Visualizing Geography of Opportunity in the Context of United Way ALICE Families

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Abstract

United Way's ALICE (Asset Limited, Income-Constrained, Employed) project offers an alternative methodology that influences the conversation on poverty and financial hardship for working class Americans. While it has played a strong role in influencing social policy, there is limited understanding in terms of the opportunities ALICE families are afforded based on where they live, primarily at neighborhood levels and given the presence of factors like technological companies. Further understanding of this connection may provide insight in policymaking meant to ameliorates social ills and disparities. Using GIS (Geographic Information Systems), this study examines the way opportunity is influenced from these factors in selected US metropolitan areas (Dallas-Fort Worth Texas, Philadelphia Pennsylvania, and Seattle Washington) to determine how technological companies are visualized and influence allocation of opportunity in US metropolitan areas at the neighbourhood level. After analysing data from the selected metropolitan areas, it is observed that a) most of block groups in Dallas, Fort Worth, and Philadelphia, have the lowest percentages of ALICE populations, but the highest levels of opportunity, b) most of the block groups in Seattle tend to have the highest percentages of ALICE populations and the lowest levels of opportunity, and c) there is a noticeably high amount of block groups in each of the metropolitan areas (Dallas, Philadelphia, and Seattle), characterized by high levels of opportunity, but low percentages of ALICE populations, in the densest technology office cluster. While some relationship might be observed in the analysis, further study is warranted to establish a more robust connection.

1. Introduction

The purpose of United Way's ALICE (Asset Limited, Income-Constrained, Employed) Initiative is to communicate and address concerns working-class American families have in affording necessities. Historically, since the War on Poverty, the United States government has set standards that determine the number and proportion of people in poverty and who public welfare programs should appropriately target (United Way, 2019). Changes in the life of American families and rising cost of living begets expansion and changes in public assistance and social programs. In addition, the vagueness associated with the term poverty, the negative connotation that it is given, and the multiple usages of the federal poverty line suggests inadequacies in using these federal standards to assess financial hardship (United Way, 2019). As a result, the ALICE project provides an alternative methodology to identifying people in poverty; the number and proportion of people who are considered ALICE is determined based on the household survivability budget, then rounded to the nearest American Community Survey income bracket. Families who do not make enough income above a certain threshold are considered ALICE. ALICE is becoming increasingly recognized among policymakers as United Way programs increasingly recognize the struggles and meet the needs of working families. In terms of influencing social services policy, there is research that assess opportunity in geography; while previous research has visualized opportunity in various American metropolitan areas, there is limited research on the way structural entities in the form of technological companies impact a community's access to opportunities, especially when examined at more granular levels. Understanding where opportunities are and how opportunities are allocated geographically helps policy makers determine what policies are effective in allocating resources for impoverished communities. Drawing from a compilation of data, the study will attempt to address these questions: how are technological companies visualized and influence allocation of opportunity in US metropolitan areas at the neighbourhood level? How is opportunity conceptualized in these settings and contexts? Answering these questions is contingent on three different requirements: a) visualize opportunity in these locations at the block group level, b) identify 'technological companies' that influence the allocation of opportunities, and c) identify patterns or implications after these two concepts of opportunity are juxtaposed. For the purposes of this research, the two concepts that will be referred to are: opportunity mapping and geography of opportunity. The former is defined as: 'a way to conceptualize and visualize the varying levels of access to the opportunities which exist throughout states and regions" (Reece et al. 2010, p. 3) while the latter is defined as: "where people live impacts their access to opportunity" (Green, 2015, p. 718). A qualitative analysis will be conducted of various factors, while drawing from previous research, using data based on a set of metropolitan areas. The output will inform viewers about the study's methodology and results and visualize the geographic information in a way that aids in answering the research question. In summary, this study will provide a methodology which will aid in informing community organizations like United Way about how communities are impacted and influence both philanthropic and community action.

2. Literature Review

Social inequality, opportunity mapping, and the geography of opportunity are three interconnected areas of urban studies relevant to the reality of ALICE families. ALICE families experience various forms of hardship: low-paying jobs, limited assets and resources, and low social mobility. Expanding resources and opportunities and access to them for communities can improve their living conditions to an extent; the presence of technological companies, which affect the life and culture of communities, make social reform difficult and there are many things that fit that category. Understanding the geography of opportunity adds context to understanding the conditions and challenges communities face. These three taken together-social inequities, opportunity mapping, and the geography of opportunity-are quintessential to sparking activism and policy changes that positively impact ALICE families across the United States.

2.1 Poverty and Social Inequities

Research on factors that influences access and attainment of resources and opportunities are vast and diverse. In the context of homelessness, recipients who receive resources and services experience positive benefits. In Chicago, data from a Homeless Prevention Call Center, handling 75,000 calls annually, was processed to determine the impact in providing resources to recipients while comparing funding availability and funding unavailability (Evans, 2016, pp. 694-696); the impact of funding availability led to an 88% decline in the likelihood of becoming homeless after three months and a 76% decline in the likelihood after six months (Evans, 2016, p. 696). The cost of reducing homelessness through rent assistance is estimated to be about $720 per caller referred, and the effect of calling the Call Center, when funding is available, has adverted about $10,300 per homeless spell (Evans, 2016, p. 697). Intervention studies, such as one directed at promoting housing stability and homelessness prevention for families with children have dramatically improved their housing status and promoted economic self-sufficiency (Portwood et al. 2015, p. 487). It can be presumed households located in proximity to locations with high investments in social services experience improvements in social equity.

There is a range of factors that influence access to opportunities and the wellbeing among families; factors are not limited to: educational factors, environmental degradation, housing costs, and transportation costs.

Despite the importance of transportation in social mobility, there are factors influencing the decisions people make to travel. In the United States, public transportation is disproportionately used among members of minority groups and low-socioeconomic status (Murphy, 2019, p. 96). In terms of automobile ownership, motivations for purchasing and owning a vehicle as opposed to two or more (Karlaftis & Golias, 2002), or as opposed none is influenced through socioeconomic factors (Brown, 2017, p. 155). Ultimately, cost to transportation is shown to limit increase social mobility, especially in lower socioeconomic groups, because of its effect in inhibiting access to social services, economic opportunities, and social inclusion (Murphy, 2019, p. 96). When examining the literature regarding homelessness and transportation, ‘not only is transportation largely overlooked in homeless literature, but research indicates that transportation planning and engineering continue to struggle to meet the needs of low-income communities at large’ (Murphy, 2019, p. 102). These findings may aid to spark discourse on how transportation planning could meet gaps that fulfil the needs of low-income and homeless riders in addition to identifying aspects to strong methodologies that examine ‘transportation disadvantage’.

Rising housing debt in the United States makes it difficult for families to afford to live and expand opportunities. This is especially true for groups of varying socioeconomic status and race/ethnicity in terms of agency, cost and magnitude; lower-socioeconomic status families that have experienced stagnating wages have increasingly borrowed to maintain their standard of living, and many struggle to meet current expenses while paying their debt (Berger & Houle, 2019, p. 1276). In children, unsecured debt is associated with increase behavioural problems, and these problems are largely observed among African-Americans and families of lower-socioeconomic status (Berger & Houle, 2019, pp. 1293-1295). Findings related to racial/ethnic groups have been consistent with others on the topic of wealth accumulation, home ownership, and investment earnings (Squires & Kubrin, 2005, p. 51). Housing is shown to be interdependent with various facets of life for American families, and the vast disparities among races in these facets are structural problems that perpetuate inequality in opportunity (Green, 2015, pp. 717-718).

Literature examining the impact of educational factors on student success and life outcomes is vast. Teachers are important in influencing outcomes like student attendance; while improving test scores may not be correlated with improving student attendance, this suggests that teaching is ‘multidimensional’ (Gershenson, 2015, p. 143). Factors like small class size produce a lasting effect on student success, even in longer periods (Konstantopoulos & Chung, 2009). Despite the controversy of use of standardized tests, several meta-analyses have shown that these tests are predictive of a student’s performance in at least graduate school; this is further supported based on research that measure test scores and other measures of student success (Kuncel & Hezlett, 2007, p. 1080). As education attainment increases among populations like older adults, there is a lesser decrease in cognition and the differences among individuals in terms of education attainment is especially true in low-educated neighbourhoods (Wright et al. 2005, p. 1074). Evaluation of education outcomes may require incorporating these mentioned factors.

The relationship between proximity to toxic release sites and health effects has been studied extensively, including its impact on minority groups. The impact of toxic exposure, even examined longitudinally from 1989-2002, is shown to contribute to infant mortality rates and other adverse health outcomes (Agarwal et al. 2010). A systematic review, examining the relation between proximity to toxic release sites and adverse health effects shows that neighbouring populations are susceptible to adverse pregnancy outcomes, childhood cancers, asthma hospitalizations and chronic respiratory symptoms, stroke mortality, PCB toxicity, end-stage renal disease, and diabetes (Brender et al. 2011). When examining the relationship between proximity to toxic release sites and sociodemographic factors, it is shown that minority communities are more burdened (Sicotte & Swanson, 2007, p. 529) (Perlin et al. 2001, p. 416) and the impact is more regionally-based (Fricker & Hengartner, 2001, p. 48).

2.2 Opportunity Mapping

There have been many instances researchers visualized opportunity in geography. Researchers at the Kirwan Institute drew from various data sources to construct opportunity indexes for White Center (2011), King County (2010) and Puget Sound (2012). There are factors that crucially affect opportunities in those regions, such as for transportation; the Link Light Rail service is structured to raise the amount of opportunities in some areas over others, such as eastern vs. southern regions (Kirwan Institute for the Study of Race and Ethnicity, 2012). While the Kirwan Institute is most prominent in opportunity mapping various communities in the United States, there are challenges to creating and producing these maps to promote social equity. Lung-Amam et al. (2018) stated that “the process of creating maps can be shown to stigmatize disadvantaged neighborhoods and undermine community development efforts” (p. 640). Their geospatial analysis draws input from Baltimore residents regarding opportunity, then analyzed based on race, income, and geography. The most significant results were: 1) location played a key role in facilitating access and/or creating barriers to opportunity and 2) race and income greatly influenced what people perceived as opportunity. For instance, Caucasian participants emphasize freedom of choice and physical health and safety while African Americans and Hispanic respondents emphasize economic mobility and gaining/maintaining employment. These drawbacks suggest community engagement is critical to the success of community reform that involve opportunity mapping.

While opportunity in geography focuses on examining assets and resources that different communities can access to inform stakeholders and community partners in social equity, geography of opportunity, a slightly different concept from the former, focuses on structural barriers that disenfranchise populations and communities. As one author suggested, “the juxtaposition between geography of opportunity and opportunity in geography can be best understood as ‘the paradox of urban space’” (Green, 2015, p. 710). Utilizing geospatial analysis to examine mapped data and regional assets in Detroit, Michigan, Green’s research stressed that decentralizing opportunities can promote neighborhood equity. However, there are drawbacks in emphasizing lacking assets over inequalities and vice-versa as the source of marginalization, which suggests applying both co-currently may provide a comprehensive approach to addressing the complexities experienced in low-opportunity neighborhoods (Green, 2015, p. 737).

2.3 Geography of Opportunity

Geography of opportunity is examined in various instances among researchers. There is growing literature on geography of opportunity as it pertains to intergenerational mobility.

There is a connection between factors that relate to upward mobility and intergenerational mobility between a period of slavery and contemporary times in parts of the United States, using cotton plantation locations as a proxy; a measured increase in slavery is associated with decrease in the shared of married families and increase in share of children living in single-parent family households (Berger, 2018, p. 1562). Intergenerational mobility is also observed in the United States where populations of European ancestry mirrors the degree of economic opportunity as that of their predecessors in European countries (Berger & Engzell, 2019, pp. 6045-6046). These findings are consistent and add insight to contemporary understanding of disparities racial/ethnic minorities experience

Among various opportunity factors, geography also affects the educational outcomes of disadvantaged populations. In the case of school choice, Lubienski's geospatial analyses examined the socioeconomic needs among each census tract or block group, then temporal variables were used to determine patterns or activities in these charter schools for various metropolitan areas. While increasing competition for school enrollment is connected to increased access to these schools and school choice, there is a hierarchical structure created with these charter schools where some students are prioritized over others. For instance, competitive incentives and subsidies provided to District of Columbia charter schools affect their educational strategies in serving high-need students (Lubienski and Gulosino, 2009, p. 640). What the geospatial analysis reflects is the impact competitive incentives have in organizational behavior and response, which in turn affects school choice for students in racially segregated and economically-poor areas. A somewhat similar finding is discovered in Tate's research on poverty and educational outcomes, in which geographical proximity of school and neighborhood does not necessarily result in functional community support structures for African-American children because "structural barriers cause them to be reassigned to schools in high-risk neighborhoods regardless of desegregation " (Tate, 2008, p. 400). This phenomenon is also seen in the case of Dallas TX, where the University of Texas's relationship with Texas Instruments allowed for the expansion of its science and engineering facilities and investments in tech organizations near the North Central Expressway. Tate's work also showed poor education outcomes in communities with notable African-American populations due to the clustering of Missouri's biotechnological labs. Both case stories demonstrate how understanding the interrelationship of cultural, social, and economic institutions in these communities is pivotal to resolving its respective problems (Tate, 2008, p. 408). This understanding may significantly influence the way resources are allocated and policies are crafted to address social inequities. Miller (2012) performed a similar geospatial analysis as Tate and Lubienski on educational opportunities, utilizing Bronfenbrenner's ecological perspective to examine differences in opportunity at the block-group level between Homewood and Squirrel Hill, Pennsylvania (pp. 196-197). The maps, reflecting differences among studied variables for both Homewood and Squirrel Hill, demonstrate that despite the impact studied variables have on children's education outcomes at various societal levels, considerable nuances in the study suggest the need to tailor programs and policies to meet the unique needs of individuals. In summary, it cannot be emphasized enough that structural barriers, even at various scales within society, affect how working families access opportunities.

3. Description of Application/Intervention

The intervention is a series of maps visualized through an opportunity index, coupled with additional layers identifying the percentages of ALICE families and locations of technological companies, and a website that communicates the research topics, methods, and results. The intervention is hosted on GitHub. There will be pages made for each geographic region included in the study, an explanation regarding the observations and results for each region, and Leaflet web maps that visualize geographic information. The web maps enable users to zoom, pan, toggle between features and base maps, enable 2.5 dimensional visualizations of buildings, display of popup labels for each area, and identify the location on the web map in relation to the larger environment (locator map). The web maps drawing from geoJSONs of the studied regions will visualize them at the block group level using a blue-white color ramp based on a) percentages of ALICE families, b) opportunity scores, and c) percentages of people of color. Other geographic information included in the web maps includes polygons of technological company densities and the regions' respective transportation rail systems for guidance and comparison. Answering the research questions is contingent on several conditions: a) identifying the locations of technological company offices and any signs of clustering if able, b) characterizing opportunity in block groups, especially given their proximity to the technological company clusters, and c) identifying any aspect in the environment that influence opportunity in the block groups. Enabling one to characterize the geographic features and make comparisons among others, in relation to the polygons of technological company densities helps address the study's research questions.

4. Methods

A qualitative approach will examine the implications of creating opportunity maps, identify barriers that may inhibit opportunity, and present these findings in a way where meaningful input can be drawn among community members. The data has been analyzed with ArcGIS Pro. Of the many ways opportunity is defined, the Kirwan Institute defines it as "a situation or condition that places individuals in a position to be more likely to succeed and excel" (Kirwan Institute, 2012, p. 5). They explain further that factors can expand or inhibit individuals' likelihood to succeed. For the purposes of this study, opportunity is quantified using a range of values based on a set of those factors. Some factors are worth examining more than others, and each are categorized for different purposes. The following areas: Dallas-Fort Worth, Texas; Philadelphia, Pennsylvania; and Seattle, Washington will be examined in this study.

Census Bureau has information on median family incomes, which can be geoprocessed to show proportions of populations that would be considered ALICE families and in poverty. United Way has different household survivability budgets for each region, used to measure ALICE; it is implied that a family of two adults, an infant, and a four-year-old making an annual income of $59,340 in Philadelphia; $52,956 in Texas; or $72,600 in Washington is categorized as ALICE. They also provide demographic information, which can be used to calculate proportions of populations that would be considered people of color. Creating separate maps that reflect these statistics, then juxtaposing them to opportunity maps, is useful to identifying patterns of social inequity and racial inequality. The Census Bureau and other organizations can provide information that can be compiled to form an opportunity index. Table II. lists the data source(s), geoprocessing methods, and opportunity indicator for each opportunity factor. To address the MAUP (Modifiable Areal Unit Problem), geoprocessing tools will be used to compile the results of surrounding entities, then used to represent the data for each block groups. Data will be examined at the census block groups level if able, if not, at the next available geographic extent. After all the geoprocessing methods have been completed and Z-Scores are created for each opportunity factor, they will be compiled to form one opportunity index, classified through quantiles. No weights have been assigned in the data processing of opportunity factors to minimize bias in the analysis.

While "geographies of opportunities" was originally coined in Xavier de Souza Briggs's research (Tate, 2008, p. 409), researchers have made various attempts to quantify and visualize it using evidence of neighborhood effects with GIS technology (Lung-Amam et al, 2018, p. 636). There are some factors that are worth considering when examining the geography of opportunities; historical context, occupancy, costs and investments, and if studied areas are a public, private, or public-private facility or infrastructure. For the purposes of this research, office locations (particularly headquarters) of technological companies will be studied. Zippia, a career searching site, and Bloomberg, a business and analytics site, are used to identify and categorize technological companies for each studied region. In addition, a mix of Google Maps (down to the street-level), official websites of compiled companies, and SEC filings are used to further validate the accuracy of the company locations. In addition to the locations of some amenities, the technological companies have undergone a reverse geocoding process through the Texas A&M Geoservices to plot the data into ArcGIS software. Next, Average Nearest Neighbor determines whether features in an area is dispersed or clustered, and whether the results of the analysis are statistically significant. If the observed mean distance for the technological companies is less than the expected mean distance, then the features are clustered. Table I provides the results of the statistical analysis.

Table 1. Summary of Average Nearest Neighbor Statistics for Each Study Area

	Dallas TX	Fort Worth TX	Philadelphia PA	Seattle WA
Observed Mean Distance	4901.0088 feet	35894.4199 feet	11074.6143 feet	1058.3948 feet
Expected Mean Distance	7343.4177 feet	17273.8828 feet	14228.5055 feet	2128.0929 feet
Nearest Neighbor Ratio	0.667402	2.077959	0.778340	0.497344
Z-Score	-4.408305	5.832814	-2.283586	-10.751190
P-Value	0.000010	0.000000	0.022396	0.000000

Table I. suggests, based on the available studied features, that the technological companies of metropolitan areas are clustered except for Fort Worth. After analyzing each feature, Kernel density will visualize the concentration and spread of technological companies. Kernel density estimation is calculated via this equation:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right),$$

where:

where $x_1, x_2, \ldots, x_n$ are random samples from an unknown distribution,
n = technological companies,
K(·) = kernel smoothing function, and
h = 10560 (feet)

After generating raster files, they are symbolized in quantiles through five classes. Then the use of Reclassify and Raster to Polygon tools enable the raster files to transform into vector shapefiles, making them useful to compare alongside opportunity maps and other relevant maps. The opportunity mapping and density analysis for this study has been completed and results have been compiled for each studied area and published onto the website.

5. Results and Discussion

Analysis results are provided for each of the following cities: Seattle, Washington (Figure I, II, III); Philadelphia, Pennsylvania (Figure IV, V, VI); Fort Worth, Texas (Figure

VII, VIII, IX); and Dallas Texas (Figure X, XI, XII). Most of block groups in Dallas, Fort Worth, and Philadelphia, have the lowest percentages of ALICE populations, but the highest levels of opportunity. In addition, the largest count of block groups in Seattle tend to have the highest percentages of ALICE populations and the lowest levels of opportunity, and b) no count of block groups have the lowest percentages of ALICE populations and the highest levels of opportunity. The trends among count of block groups suggest a negative relationship between the percentages of ALICE populations and levels of opportunity. There is a noticeably high amount of block groups in each metropolitan area, characterized by high levels of opportunity, but low percentages of ALICE populations, in the densest technology office cluster.

5.1 Dallas, Texas

The contrast among the opportunity map, ALICE families map, and populations of color map presents some fascinating findings. High opportunity block groups are in the City Centre District, then north into North Dallas and Addison and dispersed towards Reinhardt and Oldham. While there is a mix of low-mid opportunity block groups in the southwest and southeast area, there is a noticeable consolidation of low-opportunity ones, like Sargent and Fruitdale. High ALICE population block groups are located interestingly outside of Dallas's City Centre District in addition to a) outer western parts, b) outer eastern parts, and c) the southern part of the city district. Where there are high ALICE population block groups, even areas with high populations of color, there are low opportunities. The technology office clusters seem to differentiate the distribution of opportunities, ALICE populations, and populations of color for this city. Tate's case study of Fort Worth where his drive south through North Central Expressway down the Telecom Corridor is a stark contrast to his drive towards Martin Luther King Dr. Blvd (Tate, 2008, pp. 398-399) further corroborates this finding. It would suggest despite extending the DART rail lines to Buckner and Ledbetter that the amenities and opportunities are still abundant in the City Centre District and North Dallas while communities in South Dallas remain somewhat deprived. DART rail provides great movement for people within the condensed tech clusters and extends as far north as Denton and as westward towards DFW Airport and further towards Fort Worth.

Block groups are influenced in a way where there appears to be a northern-southern regional split in terms of opportunities available. There is strong polarization in terms of median income and education attainment, in which high opportunity levels are founded in block groups north of Dallas's city center district and low opportunity levels were found south from there. There is lesser polarization among the same two regions in terms of vehicle ownership and commute time, based on the amount of moderate opportunity block groups. In addition to previously mentioned opportunities, education and proximity to community resources and bus stops were moderate-high in the city's central district. Despite the presence of moderate-opportunity block groups and a neutralized effect from high and low-opportunity block groups, certain opportunities influence a geographical split within Dallas.

5.2 Fort Worth, Texas

High opportunity block groups are located near certain amenities and in particular, the western and northwest part of the city—around the Chisholm Trail Pkwy and near the NAS Joint Reserve Base—as opposed to the south eastern parts where there are low opportunity block groups. While in general, high ALICE population block groups are dispersed around Fort Worth, there are others, that also have high populations of color, located east of 35W Southbound and south of Tom Landry Hwy. Some of the block groups with high populations of color are located long the path of the Trinity Railway Express, starting at Fort Worth Central Station. Though Fort Worth's technological companies are presumably dispersed, many of the offices are located in that central, northwest region; they exist around 30 West Fwy and the Chisholm Trail Pkwy. It is important to stress the possibility that not all technological companies are represented for this region.

Block groups around the Chisholm Trail Pkwy is notable for highest opportunity levels in the following opportunities: vehicle ownership, education attainment, proximity to toxic release sites, and median income. Median income, education, and proximity to toxic release sites influence moderate-high level opportunities in the western region, with exception to very few block groups. The southeast region has the lowest levels in terms of education attainment, education, and median income. While the northern region experienced low levels of opportunity in vehicle ownership, commute time, and proximity to toxic release site, it appears the effect is counteracted based on other measured opportunity factors like education. Like Dallas, proximity to bus stops and community resources were highest in the center of the city; the effect is lesser in the outskirts.

5.3 Philadelphia, Pennsylvania

Most of the high opportunity block groups are in the city—Rittenhouse Square, Washington Square West, and Chinatown—and then dispersed in other areas of the city boundaries—Overbrook, Northeast Philadelphia, and Chestnut Hill. The low opportunity areas—Feltonville, Juniata, Kensington, and Bridesburg—not only have large ALICE populations and populations of color. There is interestingly a consolidation in the block groups among high populations of color and low populations of color into larger boundaries; for instance, high opportunity block groups with the lowest populations of color are located around the Northeast Airport and are distinguished through the Chestnut Hill West SEPTA rail segment and some part of the Trenton SEPTA rail segment that separates Bridesburg. Though there is a large amount of ALICE families north from the city and in the suburban areas, they co-occur with low ALICE population block groups. Interestingly enough, low ALICE population block groups are located near certain amenities; while some of those block groups are located near the Delaware River, Schuylkill, and across Chestnut St. down to the Delaware River, they are located along the Pennypack and Wissahickon Creeks. In the technology office clusters, there are block groups with low populations of color in the city and industrial areas (though the outer skirts of these clusters, the Grays Ferry and Point Breeze areas, are distinguished with block groups with high populations of color) and areas with mix of high and low ALICE populations distinguished with a set of low ALICE population block groups that run across Chestnut St. Chestnut St. is recognized not only for high amenities and opportunities, but historical points of interests.

Similar to Dallas, block groups are influenced in a way where there is division in terms of opportunity; unemployment, median income and partially on commute time and vehicle ownership among block groups. Both experienced similar effects regarding proximity to toxic release sites, bus stops, and community resources. Areas where there are high-opportunity block groups are also located near the Wissahickon Hills, Fox Chase – Burholme, and the airport.

5.4 Seattle, Washington

Most of the high opportunity block groups are located around Northern Admiral, Southlake Union, Queen Anne, Capitol Hill, and the University District. Low opportunities are found around the Highland Park, Georgetown, and South Seattle area. The low opportunity areas in the southern part of the city has a greater presence of ALICE families and populations of color. More populations of color can be found in Beacon Hill, Pioneer Square, and Industrial District. Most of the areas with the least populations of color are located in the outer edges of the city limits, Northern Admiral, and North Seattle. While there is high ALICE populations in the southern part of the city, there are still high ALICE population block groups located in other parts, co-occurring with block group counterparts that have low amounts; some of those areas include the Northgate and Green Lake area. Areas with the low populations of color and ALICE families are found in the Washington Park and Madrona area. It is probable given these observations that while low ALICE population block groups reside in the technology office clusters, others are dispersed into the more suburban areas, especially where opportunities are abundant. It is important to take notice that the Link Light Rail is providing movement of people among the low-opportunity areas—Northgate and South Beacon Hill—located in outer parts of the city limits and people located in high-opportunity block groups or the technology office clusters.

Among opportunity factors, it appears education, education attainment, proximity to toxic release sites, and commute time were the lowest among block groups within the White Center and South Seattle area. Vehicle ownership, education attainment, and education were the highest among block groups in Ballard and northern parts of the city. There were many factors—education attainment, median income, and commute time—that influenced level of opportunity in places like Capitol Hill and Madrona. Despite these notable observations, it is plausible the block groups of other areas experienced moderate levels of opportunity—vehicle ownership, proximity to community resources, education, and education attainment—and slight up-ticks on others.

6. Conclusion

A qualitative analysis was conducted to determine how technological companies are visualized and influence allocation of opportunity in US metropolitan areas at the neighbourhood level and how opportunity conceptualized in those settings and contexts. The analysis has partially accomplished this using a series of geoprocessing tools on ArcGIS program that show areal polygons that compare block groups in relation to them and in terms of opportunity. A series of geoprocessing tools were used to construct an opportunity index that visualizes opportunity for each metropolitan area. The Average Nearest Neighbor Analysis identified three metropolitan areas in which there is a clustering of technological office locations. Kernel Density Analysis of technological office locations generated those areal polygons. The trends observed among block groups in metropolitan areas suggest a negative relationship between the percentages of ALICE populations and levels of opportunity. There is a noticeably high amount of block groups in each metropolitan area, characterized by high levels of opportunity, but low percentages of ALICE populations, in the densest technology office cluster. Results from the analysis for each studied area is published onto the website. Observing the maps, it is clear there are aspects of metropolitan areas that are more susceptible to urban problems like gentrification, than others, and thus are more difficult to address. Despite the role technological companies may play that influence characteristics among block groups in metropolitan areas, experts and regional governments have called for or implemented recommendations that prevent displacement of minority communities in the presence of urban development (Levy et al. 2007).

There were many limitations observed when conducting this study. Though the maps generated from the analysis suggests some connection, the conclusions it draws do not extend any further given the study's scale. Despite the opportunity factors used in the analysis, there are others that were not incorporated that would have made the findings more robust. For instance, lack of science-based test performance scores, because of incomplete or failure to acquire data, would have made the education factor more complete. Also, the National Center for Education Statistics has data on student eligibility for free and reduced lunch, which can be used to calculate for the percentages of students who may experience poverty; that data was somehow not incorporated when assessing education among the block groups. Some of the data collected is missing values, partially because the data collection process for the sources used for this study has been exhausted. Philadelphia, among the studied metropolitan areas, have the most null opportunity values among block groups and this is primarily due to missing median income and mortgage data. Some of the null-valued block groups for that region are located close to the industrial and shipyard area, designated for open space and hazard control, making the areas inhospitable. Furthermore, the possibility of insufficient data collection of Fort Worth office locations may influence the results for that specific area. In fact, it is possible existing technological offices in Fort Worth are not located in a manner where they are 'dispersed' from each other. The study was initially designed to incorporate individual input in the form of focus groups to address the second research question, but failed due to lack of timing.

It is crucial when replicating this study to not only address the limitations but utilize a larger and different sampling group. Differences in metropolitan areas will reflect in both historical context and solutions that mitigate urban issues. There are two ideas worth considering in terms of significantly expanding this project: 1) as mentioned previously, incorporating data from focus groups would provide more context in understanding how opportunity is conceptualized and influenced in their respective communities in addition to methodological suggestions for conducting these analyses. And 2) incorporating government spending data on urban projects and programs in GIS analysis to identify block groups where investments are the most influential relative to the amount of ALICE families living in those areas. It is undetermined whether United For ALICE can provide input on these kinds of spatial analysis for research on ALICE families. However, United Way of Pierce County's collaboration with University of Washington Tacoma's Action Mapping Project allowed for discourse and opportunities for local-lv projects that help meets the expectations of the former's stakeholders (Matthew Kelley, personal communication, 2020). If anything, this is an indication of increased openness and incorporation of modern data visualization tools and GIS in the setting of community organizations.

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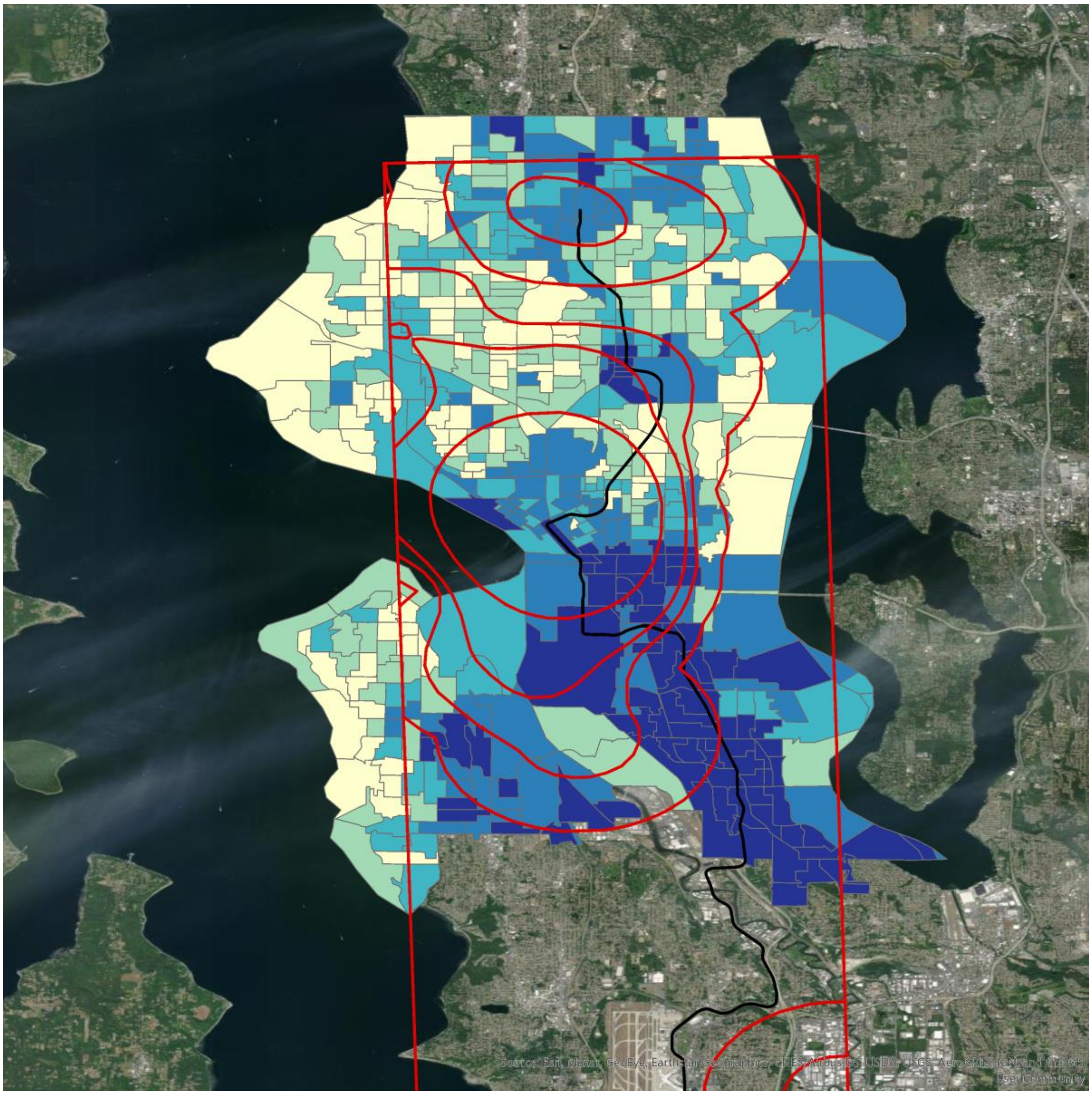

Figure I. Seattle Washington visualized based on Percentage of People of Color

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

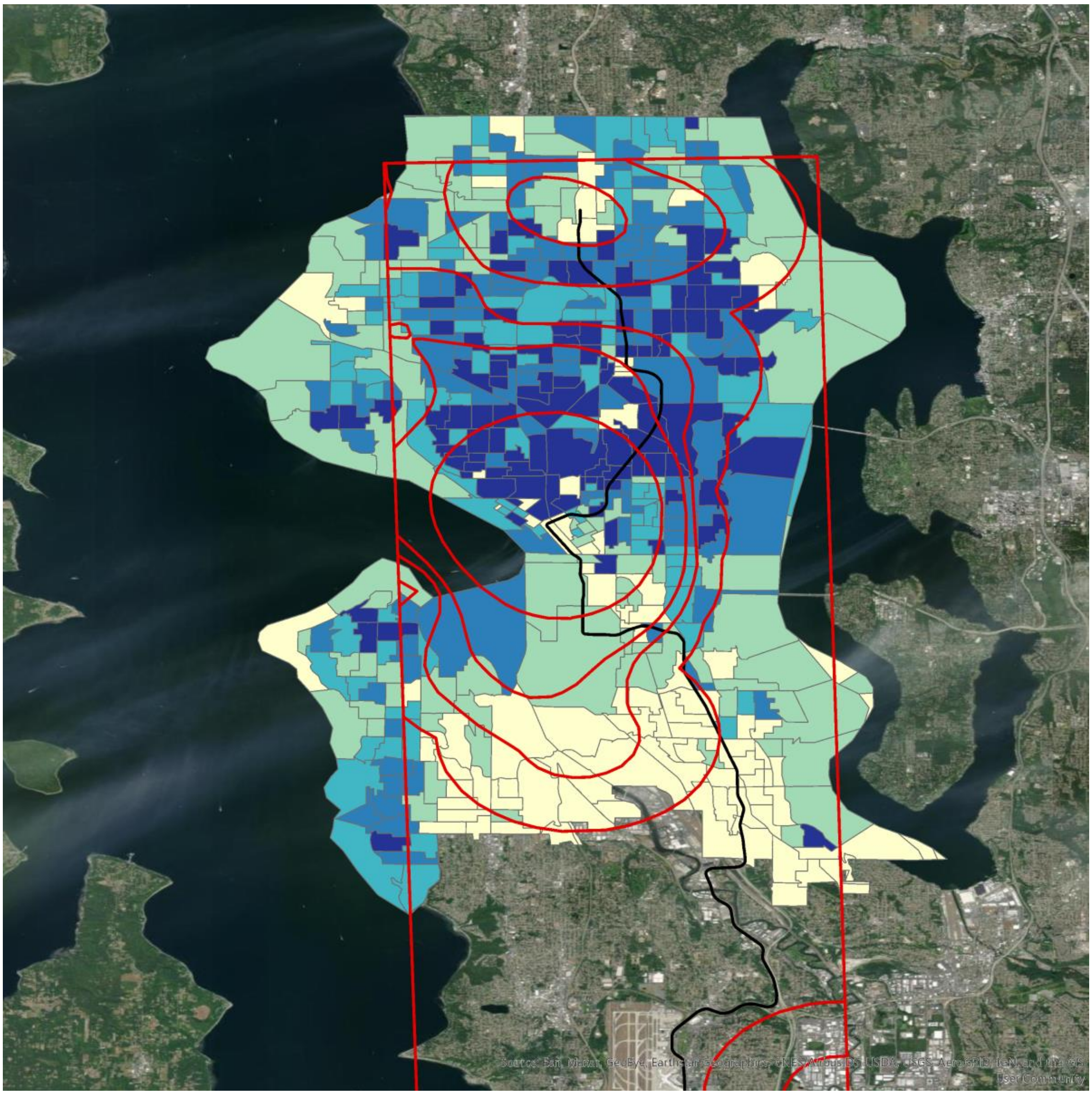

Figure II. Seattle Washington visualized based on Opportunity

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

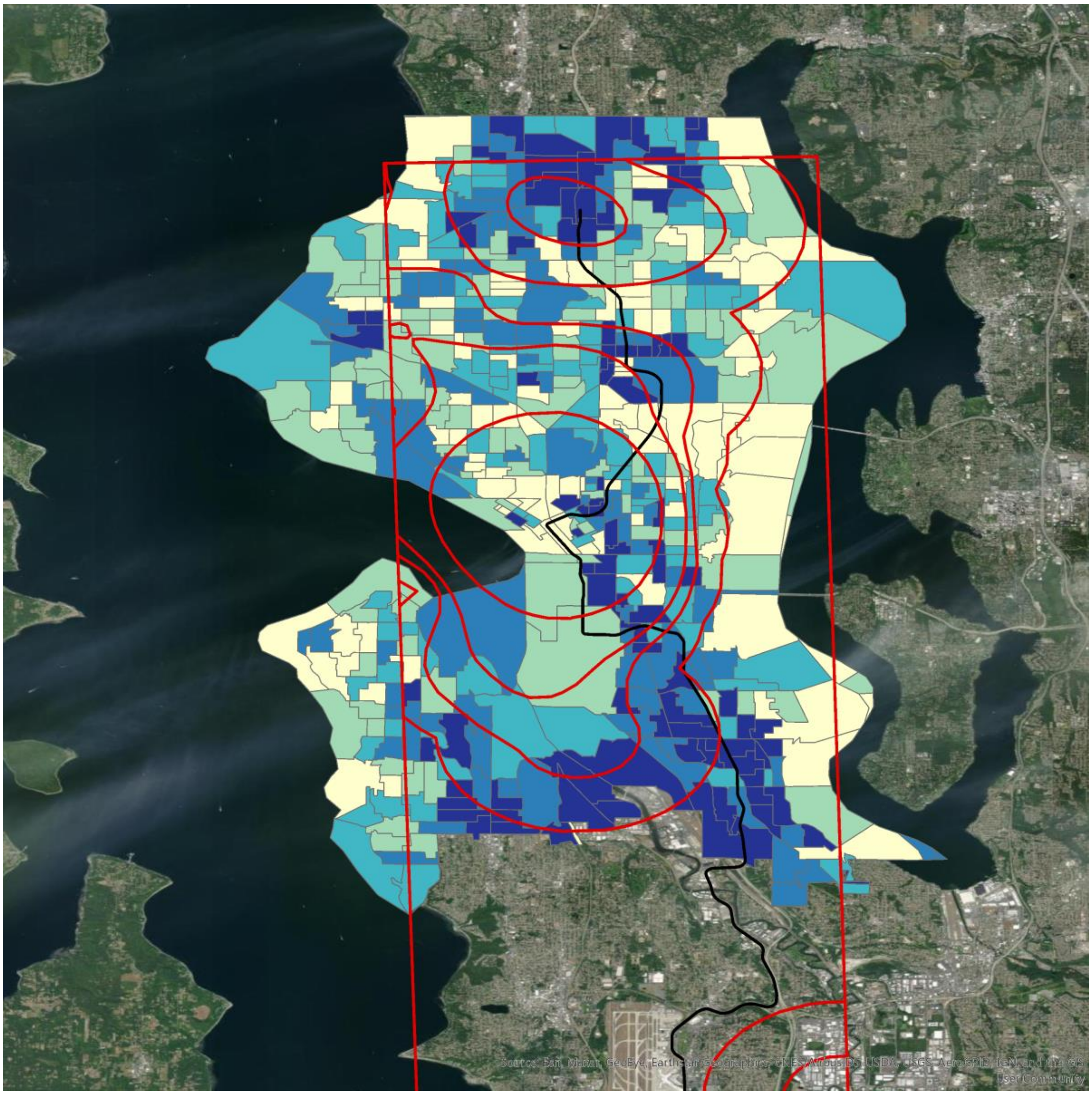

Figure III. Seattle Washington visualized based on Percentage of ALICE Families

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

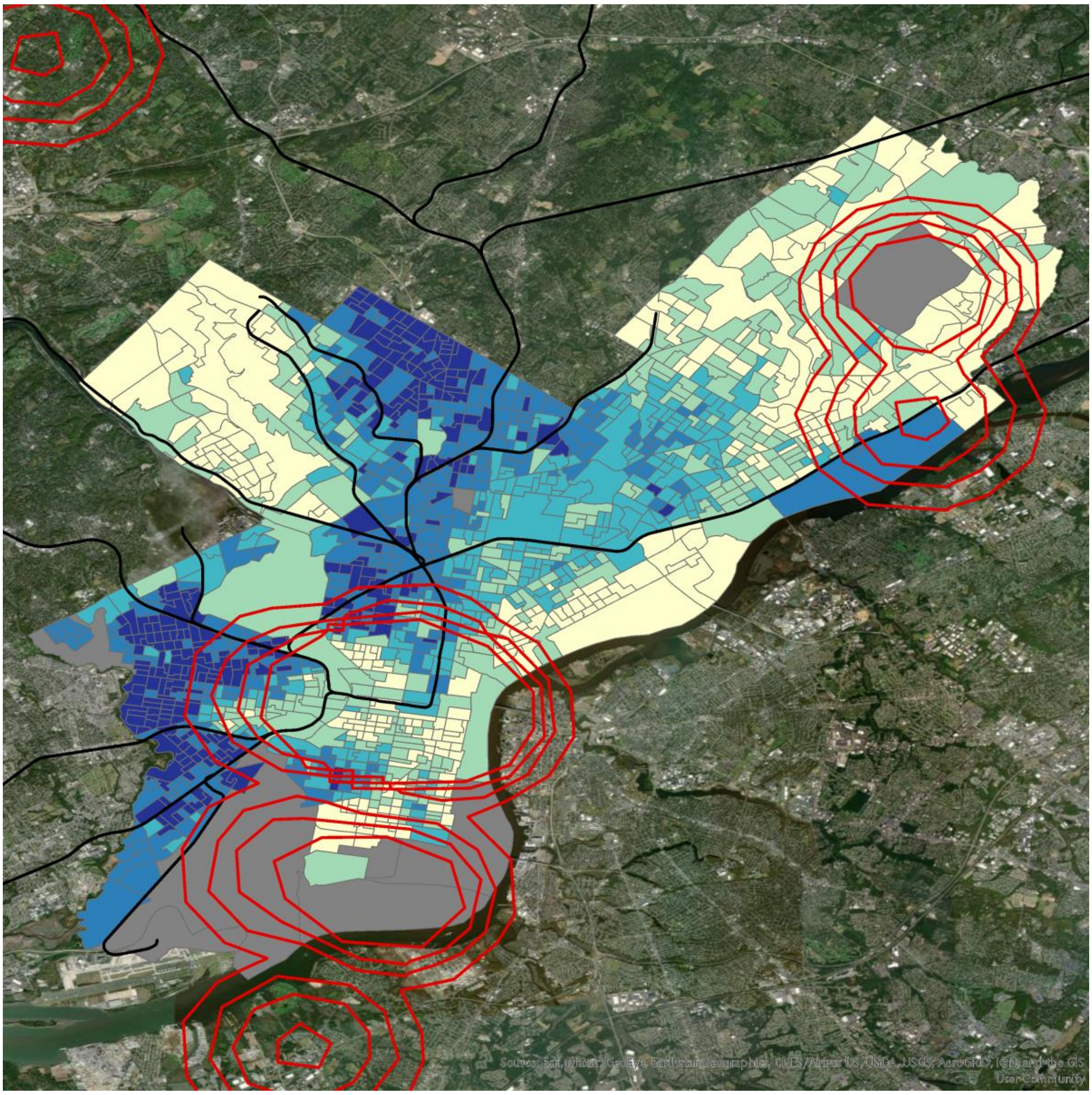

Figure IV. Philadelphia Pennsylvania visualized based on Percentage of People of Color

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

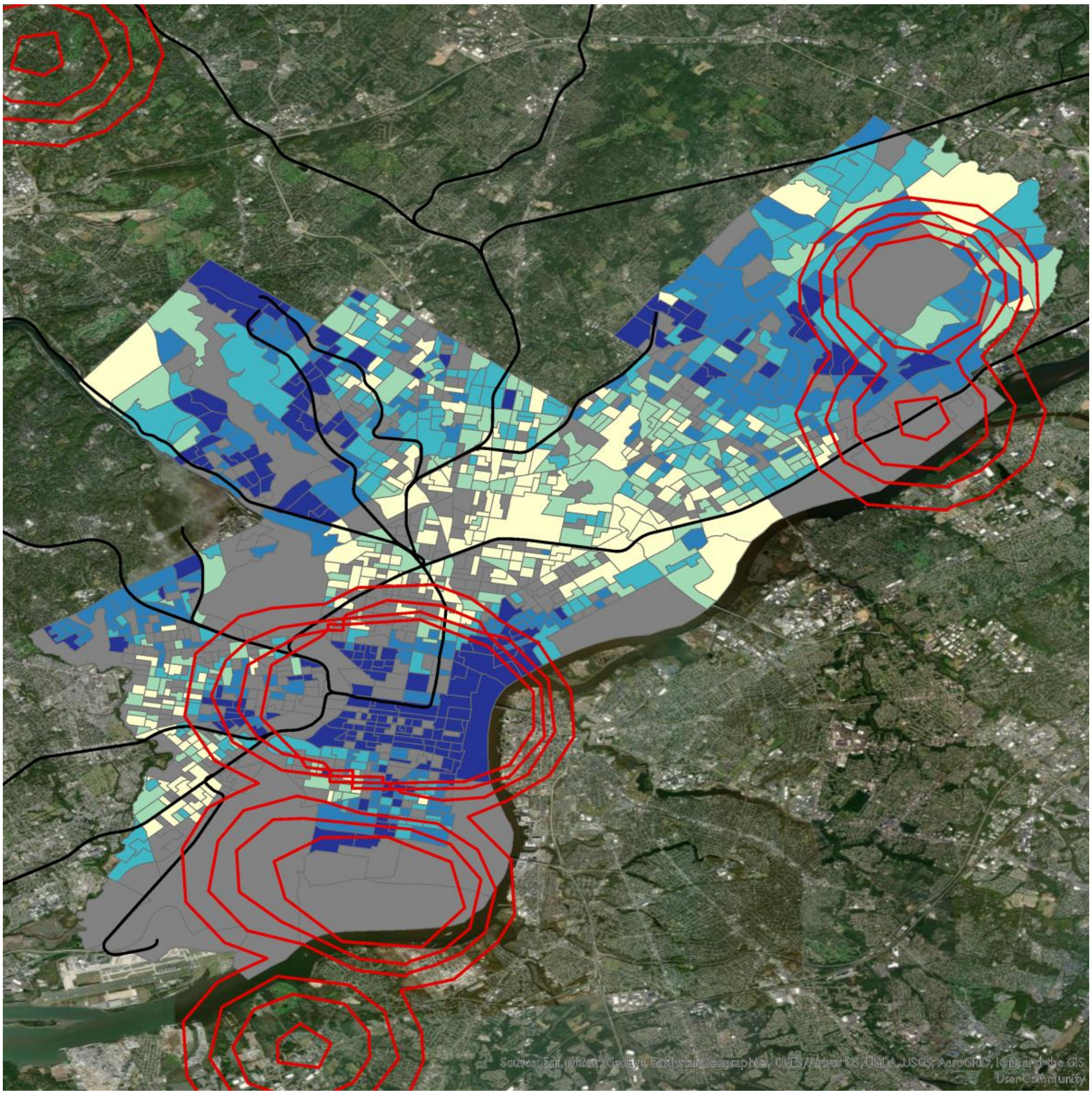

Figure V. Philadelphia Pennsylvania visualized based on Opportunity

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

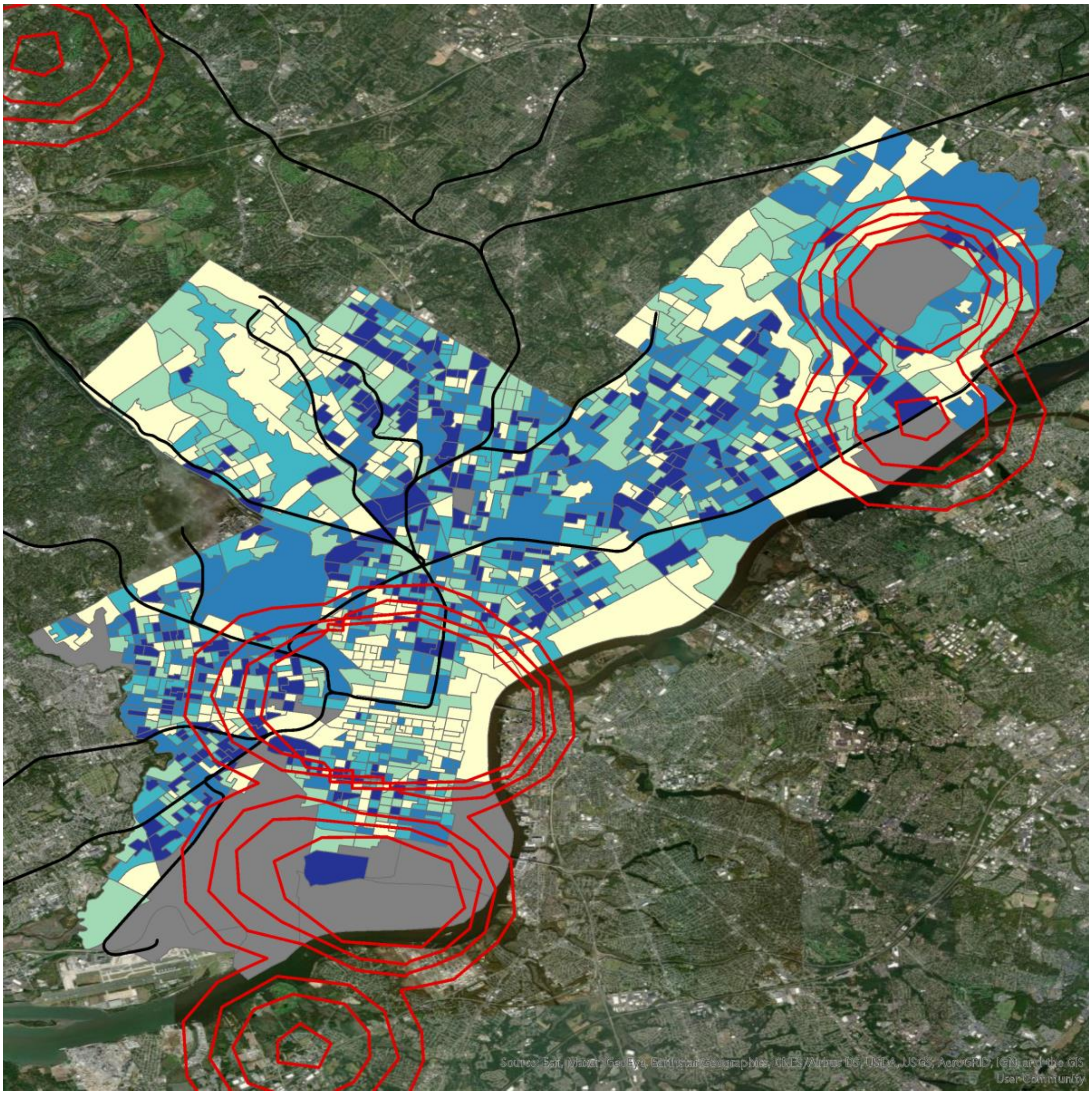

Figure VI. Philadelphia Pennsylvania visualized based on Percentage of ALICE Families

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

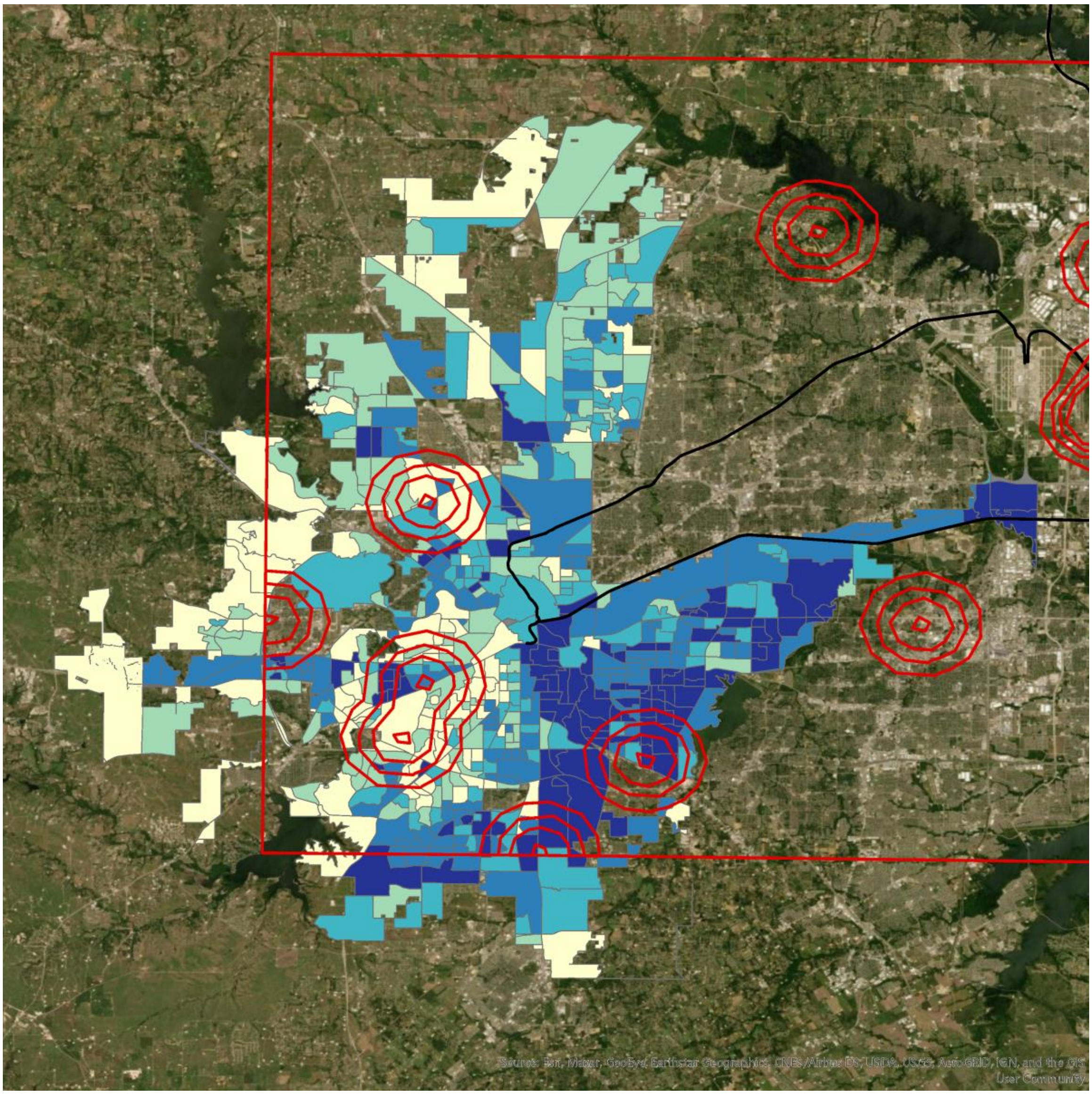

Figure VII. Fort Worth Texas visualized based on Percentage of People of Color

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

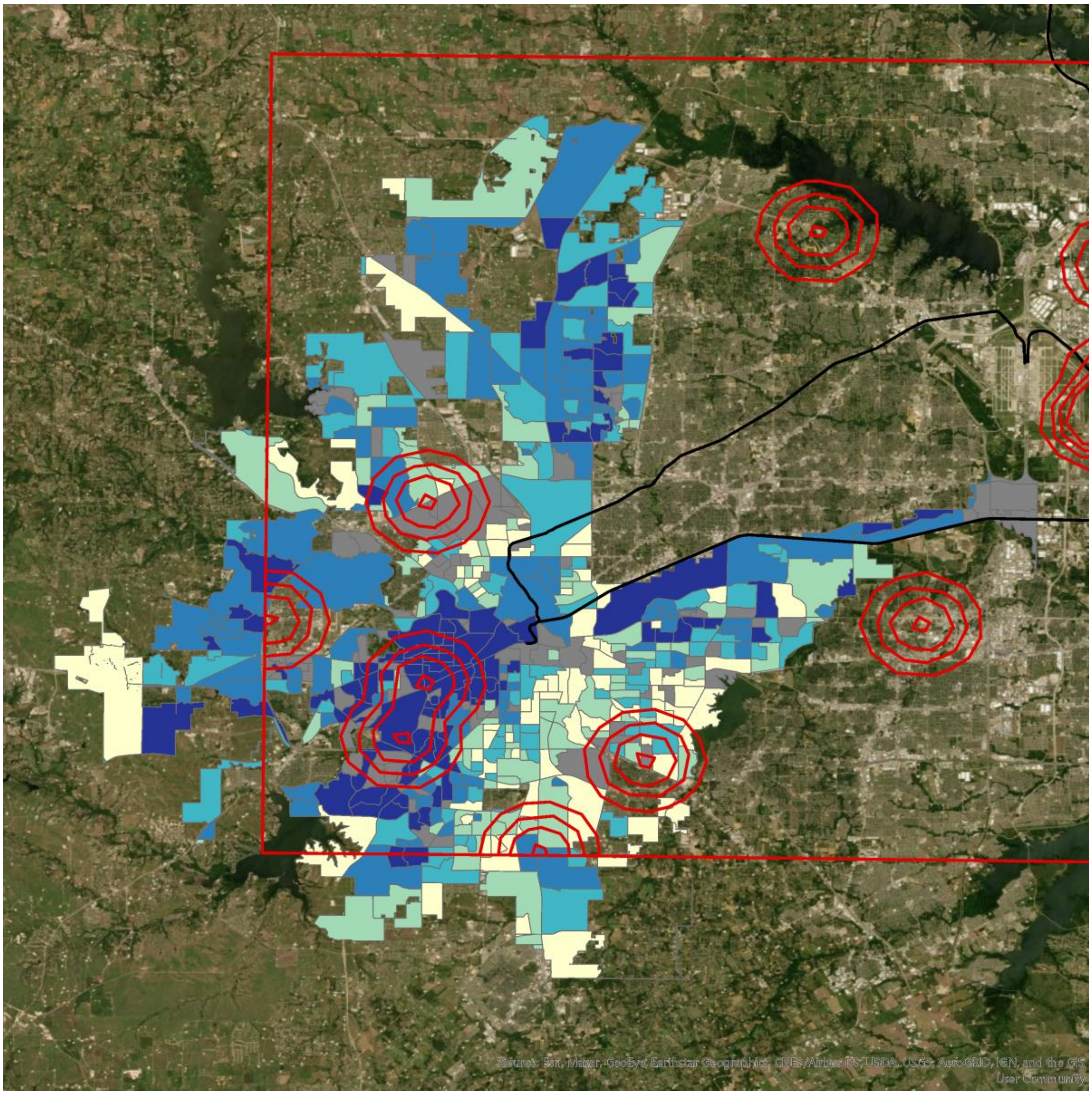

Figure VIII. Fort Worth Texas visualized based on Opportunity

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

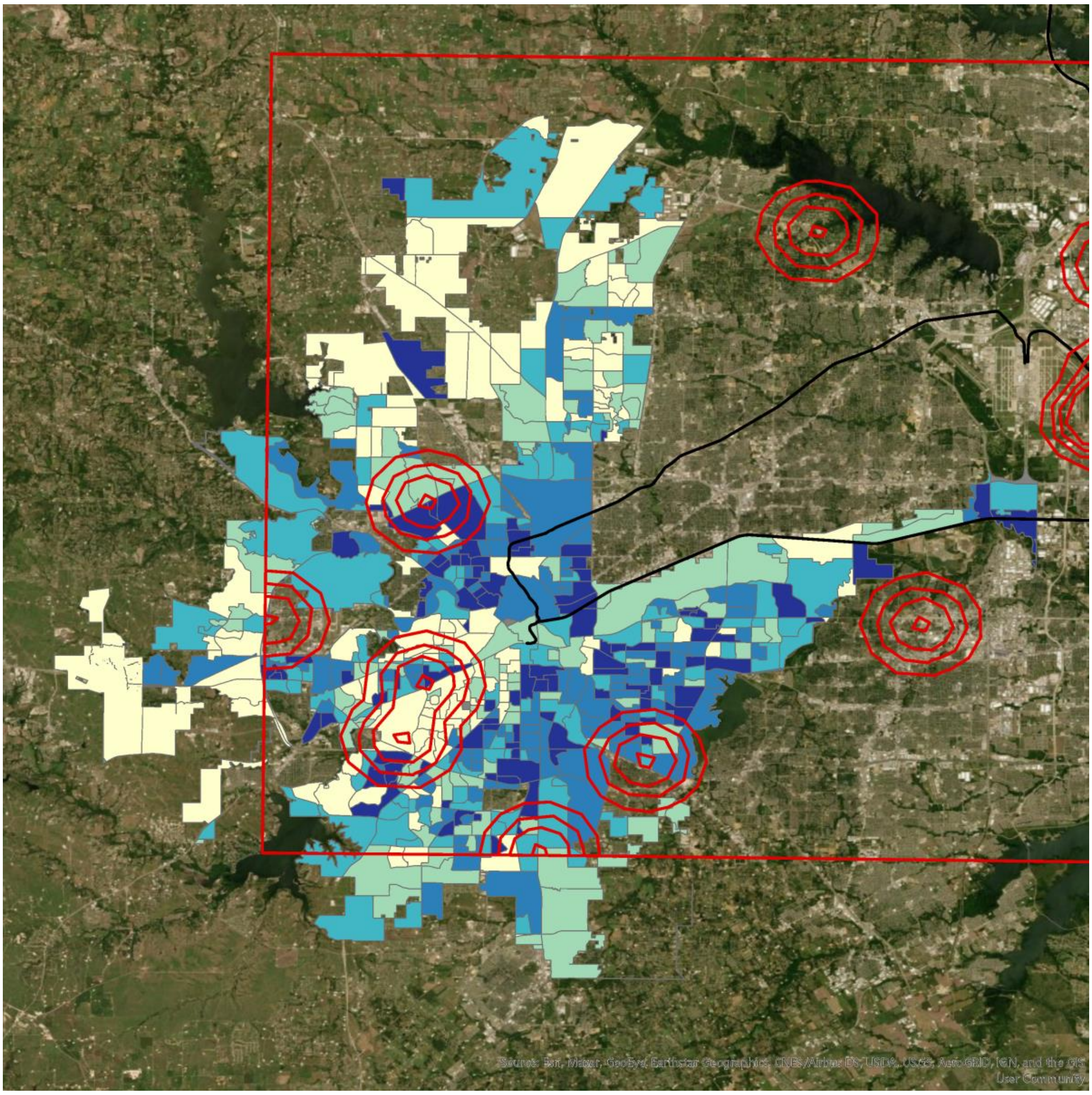

Figure IX. Fort Worth visualized based on Percentage of ALICE Families

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

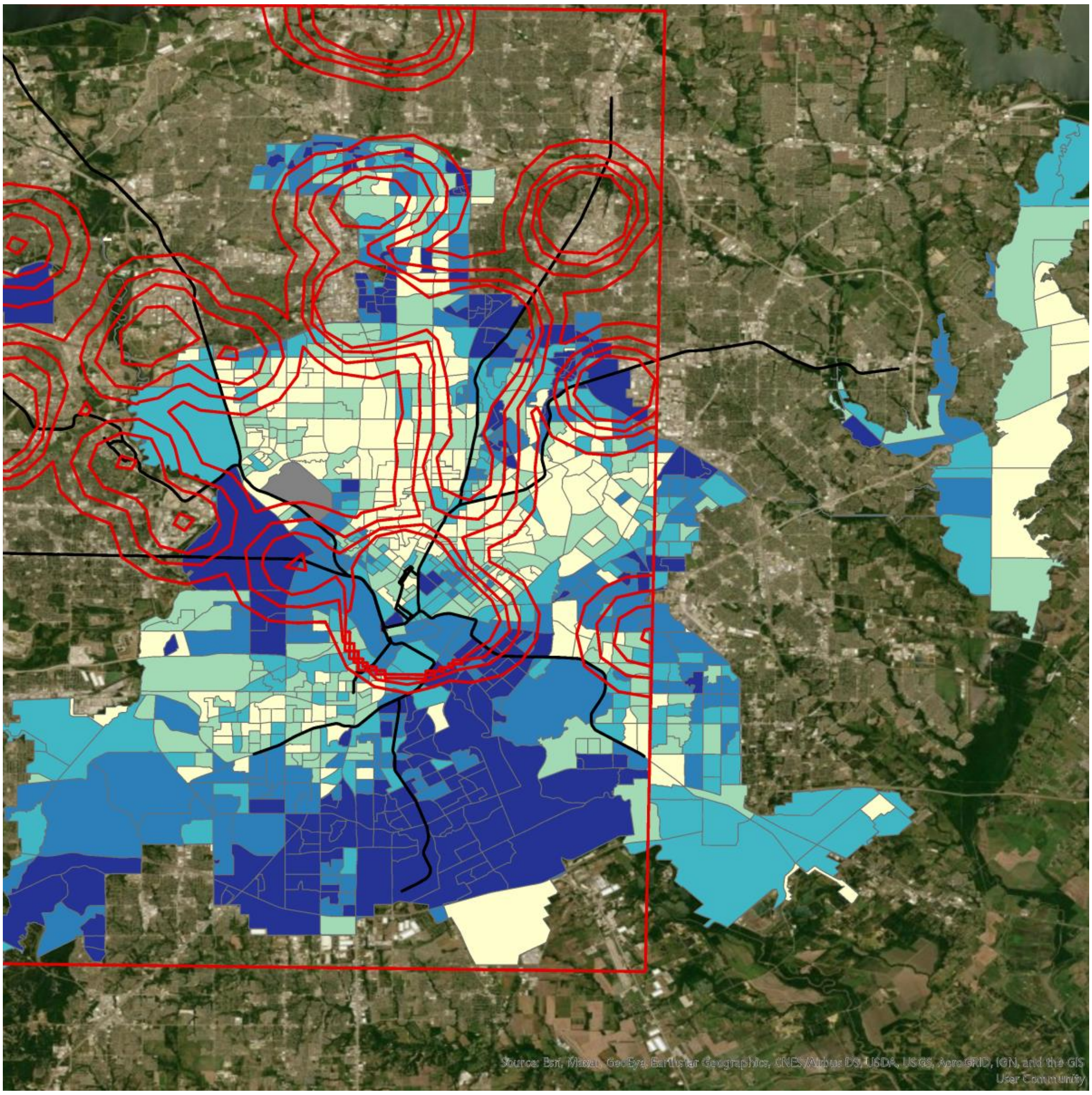

Figure X. Dallas Texas visualized based on Percentage of Percentage of People of Color

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

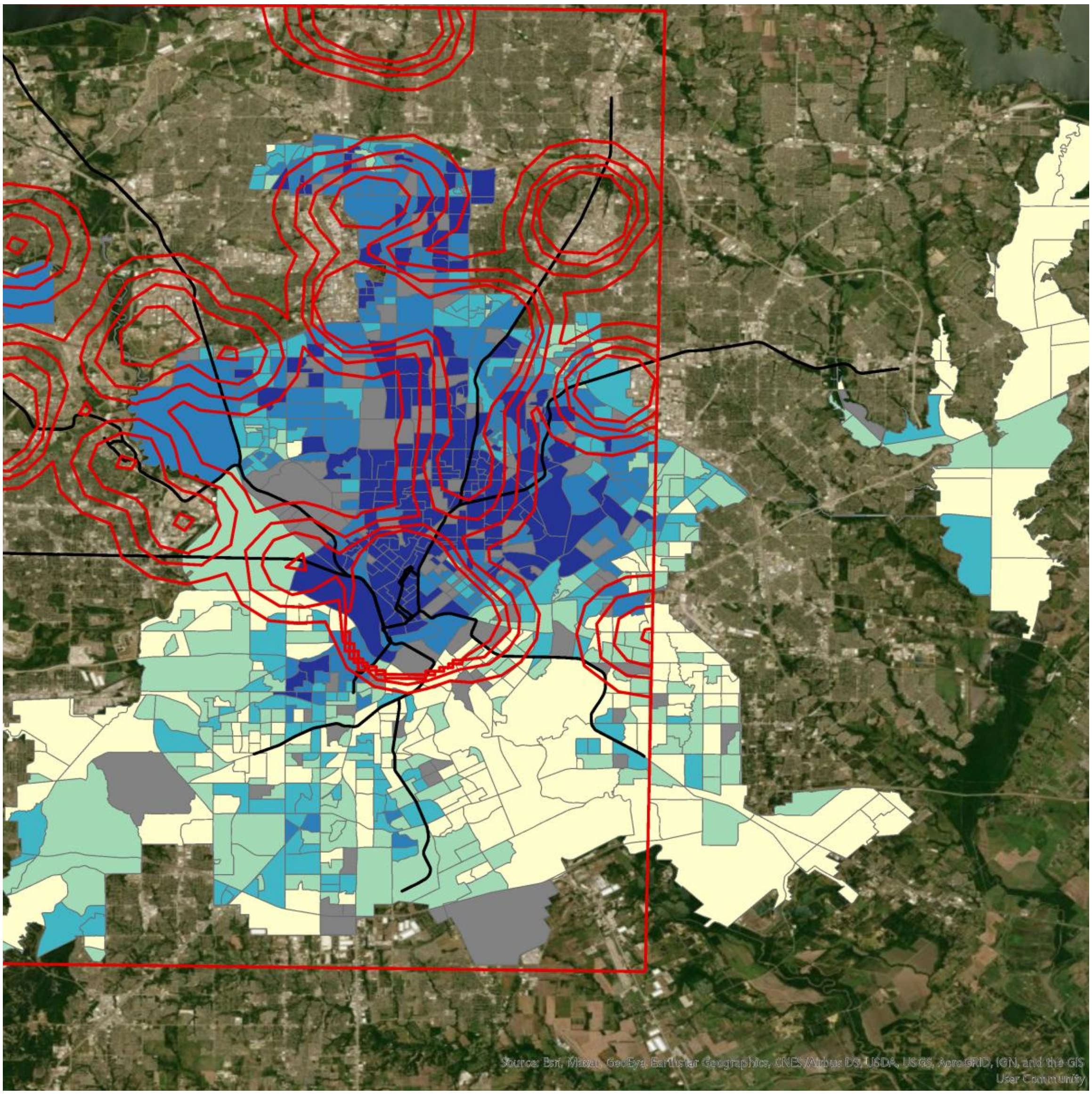

Figure XI. Dallas Texas visualized based on Opportunity

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

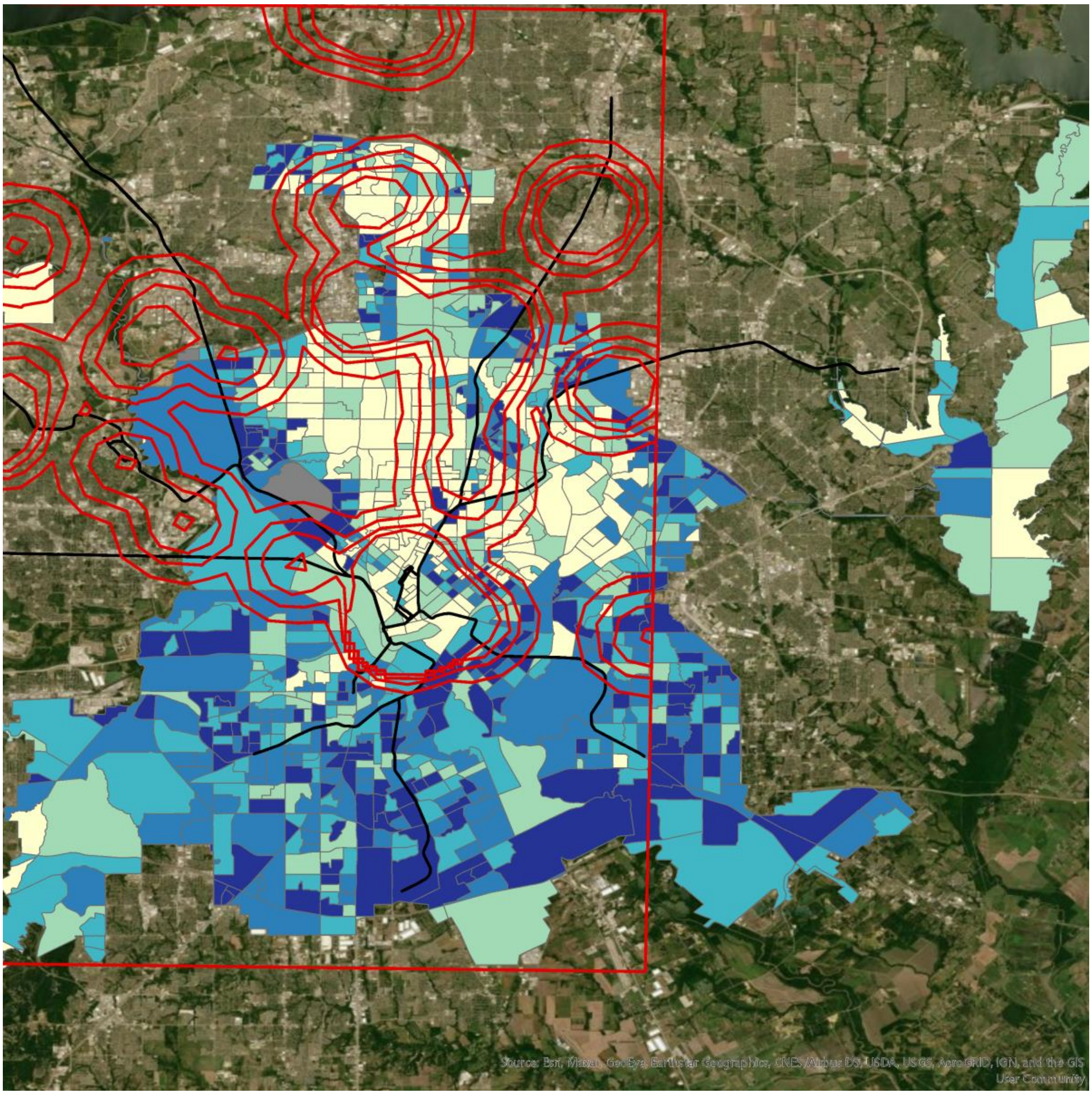

Figure XII. Dallas Texas visualized based on Percentage of ALICE Families

Gray = No Data, Blue to Green Ramp = High Percentage vs. Low Percentage, Black 2pt = Rail Line, Red 2pt = Density Polygons

Table II. Data Sources for Opportunity Index Analysis

Data	Data Source	Data Type/Subtype	Geoprocessing Method	Positive/Negative Indicator
Gross Rent as a Percentage of Household Income (<= 30 – 34%)	Census Bureau	Polygon	Join with Block Group, then compute results.	Positive
Median Selected Monthly Owner Costs as a Percentage of Household Income	Census Bureau	Polygon	Join with Block Group, then compute results.	Negative
Proximity to Community Organizations	Various Sources (King County HMIS, North Dallas Shared Ministries, United Way, and Resource Awareness for Philly)	Point, Polygon	Near (Analysis), then Tabular Join NEAR_FID with OBJECTID of Block Group centroid points, and compute results.	Negative
Proximity to Hospitals/Public Health Facilities	Various Sources (Texas Hospital Association, King County GIS Open Data, PASDA)	Point, Polygon	Near (Analysis), then Tabular Join NEAR_FID with OBJECTID of Block Group centroid points, and compute results.	Negative
Proximity to Libraries	Various Sources (PASDA, Seattle GIS Open Data, Dallas GIS Services, City of Fort Worth)	Point, Polygon	Near (Analysis), then Tabular Join NEAR_FID with OBJECTID of Block Group centroid points, and compute results.	Negative

Table II. Data Sources for Opportunity Index Analysis (cont.)

Data	Data Source	Data Type/Subtype	Geoprocessing Method	Positive/Negative Indicator
Proximity to Parks	Various Sources (King County Open GIS Data, Dallas GIS Services, City of Fort Worth, and PASDA)	Point, Polygon	Near (Analysis), then Tabular Join NEAR_FID with OBJECTID of Block Group centroid points, and compute results.	Negative
Proximity to WIC Offices	WIC Programs	Point, Polygon	Near (Analysis), then Tabular Join NEAR_FID with OBJECTID of Block Group centroid points, and compute results.	Negative
Percentage of Area within Bus Buffer (.25 Miles)	Various Sources (King County Open GIS Data, DART, Trinity Metro, and PASDA)	Point, Polygon	Create Multi-Ring Buffers, Intersect with Block Groups, Create Field to contain data, Tabular Join Intersected shapefile to Block Groups, then Calculate Field.	Positive
Vehicle Ownership (One or Two)	Census Bureau	Point, Polygon	Join with Census Tract shapefiles, then spatial join with Block Group.	Positive

Table II. Data Sources for Opportunity Index Analysis (cont.)

Data	Data Source	Data Type/Subtype	Geoprocessing Method	Positive/Negative Indicator
Proximity to Toxic Sites (2 Miles)	Environmental Protection Agency	Point, Polygon	Create Multi-Ring Buffers, Intersect with Block Groups, Create Field to contain data, Tabular Join to Block Groups, then Calculate Field.	Negative
Education outcomes ((English Test Performance, Math Test Performance, Attendance Rate)	Washington Office of Superintendent of Public Instruction, Pennsylvania Department of Education, Texas Education Agency	Point, Polygon	Generate Near Table (nearest three schools), Join with location using Near_FID, Make X/Y Events, Dissolve using IN_FID, then join to Block Groups, and compute results.	Positive
Education outcomes (Teacher-to-Student Ratio)	National Center for Education Statistics	Point, Polygon	Generate Near Table (nearest three schools), Join with location using Near_FID, Make X/Y Events, Dissolve using IN_FID, then join to Block Groups, and compute results.	Negative
Education outcomes (Percentage of those with Bachelors Education or higher)	Census Bureau	Polygon	Join with Block Group, then compute results.	Positive

Table II. Data Sources for Opportunity Index Analysis (cont.)

Data	Data Source	Data Type/Subtype	Geoprocessing Method	Positive/Negative Indicator
Economic outcomes (Unemployment Rate)	Census Bureau	Polygon	Join with Block Group, then compute results.	Negative
Economic outcomes (Commute Time (25-29 min))	Census Bureau	Polygon	Join with Block Group, then compute results.	Positive
Economic outcomes (Median Family Income)	Census Bureau	Polygon	Join with Block Group, then compute results.	Positive