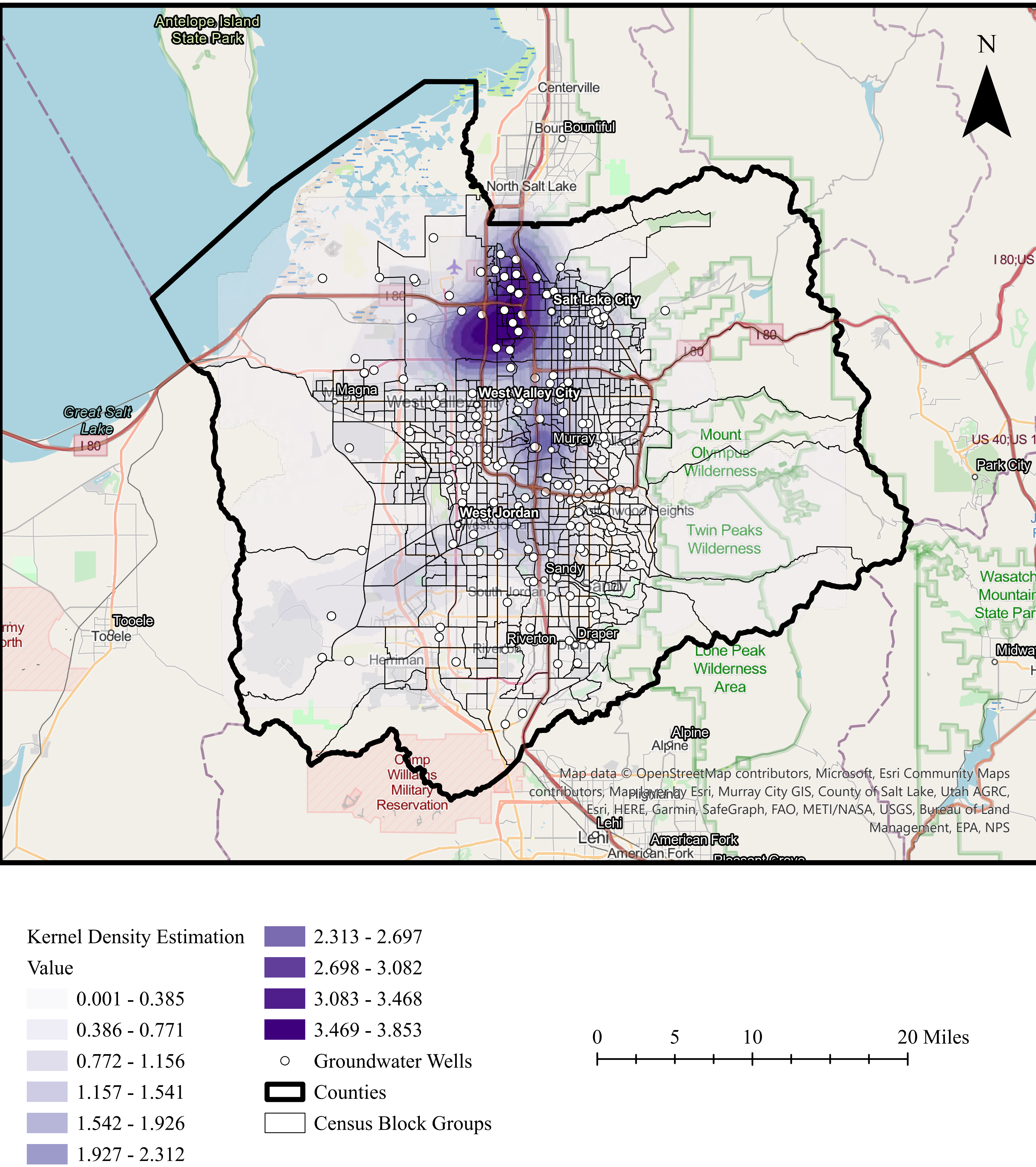


Figure 15: Population Density and Kernel Density in SL

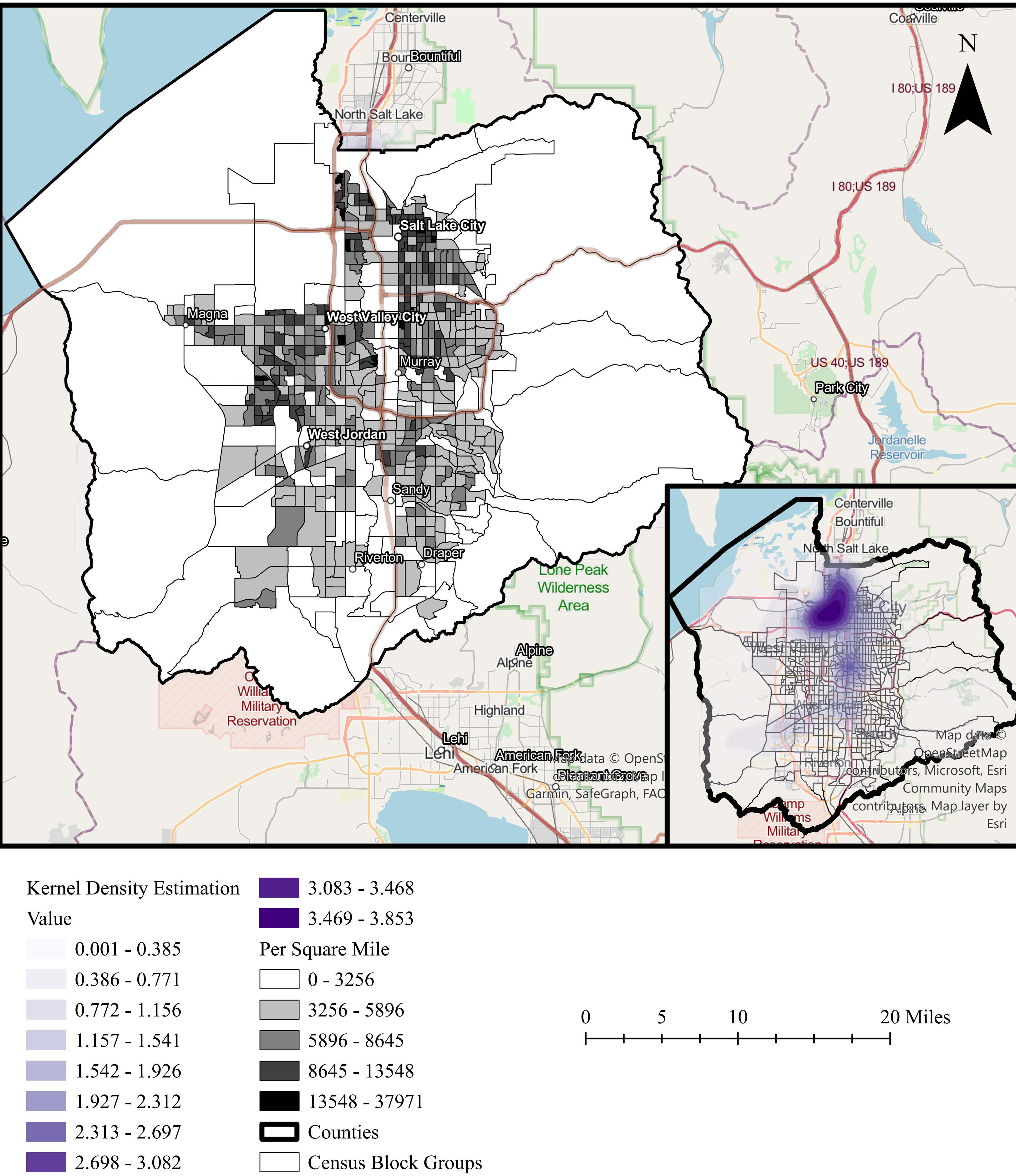


Figure 16: White Population and Kernel Density in SL

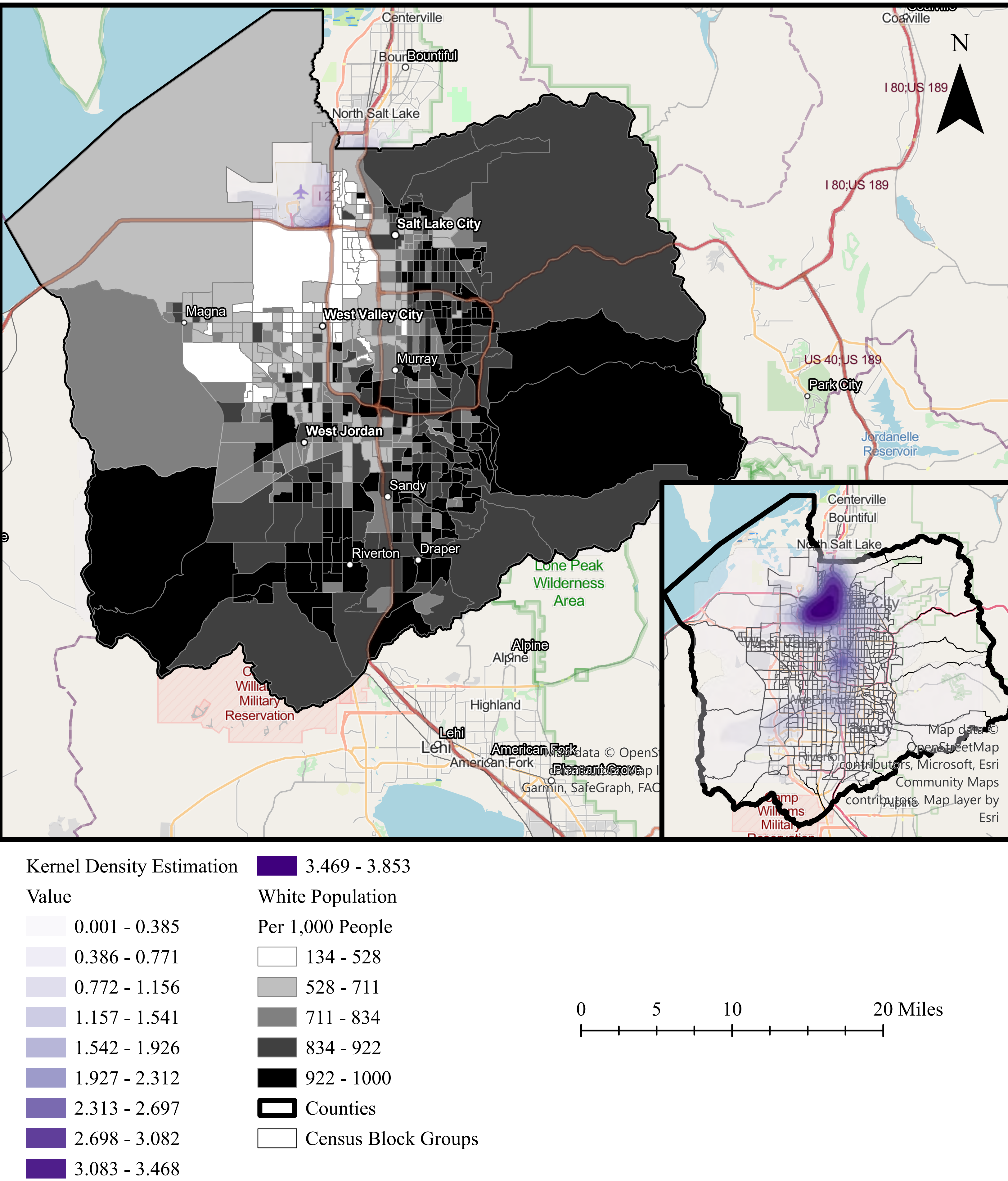


Figure 17: Black Population and Kernel Density in SL

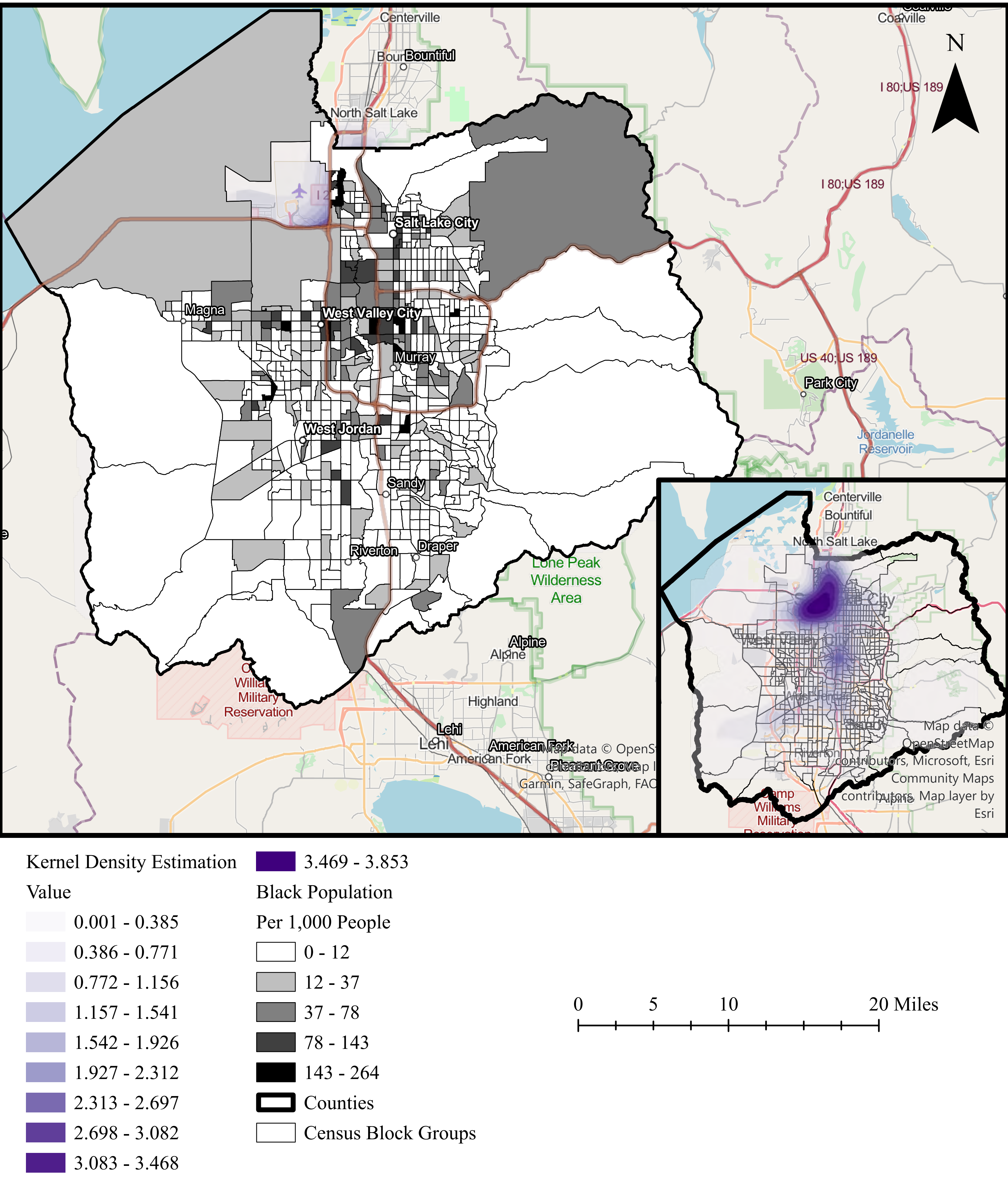


Figure 18: Hispanic/Latino Population and Kernel Density in SL

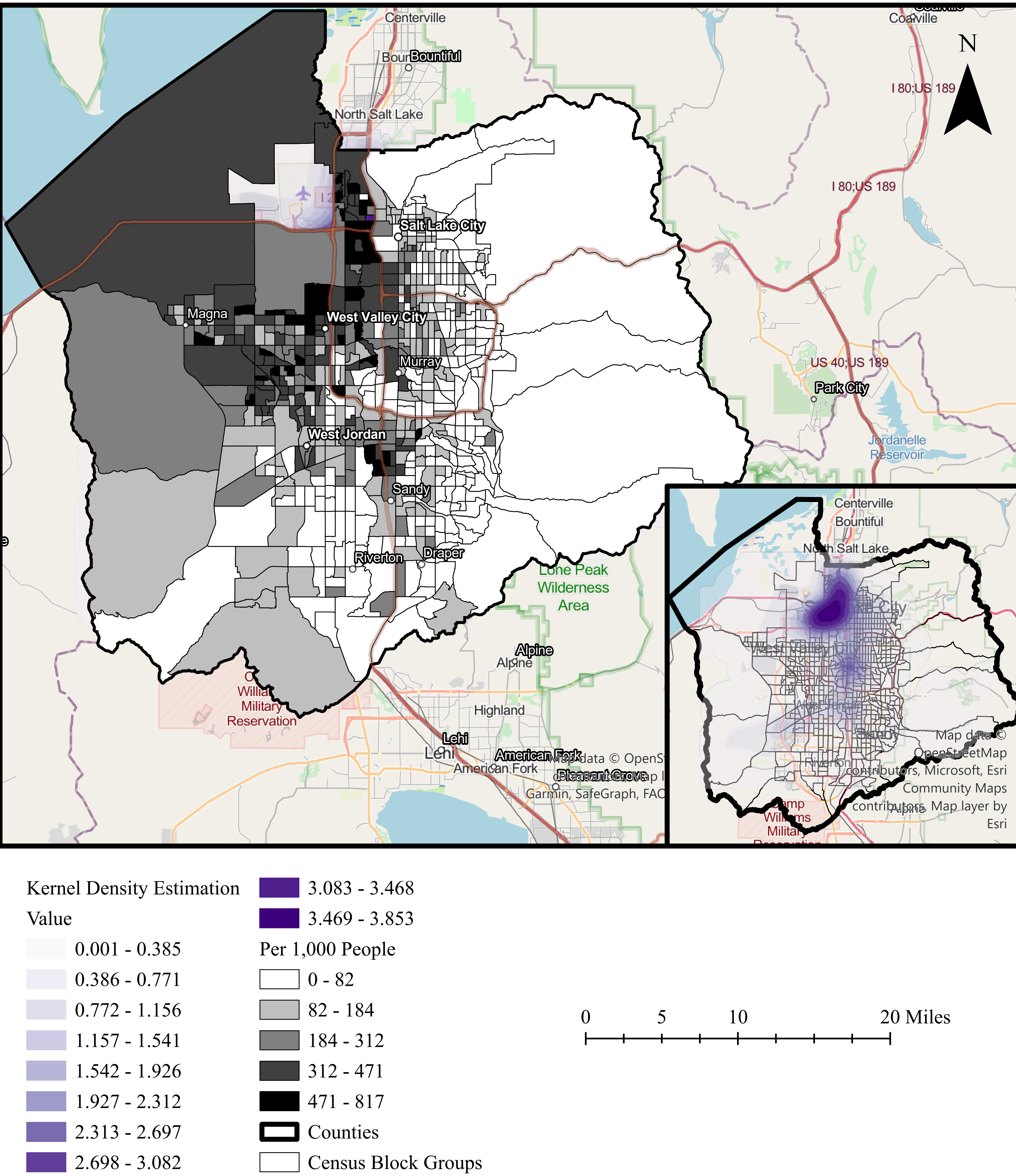


Figure 19: Native Indian Population and Kernel Density in SL

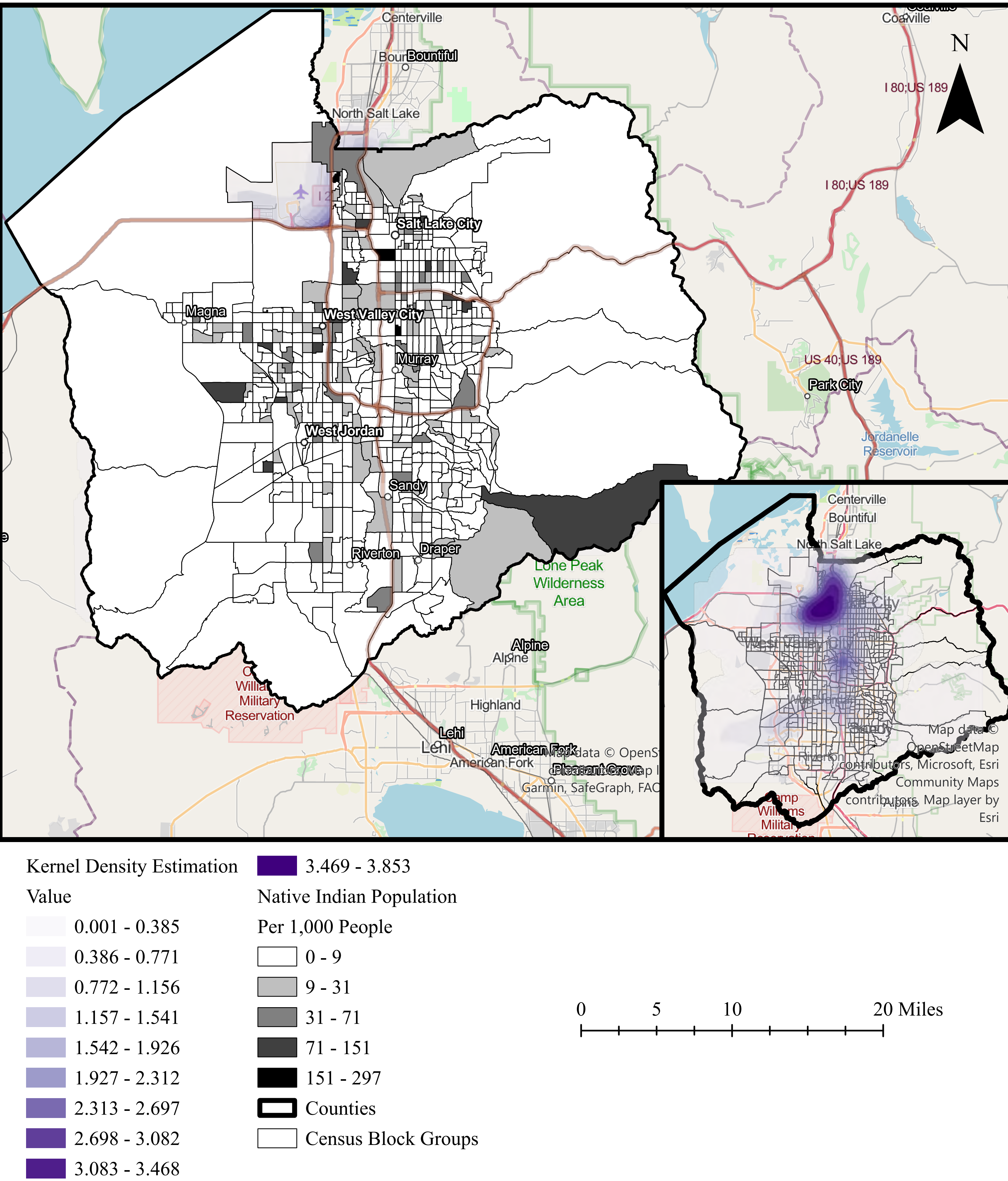


Figure 20: Islander Population and Kernel Density in SL

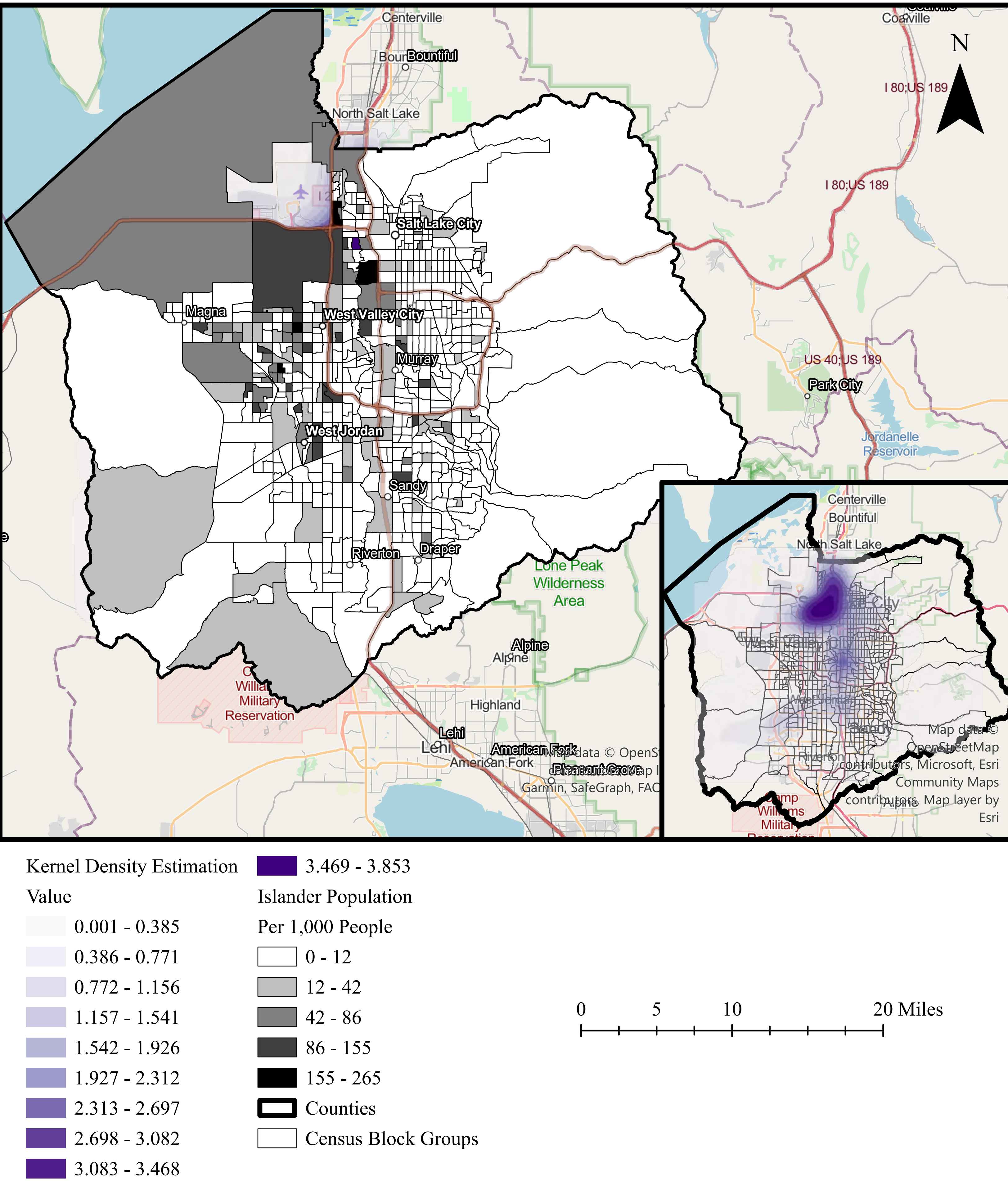


Figure 21: Asian Population and Kernel Density in SL

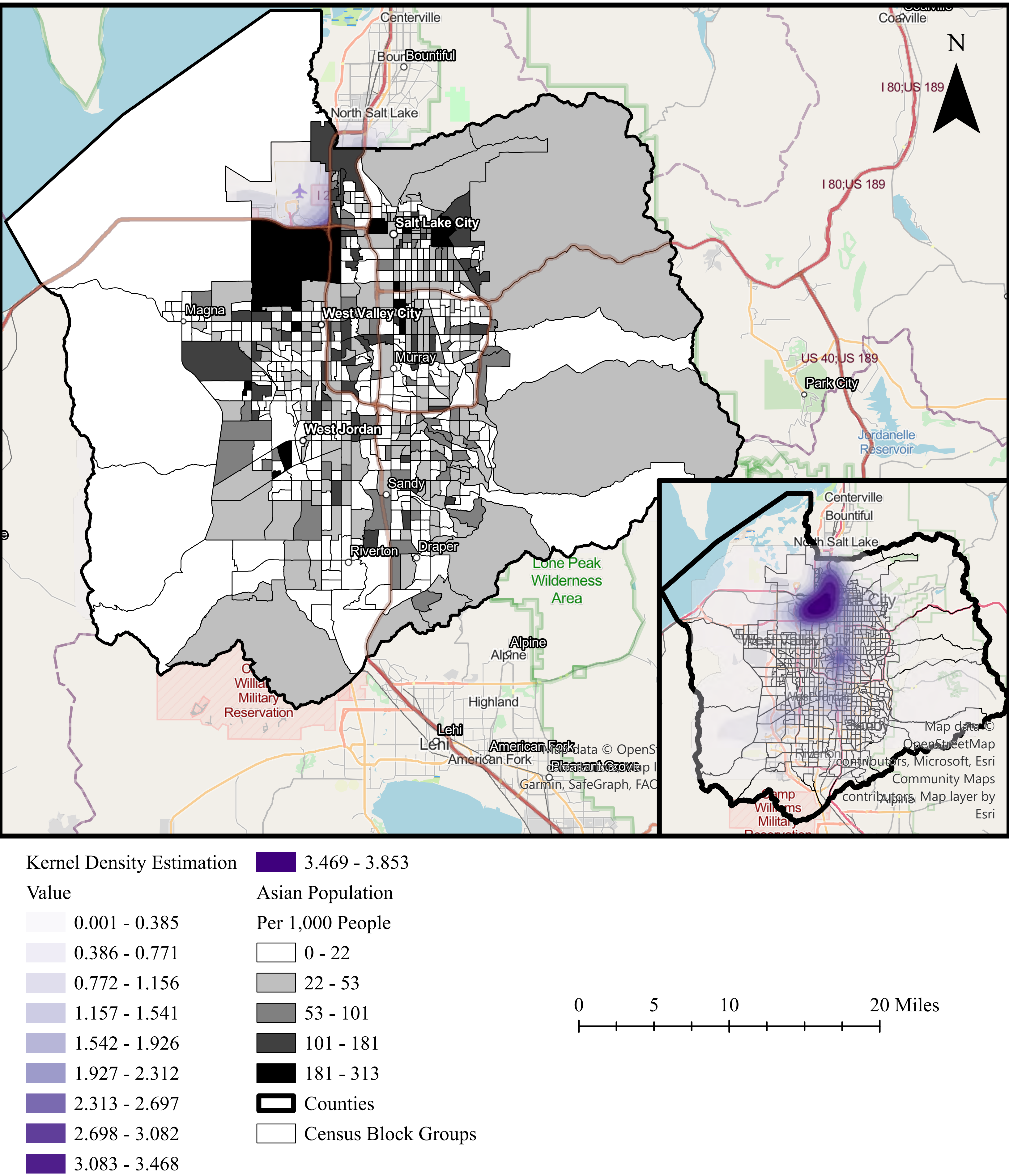
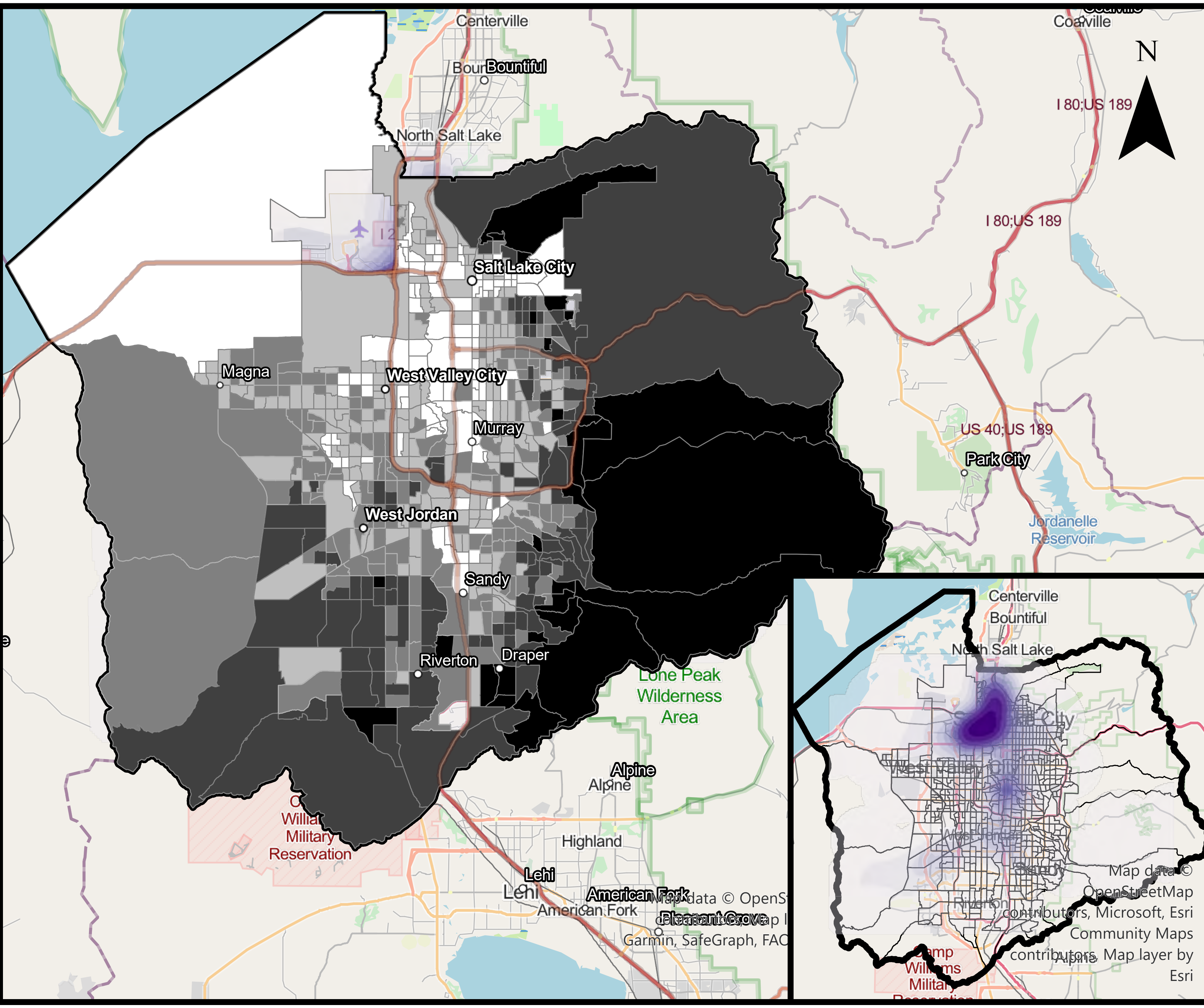


Figure 22: Median Household Income and Kernel Density in SL



Kernel Density Estimation

Value

- 0.001 - 0.385
- 0.386 - 0.771
- 0.772 - 1.156
- 1.157 - 1.541
- 1.542 - 1.926
- 1.927 - 2.312
- 2.313 - 2.697
- 2.698 - 3.082
- 3.083 - 3.468
- 3.469 - 3.853

Median Household Income

Dollars per Year

- 20,000 - 50,000
- 50,000 - 75,000
- 75,000 - 100,000
- 100,000 - 140,000
- 140,000 - 250,000
- Counties
- Census Block Groups

0 5 10 20 Miles

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