



Vacant Land Conversion in Detroit, Michigan: A Spatial Analysis of Neighborhood Stabilization and Communal Access

Citation

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Vacant Land Conversion in Detroit, Michigan:
A Spatial Analysis of Neighborhood Stabilization and Communal Access

Elizabeth P. Nolan

A Thesis in the Field of Sustainability and Environmental Management
for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

May 2017

Abstract

This research explores vacant land conversion in Detroit, Michigan and the extent to which vacant land is being utilized towards sustainability through urban agriculture. The main statistical hypotheses of this study are that the extent of vacant land is positively associated with socioeconomic conditions at the neighborhood level; that the conversion of vacant parcels to agricultural use has increased in the city between 2009 and 2014; and that agricultural businesses vary by neighborhood - with neighborhoods with greater land vacancy having higher proportions of businesses. Decades of depopulation and economic downturn have given rise to blighted neighborhoods and fallow lands. A spatial analysis of vacant land, agricultural businesses and changing socio-demographics was conducted at the block group level in ArcGIS using ArcMap. A series of choropleth maps were created to examine changes in vacant lots, agricultural businesses and socio-demographics across neighborhoods.

All three sets of variables were unevenly distributed across block groups and neighborhoods. A spatial regression was ran in ArcMap to model the relationship between vacant lots and socio-demographic key variables, and a second OLS regression was run to explore the relationship of vacant lots to agricultural businesses. The results of the vacant lots & SES ordinary least squares and geographic weighted regressions showed that socio-demographic variables only explained 7% and 18% of the variation in vacant lots. The results of the vacant lots & agricultural businesses OLS regression indicated that vacant land is not a predictor of agricultural businesses. Between 2009 and

2014 agricultural businesses grew by 165%, and vacant lots decreased by 13.5% across the city. A spatial analysis showed a pattern of agricultural businesses in block groups with fewer vacant lots. Yet, more research is needed to determine if vacant land is being repurposed for agricultural purposes in the city of Detroit, and what factors are driving the uptick in agricultural businesses.

Dedication

For my daughter Mathilde who was conceived at the start of this journey, and who spent the first two months of life by my side as I wrote this.

Acknowledgements

I would like to thank Gary Adamkiewicz for his valuable guidance, encouragement, and patience.

I would like to express my gratitude to Mark Leighton for critiquing the proposed research and for his patience in the end.

This research would not have been possible without the assistance of the Center for Geographic Analysis at Harvard University. A special thank you to Jeff Blossom for teaching me how to use ArcGIS, for his tremendous help with manipulating data, and for always making himself available.

Thank you to Data Driven Detroit for their help in verifying data and for kindly providing metadata.

Finally, thank you to my husband Pierre for his unwavering support, and for keeping me well nourished these past ten months.

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Chapter I

Introduction

Current literature and media coverage on Detroit paint a deserted landscape and a level of socioeconomic collapse and subsequent environmental degradation unparalleled by any other American post-industrial city. To date, no city in the country has succumbed to such a scale of blight as that which Detroit faces (Detroit Future City, 2012). The upsurge in vacant land parcels is a testimony of the city's toll of foreclosed homes and abandoned essential infrastructure which have in turn devastated surrounding communities, and yet, few studies have examined how the city's conversion of vacant land is now impacting Detroiters who could not afford to flee.

Following decades of deindustrialization, disinvestment, and depopulation, the city of Detroit has become a global symbol of urban decline. Plagued by crumbling infrastructure, abandoned buildings and subsequent razed lots, the incidence of vacant land is evidence of the economic, and ensuing social and environmental devastation afflicting the city's long-settled communities. With enticing incentives attracting new investments to refashion the economic downturn that continues to afflict Detroit, it is crucial to assess how land conversion is affecting remaining Detroit residents at the neighborhood level, in order to promote environmental justice, social equity, and community empowerment in already disproportionately burdened and marginalized communities. Equally, as some observational studies have explored the characteristics of built environments such as parks, grounds, and neighborhoods to positive health

outcomes, a neighborhood-level analysis of vacant land is relevant to understanding the role built environments play in mitigating health disparities (Sallis, Floyd, Rodriguez, & Saelens, 2012). Similarly, other studies have examined the differential effects of greenness on health in populations of low socioeconomic status (SES), and have also shown greenness to be protective against certain adverse health outcomes (James, Banay, & Laden, 2015). As the city aggressively turns over abandoned lots to new land uses, there is a need to examine if changes in vacant land are being driven by any significant demographic trends, and if urban agricultural land use is benefitting surrounding communities. Few studies have examined how the city's conversion of vacant land is now impacting Detroiters who have remained within the city limits.

Research Significance and Objectives

Focusing on the city's vacant land conversion, this research will explore, map, and assess if vacant land is being utilized towards sustainability through urban agriculture in order to benefit current residents. The mapping of Detroit neighborhoods in correlation with these statistics will help ensure a better understanding of what lies in store for the city's sustainability, with regard to the social, economic, geographic, and environmental landscapes.

The mapping of reclaimed vacant parcels by neighborhood will examine how democratic and inclusive the city's land conversion policies have been on the neighborhood level. The findings from this research will provide new insights about the dynamics of vacant land conversion and urban decline, to better inform policy makers of the broader social impacts of land management and urban redevelopment. Land use trends from these findings will provide a lens as to how urban revitalization efforts (via

vacant land conversion) are affecting access, affordability, and community stabilization for all Detroiters, and the results are likely to be of significance for other legacy cities experiencing similar trends in urban decline.

The objectives of this study are: 1) to understand how repurposed vacant plots are impacting long-settled Detroit communities; 2) to examine if there are any trends in the prevalence of vacant lots and urban agricultural land uses from 2009-2014; and 3) to conduct a neighborhood-level spatial analysis of vacant lots with socio-demographic key census data indicators (e.g. median household income, race, unemployment).

Background

Shifting demographic distributions in cities are important indicators of a city's trajectory and future prospects with regard to neighborhood revitalization efforts. As many American cities have followed a similar trajectory of middle class flight following the Second World War, it is important to examine how demographic trends are affecting the nation's distressed post-industrial cities (Mallach, 2014). As vacant land represents a valuable and untapped asset of any city, a geospatial analysis of vacant land in Detroit may provide an important narrative and metric for assessing significant land use changes for other "legacy cities."

Equitable Land Use in U.S. Post-Industrial Cities

Urban disinvestment is not unique to Detroit. Uneven population decline and changes in housing prices, educational attainment, and income have created spatial patterns in urban decline in the Rust Belt cities of Buffalo, Cleveland, and Pittsburgh

(Hartley, 2013). Since the 1970s Buffalo, Cleveland, Pittsburgh and Detroit have each lost more than 40 percent of their populations due to suburban sprawl and migrations elsewhere (Hartley, 2013). These shifts in urban decline and distributions in socioeconomic status, however, did not occur in every neighborhood at the same rate. A 2013 study of these four Rust Belt cities suggests that changes in land values are driven by changes in the characteristics of neighborhoods that are associated with the income of residents (Hartley, 2013).

Along with Detroit, these cities exemplify how overdependence in industry, loss of manufacturing, and drops in labor demand can lead to adverse social and economic outcomes for city residents, and for the city on the whole as it struggles to remain economically viable. While pathways of inequality and access are likely to be complex – including downturns in manufacturing activity, an expendable workforce, middle class flight, poor market conditions, and gentrification – policymakers and city planners must examine how these changes in neighborhood dynamics evolve over time, and how they affect current residents.

From Industrial Motor City to Urban Decay

Today Detroit symbolizes the decline of the golden age of the American car industry and manufacturing. What was once was the jewel of the manufacturing might that propelled the U.S. towards becoming the world's richest nation is now an eyesore for the city, its residents, and the country. In a matter of a few decades Detroit went from a highly centralized and booming motor city mecca, to a decentralized metropolis plagued by depopulation (i.e. massive white flight), disinvestment, and later race riots that further

polarized segregated neighborhoods. Rising unemployment from declining industries fueled a great exodus of countless city residents, and those communities that stayed back could no longer afford to remain in their homes - paving the way for the dilapidated buildings and later abandoned lots which residents are exposed to today.

These less privileged communities, which were predominantly African American, were trapped within Detroit's city limits and forced to find means to make due in a city with dwindling public services. As of 2012 it was estimated that the city had as much as 20 square miles of total vacant land, and that number continues to grow, climbing to as much as 40 square miles of vacant land. This discarded land area amounts to a third of Detroit's total 139 square miles (Detroit Future City, 2012). This vacant land geographically translates to greater distances between residents, homes, and infrastructure, and creates a heavier burden for those communities who are exposed to greater vacancy, and also creates land usage issues for the city servicing its residents. In order to assess the trends in socio-demographic changes and the incidence of vacant land, one must first examine any prior changing population dynamics of this post-industrial city.

Changing Population Dynamics: 1950s-Present

In 1950 Detroit reached its peak population of 1.8 million people (World Population Review, 2015). Almost 65 years later, the population had declined by 63% to approximately 680,000 in 2014 (U.S. Census Bureau, 2015). Having lost almost the equivalent of the population of Boston, Massachusetts in that time, the declining population demographically changed with suburban sprawl. Between 1950-1970, the

predominantly white population migrated to suburban areas, while the African American population grew in Detroit and surrounding areas. The 1950s brought new highways, which lead to the creation of suburban neighborhoods that favored white residents. Freeways isolated Detroit's industrial areas and residential neighborhoods, and as automobile makers moved their factories to surrounding suburban areas, white populations could find work outside of Detroit and frequented the city less and less.

Racial segregation and high crime rates in the 1990s drove more affluent African Americans to move to surrounding suburbs, exacerbating the depopulation crisis. Since 1990, Detroit's overall population has declined by approximately 34% to 677,116 (U.S. Census Bureau, 2016). As of 2010, approximately 11% of the population was white, with 83% of the population being African American. By 2005 Detroit had experienced one of the most severe levels of racial segregation between blacks and whites of any metropolitan region in the United States (Stoll, 2005). This reverse shift in racial demographics closely mirrors the city's history of urban decline and disinvestment. As blacks and low-income Detroiters within the city became geographically isolated from jobs and public services due to decentralized industries, job sprawl, and decades of disinvestment, exposure to blight and land vacancy was disproportionately felt in predominantly African American and low-income neighborhoods. In 2014 Detroit had the highest poverty rate of America's major cities, with 39.3% of the population living below a poverty line of \$24,008 for a family of four – less than half of the median U.S. household income of \$53,657 (Bouffard, 2015).

Disinvestment and Post-Industrialization: Hardship, Foreclosures, Diminishing Taxes Revenues, and Demolition

While regional sprawl and fragmentation are at the core of Detroit's abandonment, spatial decentralization of the metropolis fostered geographic divisions between affluent and mobile populations, isolating the disadvantaged left behind in the inner city (Thomas & Bekkering, 2015). The downward trends in economic and social conditions have resulted in joblessness, housing foreclosures and abandoned structures disproportionately experienced by residents in the central city. When residents were unable to sell or rent their homes, delinquent mortgages were reverted back to financial institutions that then faced difficulties selling unmarketable housing units. When owners and financial institutions failed to pay property taxes owed on buildings, residential buildings were repossessed by the state, county or local city government (Thomas & Bekkering, 2015). Since 2005, 1-in-3 Detroit properties have been foreclosed, owing to mortgage defaults or foreclosures for delinquent taxes, and amounting to a total of 139,699 foreclosed homes (Kurth & MacDonald, 2014). Massive foreclosures have led to abandonment, squatting, demolition, blight, and devastation for surrounding communities.

The myriad influences of white and middle class flight, inadequate public services, a high tax base, a depreciated housing market, and lower incomes have all created a recipe for substantial economic losses for residents, private businesses, and the city itself. Early foreclosure, joblessness, and land use changes have translated into less tax revenues for the city and local government with regard to property and income taxes.

As of 2013 it was estimated that Detroit property foreclosures have resulted in \$744.8 million in lost city property taxes for Wayne County (Detroit Future City, 2012).

On July 18, 2013 the city of Detroit filed for Chapter 9 bankruptcy. The significance of this lost revenue transcends the local and regional economy, creating physical blight and issues of land management, as foreclosure and property abandonment have resulted in condemned properties and more residential structures for which the city cannot feasibly afford to maintain. Properties beyond repair continue to be demolished, and these demolished structures have resulted in thousands of vacant land parcels.

Addressing Blight

In September 2013 the Obama Administration earmarked \$300 million dollars in federal aid to address Detroit's urban revitalization issues - which included areas of importance related to public works, public safety, and blight removal (Detroit Future City, 2012). The creation of the Detroit Blight Removal Task Force (Task Force) was announced that same year, with the mission of addressing "every blighted residential, commercial, and public structure in the entire city as quickly as possible, as well as to clear every neglected vacant lot" (Detroit Future City, 2012). In 2014 the Task Force recommended that the city spend \$850 million to demolish 40,000 dilapidated structures, renovate tens of thousands more, and clean thousands of vacant lots with dumping. Further, their 2014 blight report found that 30% of buildings (78,506) were soon to be derelict, and that 114,000 parcels or 30% of the city's total were vacant (Davey & Williams, 2014). What the report did not discuss were recommendations for what to do with these vacant lots, and those to come stemming from future demolitions.

Importance of Mapping Vacant Land Conversion at the Neighborhood Level

By 2014 demolition and abandonment had led to nearly 70,000 vacant publicly owned parcels (Detroit Future City, 2012). Through the Detroit Land Bank Authority residents could recently purchase adjacent side lots for as little as \$100, while other publicly vacant lots are sold at auction (Detroit Land Bank Authority, 2014). As this major city sees its residents being engulfed by greener pastures and becoming more self-determined through urban agriculture, Detroit may have found the right recipe for urban renewal by playing the environmentally friendly and self-reliant sustainable card by providing cheap incentives to help recreate a functioning socio-economic fabric in the city itself. However, little is known about how land conversion measures are directly impacting the residents that have been there all along. As some studies have correlated the prevalence of vacant lots with adjacent low-income neighborhoods, access to these lots and their potential subsequent agricultural issue must be examined at the neighborhood level in order to examine broader socioeconomic dynamics within the city (Foo, Martin, Wool, & Polsky, 2014).

Many studies on Detroit's population decline, economic downturn, and subsequent foreclosures, land abandonment, and mass demolition of dilapidated homes and structures have focused their efforts on correlations between urban decline and economic decline (Hackworth, 2014). Other studies have focused largely on the growing urban agricultural trends of converting vacant lots to small urban farms and community gardens, and the social, economic and environmental implications of these actions. Few studies, however, have looked at how these vacant land conversion dynamics are operating on the neighborhood scale. To what degree are some neighborhoods faring

better than others on reclaiming idle lands to create economic opportunities and empower communities?

Research Questions and Hypotheses

Specific research questions I examined are: 1) How is vacant land conversion impacting and benefiting Detroit's declining population? 2) Are newly reclaimed lots for agricultural uses more prevalent in some neighborhoods than others? 3) Are changes in vacant lots or agricultural establishments correlated with neighborhood demographics?

The primary hypothesis to be evaluated is that the conversion of vacant lots and trends in urban agricultural land uses vary by neighborhood demographics. A neighborhood level analysis of vacant land, agricultural business establishments, and socio-demographic indicators examined if these variables are associated with one another. The main statistical hypotheses of this study are:

Hypothesis 1: that vacant lots are positively associated with specific socio-demographics conditions: higher unemployment rates, lower median household incomes, predominantly black neighborhoods, and less densely populated block groups

Hypothesis 2: that the conversion of vacant parcels to agricultural use has increased in the city between 2009 and 2014

Hypothesis 3: that new agricultural businesses vary by neighborhood - with neighborhoods with greater land vacancy having higher proportions of agricultural businesses

Chapter II

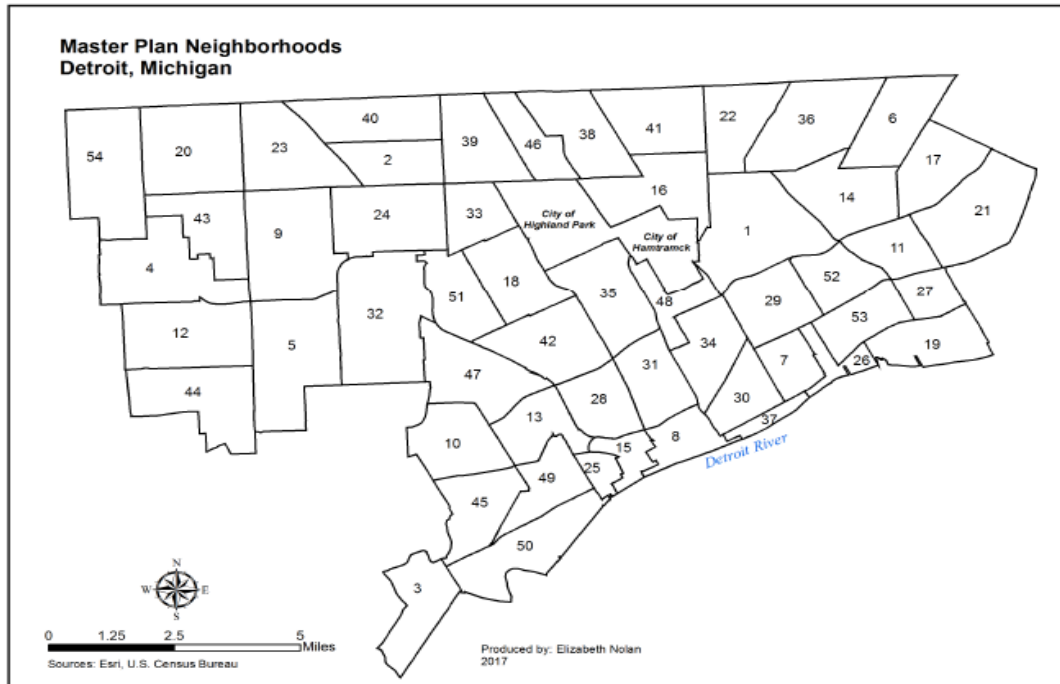
Methods

The spatial analysis for this study was conducted using ArcMap. ArcMap is the main application used in ArcGIS to perform visual and analytical analyses using Geographic Information System (GIS) datasets. ArcMap allows for geospatial analyses of statistical information as a collection of layers and other elements in a map (Esri, 2016). Datasets containing socio-demographic features, agricultural businesses, and vacant lot data for the city of Detroit were all downloaded into ArcGIS as shapefiles. Each shapefile was then added into ArcMap as a separate data layer. Variables (field values) of interest were extracted and represented on maps using symbology.

At the time of this study vacant lot data for the city of Detroit was only available for 2009 and 2014, so these are the only years used in this study. Data for the year 2009 is based on the 2000 census geography, whereas data for 2014 is based on 2010 census geography. To reconcile these differences, the 2014 data area was reapportioned to the 2009 spatial boundaries so that both sets of maps shared the same boundaries. This was accomplished using the geoprocessing clip tool in ArcMap, and was only done for visual purposes. The corresponding data values did not change. Similarly, Belle Isle was manually added as a polygon to the 2014 maps because it was missing from the corresponding dataset.

All data are mapped at the census block group and neighborhood levels. Gray polygons represent census block groups, which generally are defined to contain between

600-3,000 people, with the average being 1,500. The 142.9 square miles of the city of Detroit are contained within the Detroit Master Plan Neighborhoods layer (Figure 1). The layer was obtained from ArcGIS, and represents the boundaries of 54 neighborhoods (ArcGIS, 2017).



- | | | |
|------------------------------|-------------------------|--------------------------|
| 1. Airport | 19. East Riverside | 37. Near East Riverfront |
| 2. Bagley | 20. Evergreen | 38. Nolan |
| 3. Boynton | 21. Finney | 39. Palmer Park |
| 4. Brightmoor | 22. Grant | 40. Pembroke |
| 5. Brooks | 23. Greenfield | 41. Pershing |
| 6. Burbank | 24. Harmony Village | 42. Rosa Parks |
| 7. Butzel | 25. Hubbard Richard | 43. Rosedale |
| 8. Central Business District | 26. Indian Village | 44. Rouge |
| 9. Cerveny / Grandmont | 27. Jefferson / Mack | 45. Springwells |
| 10. Chadsey | 28. Jeffries | 46. State Fair |
| 11. Chandler Park | 29. Kettering | 47. Tireman |
| 12. Cody | 30. Lower East Central | 48. Upper East Central |
| 13. Condon | 31. Lower Woodward | 49. Vernor / Junction |
| 14. Conner | 32. Mackenzie | 50. West Riverfront |
| 15. Corktown | 33. McNichols | 51. Winterhalter |
| 16. Davison | 34. Middle East Central | 52. St. Jean |
| 17. Denby | 35. Middle Woodward | 53. Foch |
| 18. Durfee | 36. Mt. Olivet | 54. Redford |

Figure 1. Map of master plan neighborhoods in Detroit. Data source: Esri.

Data Analysis

Demographic and agricultural business data were gleaned from Esri Business Analyst for the years 2009 and 2014. Esri Business Analyst is an ArcGIS suite of Geographic Information System (GIS) tool that compiles business, consumer spending and demographic data. Demographic data are based on U.S. Census Bureau data for states, counties, tracts, and block groups, among other geographic divisions (Esri, 2016). As the U.S. Census takes place every 10 years, the 2009 and 2014 data are derived from 2000 and 2010 geography, respectively. Agricultural business data was gathered using Esri's Retail MarketPlace database, which is updated annually and includes a list of businesses, type of retail or industry, and their North American Industry Classification System (NAICS) codes.

Both Esri Business Analyst datasets were collected for the city of Detroit on the census block group level. The Esri data files were obtained from the Harvard University Center for Geographic Analysis, and were provided as shapefiles, which were then extracted and added as data layers into ArcMap. With the demographic and business data provided by Esri Business Analyst, statistical data could be mapped to further conduct a spatial analysis of statistical trends.

Data for vacant land was gathered from Data Driven Detroit. The 2009 and 2014 vacant land data was collected from Data Driven Detroit's Open Data Portal under the Property & Land Use category. Data Driven Detroit is a data intermediary that provides data and analysis to help impact decision-making (Data Driven Detroit, 2015). The 2009 vacant plot data was obtained from the 2009 Detroit Residential Parcel Survey. The survey dataset contains information on property type, condition, fire damage, vacancy, 1-

4 unit residential structures, and vacant lots in the city of Detroit (Data Driven Detroit, 2015). The 2009 survey file is comprised of a total of 24 dataset attributes covering 343,849 locations. The 2014 vacant plot data was extracted from the Motor City Mapping, Enhanced File (October 1st 2014 Survey Results) dataset. The file contains 46 dataset attributes for 379,549 locations, including information on condition of structures, fire damage, occupancy, boarding, and improved and unimproved lots through October 1, 2014. Data for both 2009 and 2014 datasets were collected on the parcel level, and downloaded as shapefiles and added as data layers in ArcMap.

Demographic Data

The following socio-demographic variables were extracted from the Esri Business Analyst 2009 and 2014 shapefiles: median household income, unemployment rate, total population, and race. Each shapefile was then added as a layer into ArcMap, and each respective demographic variable was extracted as a field value. Once extracted, a separate choropleth statistical map was created for each variable using graduated colors symbology to indicate variable values. Distributions for values for each variable were manually classified to represent the minimum and maximum values.

A total of five themed choropleth maps were built to illustrate the distributions of four socio-demographic variables for both 2009 and 2014. These maps on median household income, poverty threshold, racial makeup, total population, and unemployment were all mapped on the block group level, and visually reveal the socio-demographic baseline conditions at the block group and neighborhood levels. In 2009 Detroit's population was 880,107, with 95% of the block groups containing less than the census

average of 1,500 people (Figure 2). The majority (75%) of block groups appear to contain less than 1,000 people, with an average of 825 residents.

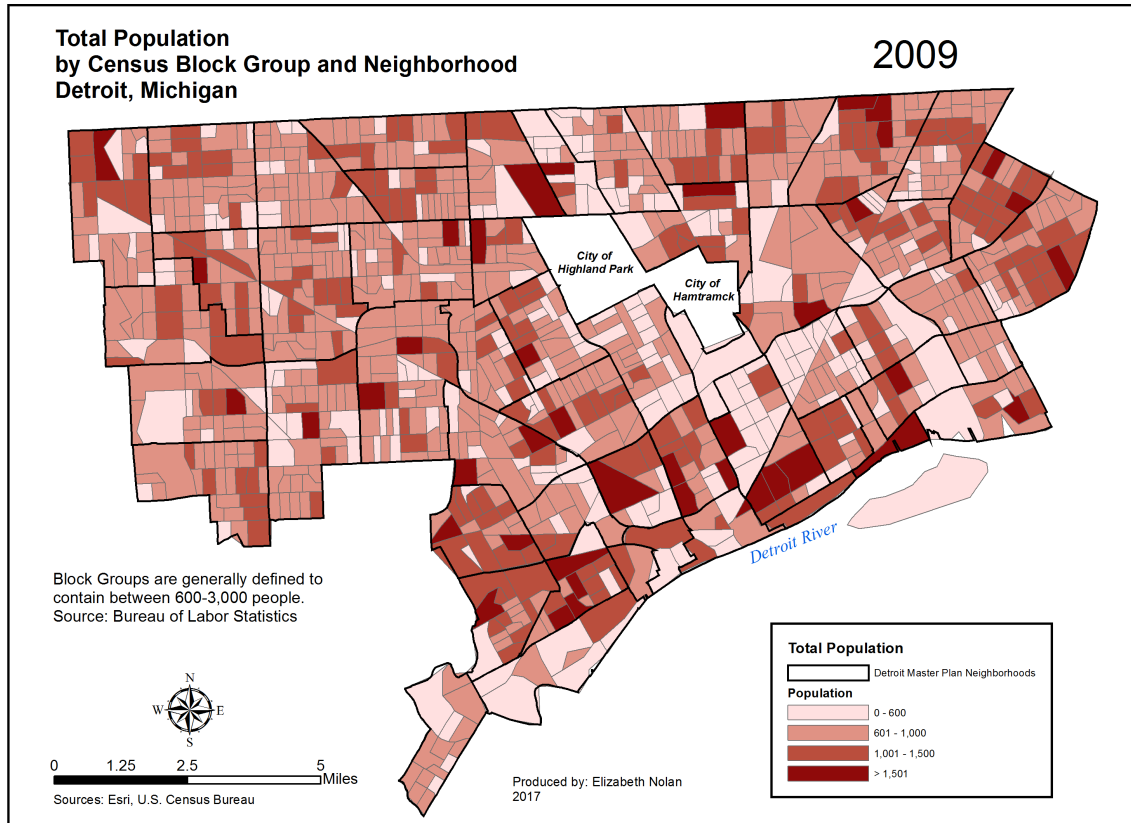


Figure 2. Total population by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

By 2014, Detroit's population had declined to 672,555. With 97% of the block groups containing fewer than 1,500 people, the average was 735 people per block group. Again, the majority (80%) of block groups contained less than 1,000 residents (Figure 3). For both years, portions of Southwest Detroit appear to have the greatest population density.

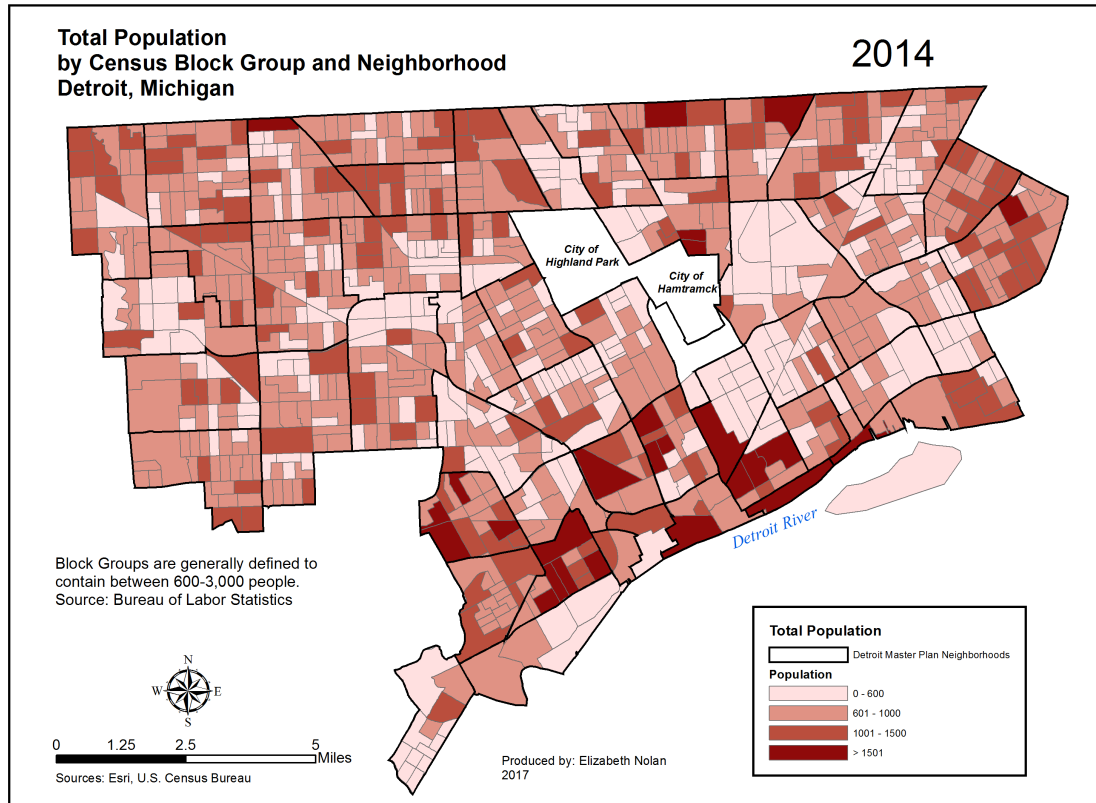


Figure 3. Total population by census block and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

For the Race Makeup map, dot density symbology was used to represent the 2009 and 2014 populations. With the black and white populations accounting for more than 90% of Detroit’s population, only “Black” and “White” racial field values were mapped (U.S. Census Bureau, 2015). However, looking at Figures 4 and 5, it is evident that vacancy, population decline, and the city’s overall depression are issues disproportionately affecting Detroit’s black majority. In 2009 the black community accounted for 85% of the Detroit’s total population. Moreover, Figure 4 illustrates the highly segregated landscape, with contiguous pockets of white communities dispersed

throughout the city (Figure 4). Here, white residents are well represented in the neighborhoods of Southwest Detroit, along with the Rouge and Finney neighborhoods.

By 2014, Detroit's black population accounted for approximately 83% of the city's population. In five years, the white population declined, and yet went from 8% of the total population in 2009, to 10% in 2014. Still, across the city the overall population dwindled, neighborhoods remained heavily segregated, and the racial distribution across neighborhoods was stagnant (Figure 5).

To evaluate correlations between vacant land, agricultural businesses and economic capital, data on median household income was collected and mapped for both years. In 2009 the average household in Detroit earned approximately \$37,000, with much of the West Side and portions of the East Side outperforming the average (Figure 6).

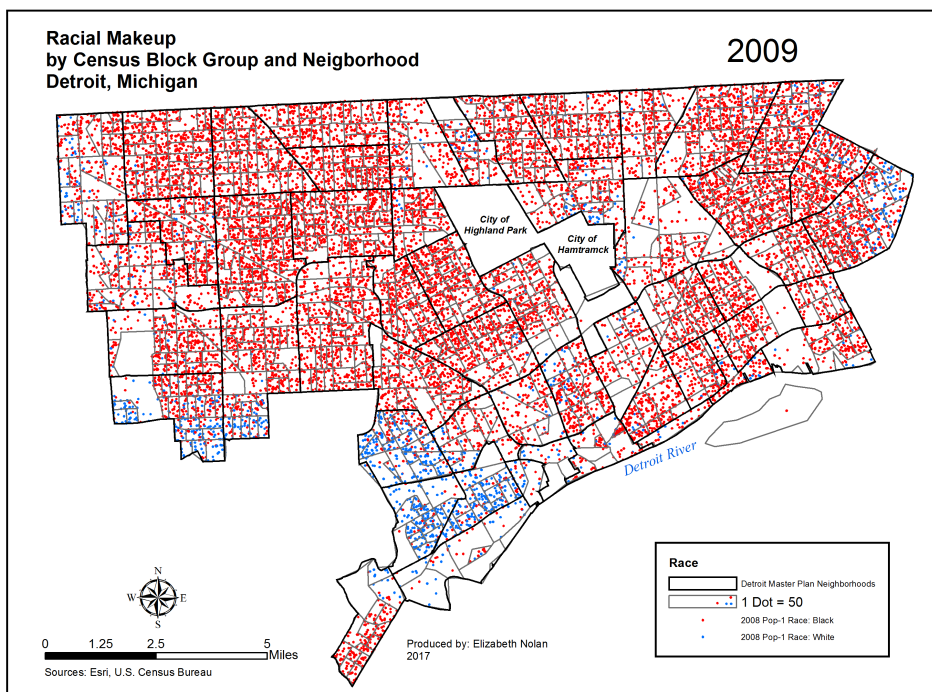


Figure 4. Racial makeup by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau

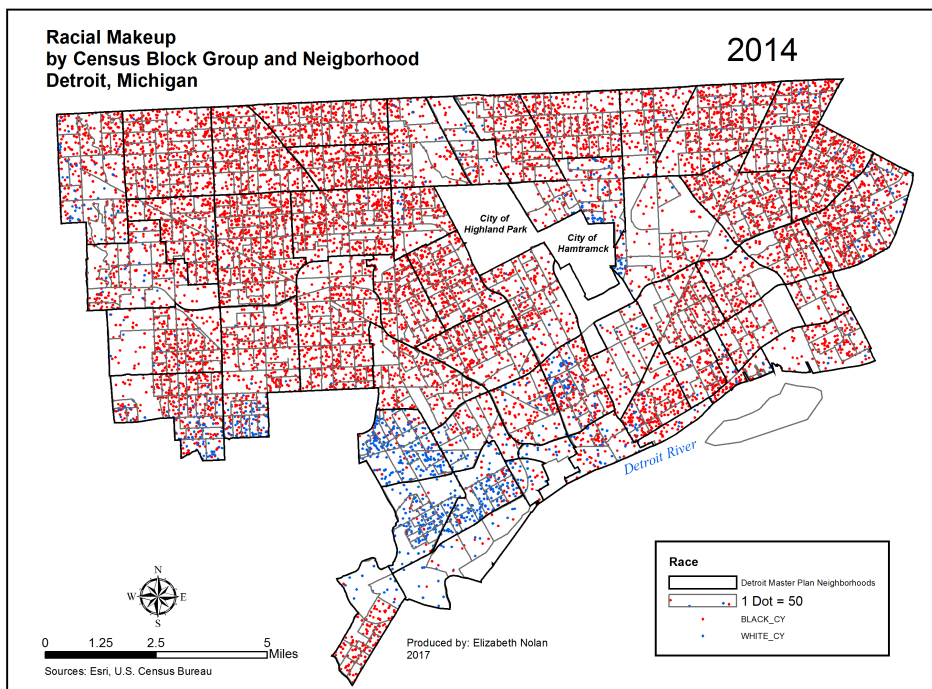


Figure 5. Racial makeup by census block and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

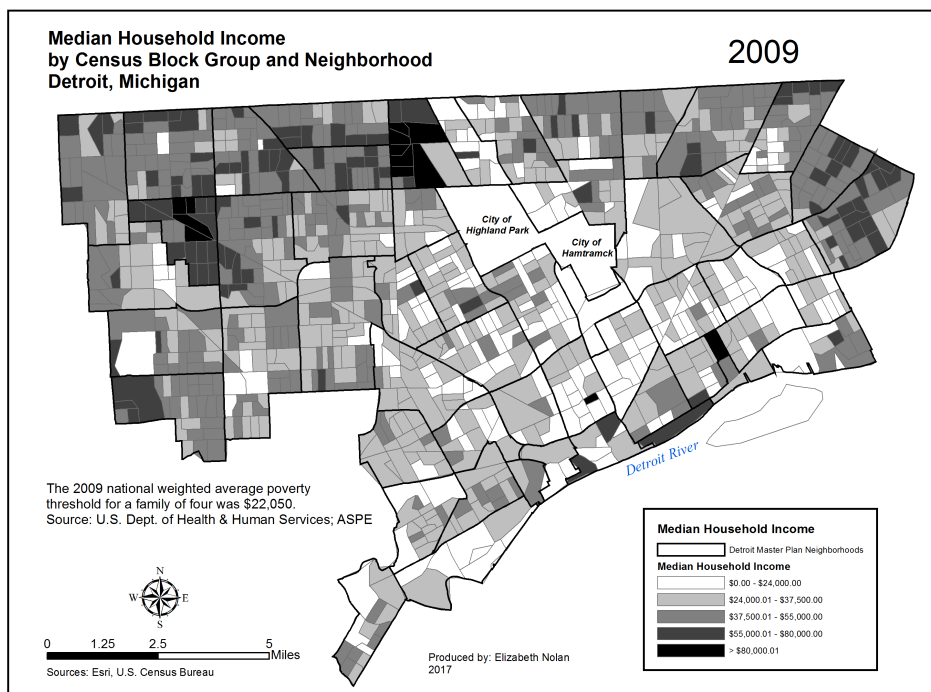


Figure 6. Median household income by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

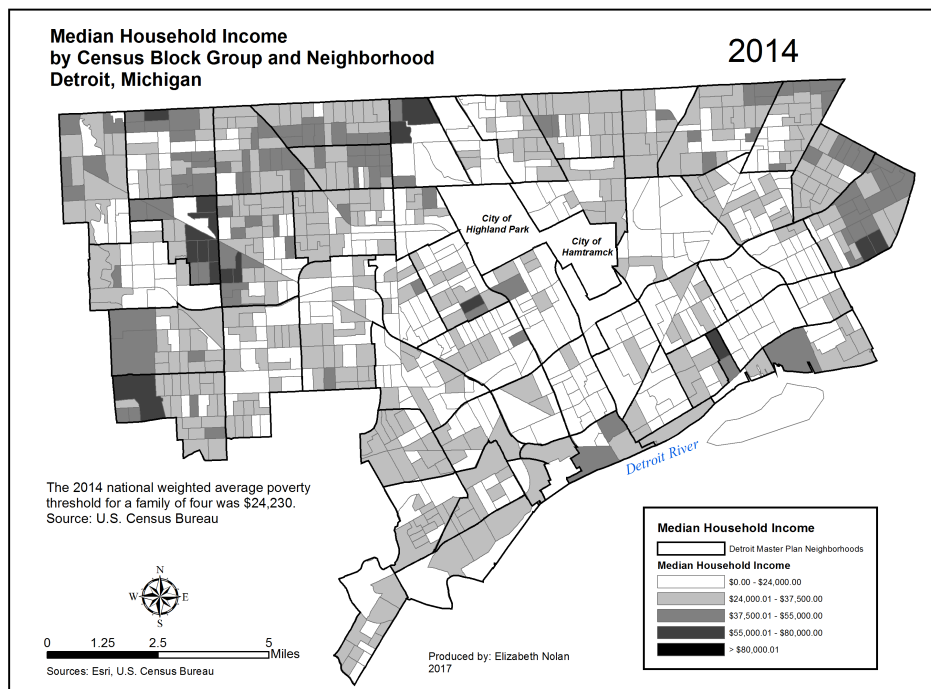


Figure 7. Median household income by census block group and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

By 2014, the median household income had declined by 26% to approximately \$27,500. Again, high earning residents were located mainly in the West Side and East Side of Detroit (Figure 7).

To compare Detroit to the rest of the nation, an additional choropleth map was created to map Detroit's median household income and poverty threshold for 2009 and 2014. To achieve this, the median household income field value was extracted, and threshold values were mapped based on the respective 2009 and 2014 national weighted average poverty thresholds for a family of four. Graduated colors symbology was used, and a manual data classification was set with two classes to map the income values below and above the thresholds. The results are Figures 8 and 9. In 2009 approximately 14% of block groups were living below the national weighted average poverty threshold of \$22,050. By 2014, almost 41% of Detroit's block groups were living below the poverty threshold of \$24,230. Figures 8 and 9 show how poverty levels almost tripled in five years, spreading out from the city's center and reaching nearly every neighborhood.

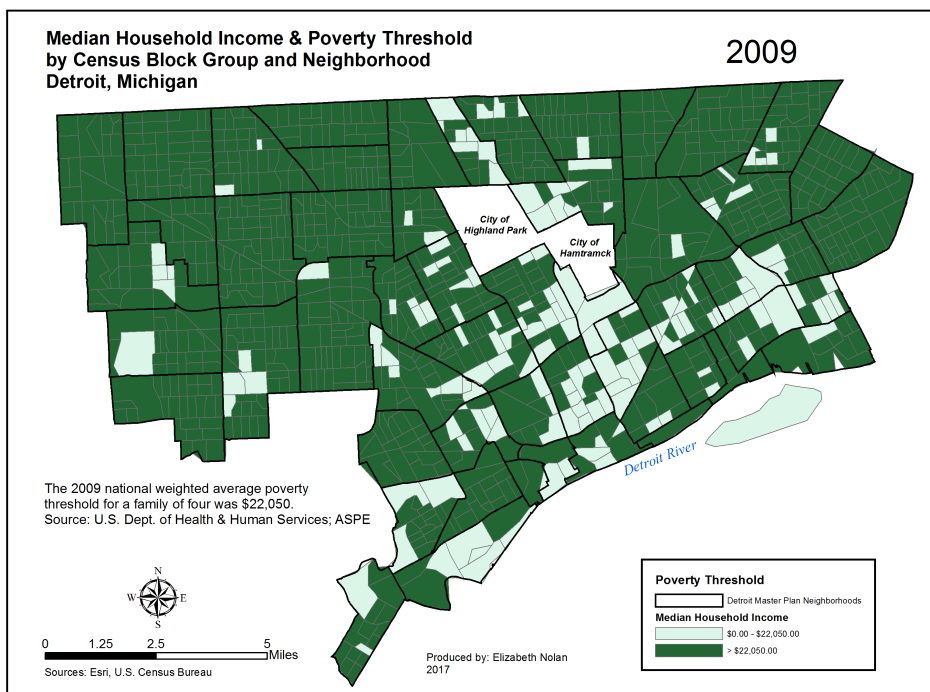


Figure 8. Median household income & poverty threshold by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

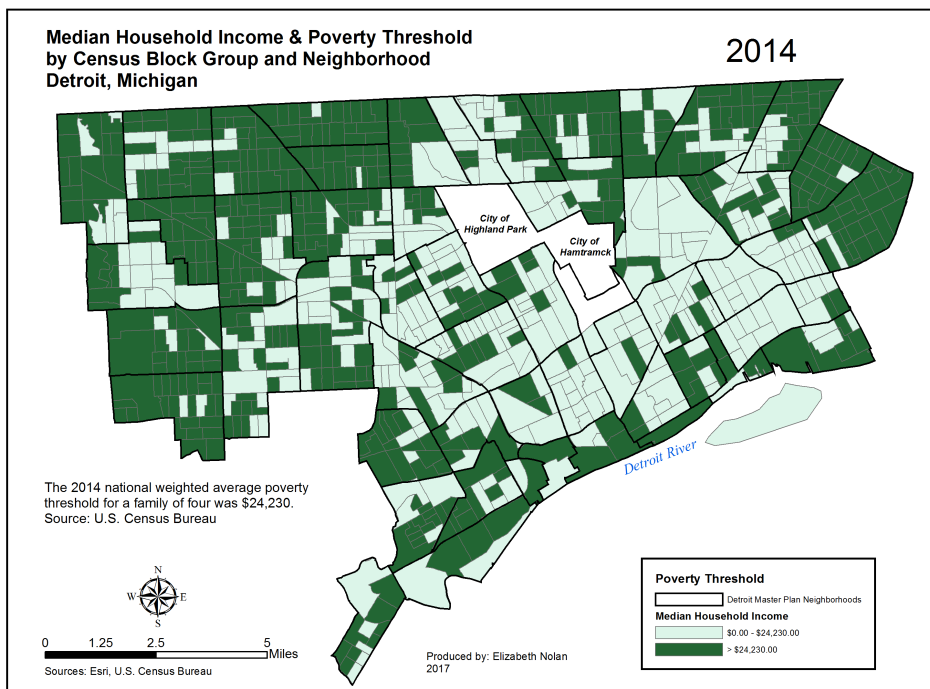


Figure 9. Median household income & poverty threshold by census block group and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

Finally, unemployment rate was extracted as a fourth variable to assess disparities on the neighborhood level. In 2009, the city's median unemployment rate was 23.7%, or 2.5 times the national average of 9.3%. On the neighborhood level, the West Side and outer city limits exhibited lower rates of unemployment (Figure 10).

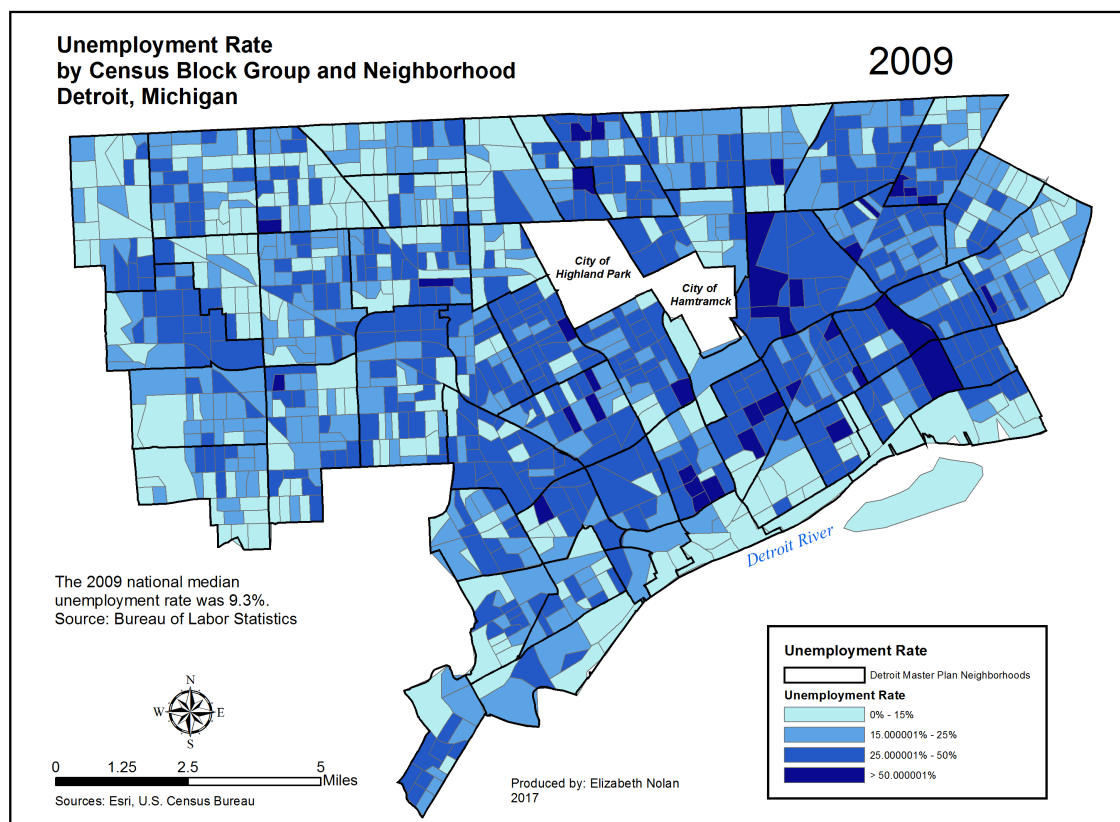


Figure 10. Unemployment rate by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

By 2014, Detroit's unemployment rate climbed to 25.7%, or 4 times the nation's median unemployment rate of 6.2%. Again, portions of the West Side and city's outer limits fared better than the rest of Detroit (Figure 11). The choropleth map in Figure 11 also shows that the unemployment rate decreased in many block groups in neighborhoods located in the East Side of the city.

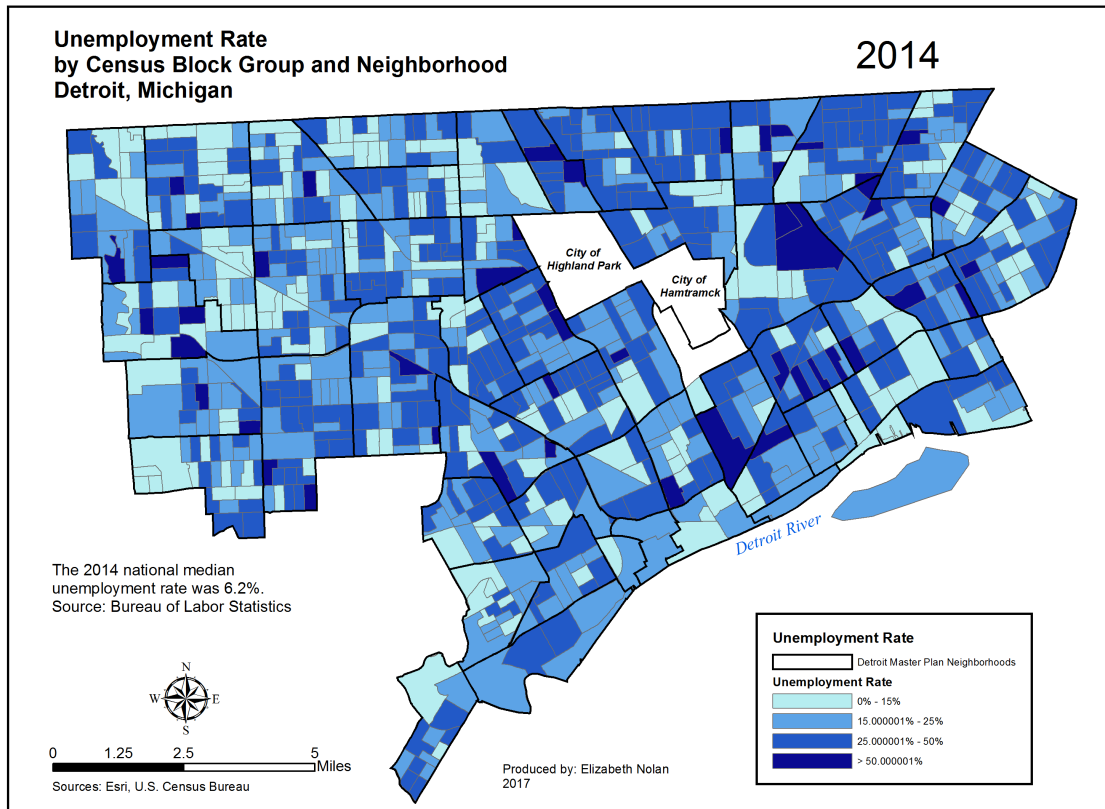


Figure 11. Unemployment rate by census block group and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

Agricultural Business Data

To measure whether reclaimed vacant plots are being used for agriculture, data on agricultural business locations was collected on the block group level for the city of Detroit. From Esri's Business Analyst, the RetailMarketPlace database provides information on demographic, consumer, and business variables. To start, business codes pertaining to agriculture and farming were identified using the North American Industry Classification System's (NAICS) Identification Tools (NAICS, 2017). From there, the respective NAICS business codes were searched in Esri Business Analyst's 2015 Desktop Variable Report, which was provided as an Excel spreadsheet from Harvard's Center for Geographic Analysis. Variables were explored to identify specific variables corresponding to the NAICS agriculture codes, and with descriptions indicating agriculture and farming. The following two variables were identified: "INDAGRI_CY" and "OCCFARM_CY," which are referred to as "Industry: Agriculture" and "Occupation: Farming" herein. "INDAGRI_CY" corresponds to a list of businesses categorized under the agriculture, forestry, fishing, and hunting industries. The "OCCFARM_CY" variable denotes farming, fishing, and forestry occupations. Accordingly, for the purposes of this research, "agricultural uses" are defined as businesses categorized under the agriculture, forestry, fishing, and hunting industries, and/or occupations that include farming, fishing, and forestry.

The "INDAGRI_CY" and "OCCFARM_CY" Business Analyst datasets were provided as shapefiles from the Harvard University Center for Geographic Analysis, and then added as data layers into ArcMap. The 2009 data (based on 2000 census geography) contains 1,067 block groups, whereas the 2014 shapefile (based on 2010 census

geography) lists 876 block groups. While it is not known why the block groups changed, the change is likely to be attributed to the decennial census conducted by the U.S. Census Bureau. The remapping of block groups is likely the result of land use changes in a city with a dwindling population.

In 2009 there were 433 businesses coded “Industry: Agriculture” in the city of Detroit, located within 56 census block groups (Table 1). That number increased by approximately 61% to 700 in 2014, spanning 86 block groups. In 2009 there were 54 businesses coded as “Occupation: Farming” within 8 census block groups in Detroit. By 2014 “Occupation: Farming” businesses increased by eleven-fold, or over 1000% to 595, and were spread over 80 census block groups (Table 1).

Table 1. Agricultural businesses in Detroit, MI (2009 & 2014).

Agriculture Variable Count			
Year	Industry: Agriculture	Occupation: Farming	Agriculture Merge
2009	433	54	487
2014	700	595	1295
% Change	61.7%	1001.9%	165.9%

To account for and spatially analyze the distribution of both agricultural business variables, both “INDAGRI_CY” and “OCCFARM_CY” variables were merged to create a combined “AgriMerge” (Agricultural Merge) variable in ArcMap. In 2009 there were a total of 487 agricultural businesses in Detroit, and that number almost tripled to 1,295 by 2014 (Table1). Once aggregated, the agricultural business data was plotted using a choropleth map and graduated colors symbology to represent values. A manual

classification with five ranges was used to illustrate the distribution of businesses for 2009 and 2014 (Figures 12 and 13).

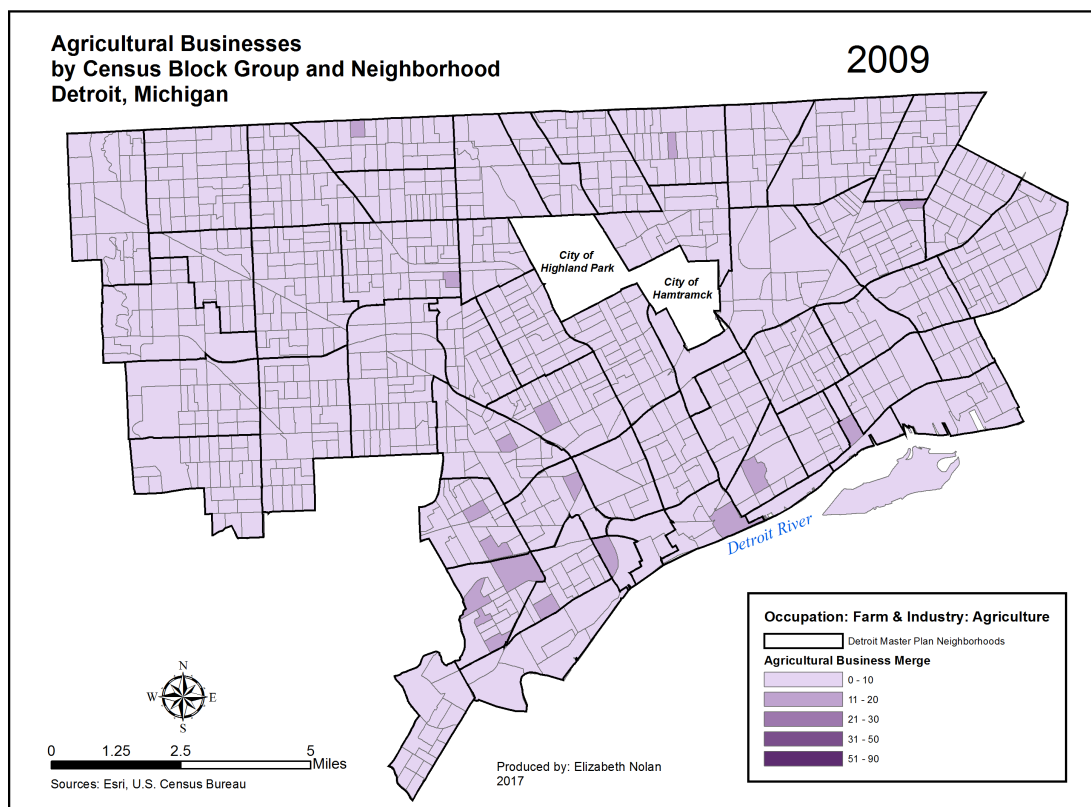


Figure 12. Agricultural businesses by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

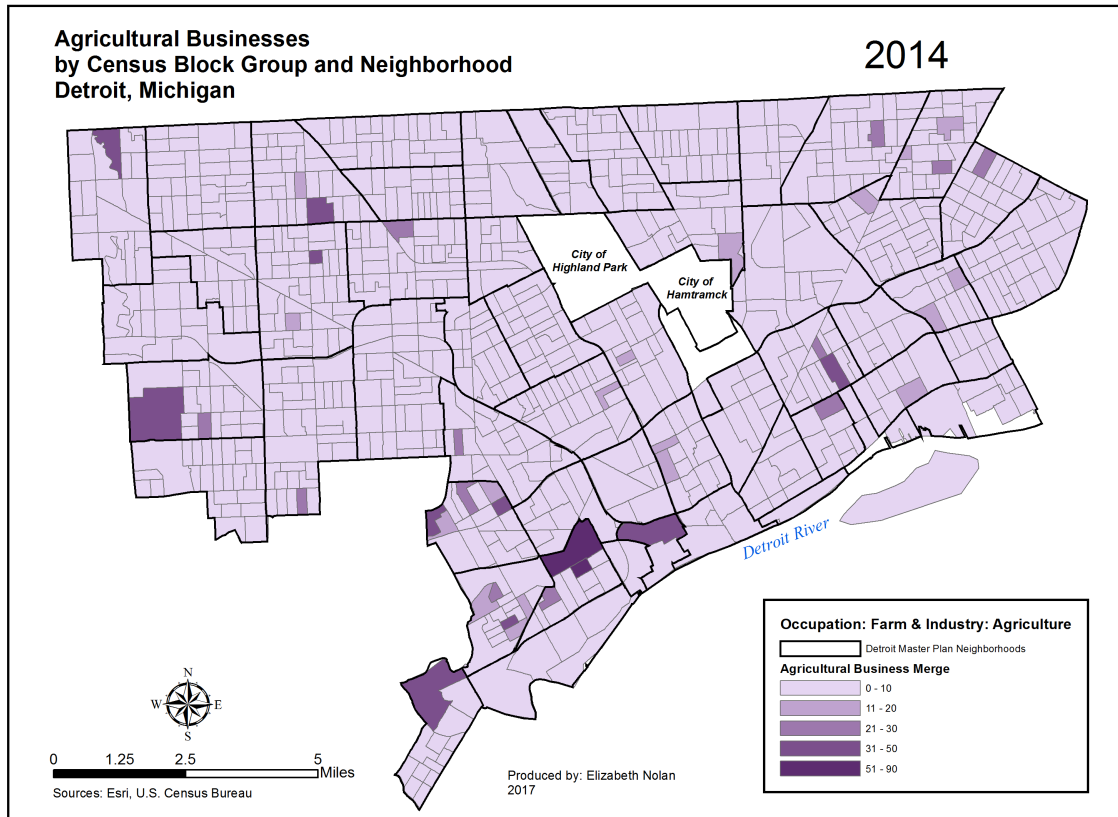


Figure 13. Agricultural businesses by census block group and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

While the overall growth in agricultural businesses was significant over the five-year period between 2009 and 2014, the choropleth maps illustrate that the West Side and Southwest Detroit had the highest concentrations of businesses in 2014. In 2014, five block groups contained over forty agricultural businesses each. These darker polygons correspond to the following neighborhoods: Redford, Corktown, Boynton, and Vernor/Junction. Located in Southwest Detroit, the Vernor/Junction neighborhood had by far the highest concentration with 143 businesses in 2014.

Vacant Plot Data

The 2009 vacant plot data was obtained from Data Driven Detroit's Property & Land Use site in the Open Data Portal. The shapefile contains the 2009 Detroit Residential Parcel Survey data. The survey collected information on 1-4 unit residential structures and vacant lots in the city of Detroit (Data Driven Detroit, 2017). Surveyors collected information on property type, condition, vacancy, and improvements on vacant lots, among other features. The 2009 dataset contains 24 attributes for 343,849 locations on the parcel level. Of this, a total of 91,488 vacant lots were surveyed.

For 2014, vacant lot data was obtained from the Motor City Mapping, Enhanced File (October 1st Survey Results) from Data Driven Detroit's Open Data Portal. The Motor City Mapping was a joint venture of over 200 surveyors and associates who collected data which included whether a structure was present, structure condition, dumping, type of ownership, and vacant lot status of over 370,000 properties (Data Driven Detroit, 2017). The dataset contained 46 attributes for 379,549 properties, all towards the effort of surveying every parcel in the city of Detroit.

To extract information on vacant lots in 2014, metadata for the 2014 dataset was reviewed. The "Structure" attribute in the data is a field that identified whether or not there was a structure on the parcel. If "yes," this indicated that there were permanent structures or buildings. If "no," then it described a lot empty of structures. Further, the "Improved" field in the data assessed whether a lot without a structure is improved or unimproved. "Unimproved" indicated the lot revealed a lack of people activity. Unimproved lots were without structures or fences, and mowed empty lots were considered unimproved (Data Driven Detroit, 2016). Thus, to determine the number of

vacant lots in 2014, parcels meeting the criteria/attributes “Structure = No” AND “Improved = Unimproved” were extracted from the shapefile in ArcMap. The result was 79,120 properties thereby defined as vacant lots for 2014.

As with the demographic and agriculture maps, both 2009 and 2014 vacant lot data shapefiles were downloaded into ArcMap. Since block group was the unit of analysis for the abovementioned maps, a spatial join was conducted to aggregate both 2009 and 2014 parcel level datasets to the census block group level. This resulted in 91,488 vacant lots located in 1,067 block groups in 2009; and 79,120 vacant lots spread over 877 block groups for 2014 (Table 2). After the spatial join, the 2009 vacant lot count was reduced from 91,488 to 91,485; and the 2014 count dropped from 79,120 to 79,014. The discrepancy in the vacant lot count in both datasets is the result of null values found in the data once aggregated at the block group level.

Table 2. Vacant lots in Detroit, MI (2009 & 2014).

Vacant Lots Count				
Year	Block Groups	Vacant Lots in Data	Vacant Lots after Spatial Join	% Change
2009	1067	91,488	91,485	-0.003%
2014	877	79,120	79,014	-0.1%
% Change	-17.8%	-13.5%	-13.6%	

Similar to the demographic and agriculture maps, the vacant lot data were spatially analyzed using a choropleth map, graduated colors symbology, and a manual classification to represent the distribution of values (Figures 14 and 15). Block groups containing null values are filled in white. A spatial analysis of vacant lots over the five-

year period shows a wide spread across Detroit's neighborhoods, with the East Side and Southwest Detroit areas having the highest concentration of lots in 2009, and the lot density increasing by 2014.

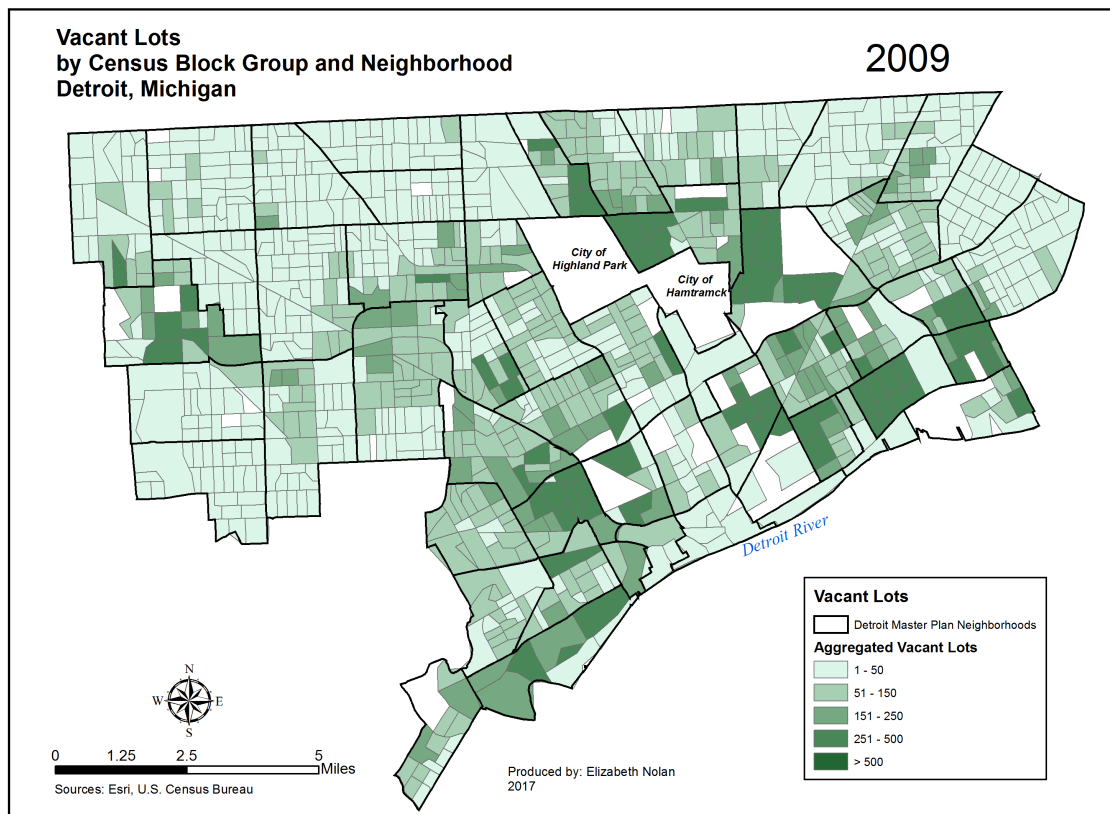


Figure 14. Vacant lots by census block group and neighborhood, Detroit, MI (2009). Data source: Esri, U.S. Census Bureau.

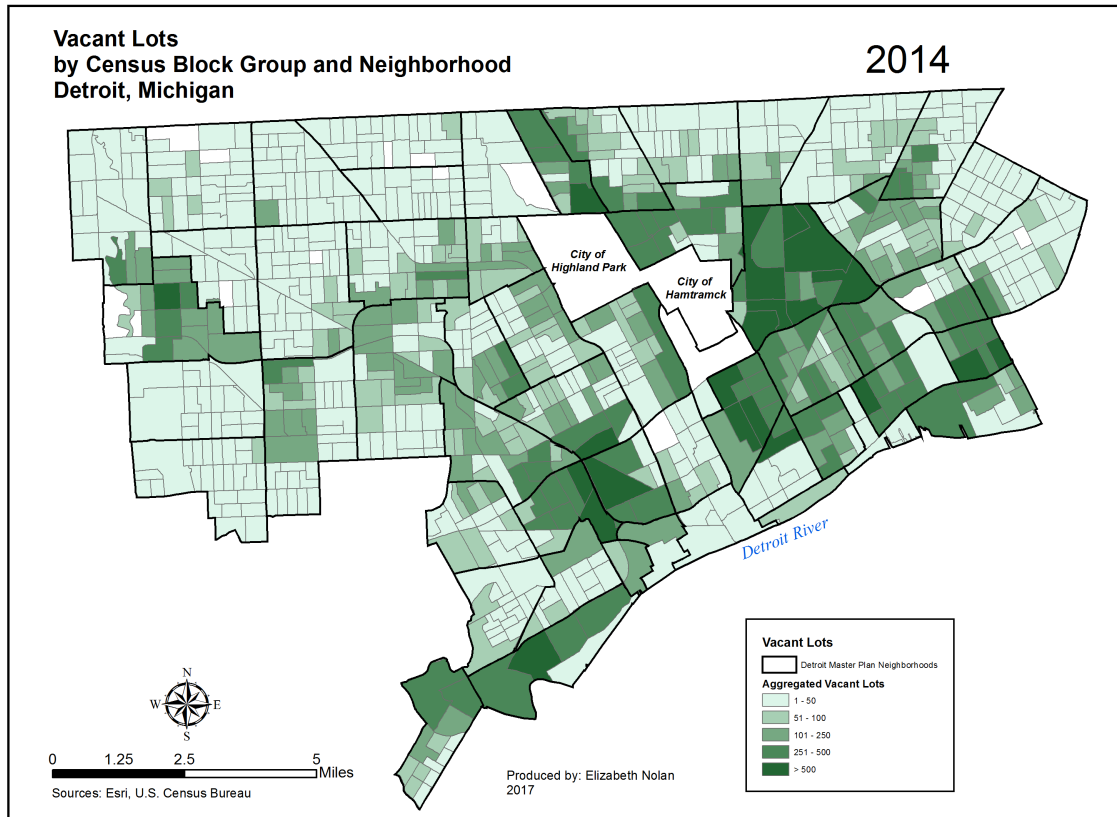


Figure 15. Vacant lots by census block group and neighborhood, Detroit, MI (2014). Data source: Esri, U.S. Census Bureau.

Spatial Regression

To test Hypothesis 1 (that vacant lots are positively associated with higher unemployment rates, lower median household incomes, predominantly black neighborhoods, and less densely populated block groups) a spatial regression was conducted in ArcMap to analyze if the vacant lot and demographic data were correlated. Borrowing from an analogous study looking at wealth and land cover in Massachusetts, two different regression analyses were performed to spatially analyze correlations among variables (Ogeneva-Himmelberger, Pearsall, & Rakshit, 2009). Both ordinary least

squares regression (OLS) and geographic weighted regression (GWR) were performed to explore the relationship between vacant lots and socio-demographic variables (e.g. population, race, median household income, unemployment rate). An OLS linear regression performs a global estimated linear regression, and is the most common used regression analysis to model the relationship of a dependent variable to a set of explanatory variables. An OLS regression generates a single regression equation and does not capture local variations in the relationship of the variables. For this reason, a geographic weighted regression was performed because it captures local variations and accounts for multicollinearity among variables. A GWR regression calculates a separate regression equation for each observation/feature based on the values of the neighboring observations/features (Ogeneva-Himmelberger et al., 2009).

In order to conduct the OLS and GWR regressions, a new data layer was created in ArcMap by merging the vacant lot and demographic datasets. The Geographic Coordinate System was change from the “GCS_WGS_1984” projected system to “North America EquiDistant Conic” so that the data would accurately be projected in the spatial regression. Using the Modeling Spatial Statistics tool in ArcMap, both OLS and GWR regressions were run with vacant lots as the dependent variable and socio-demographic variables as explanatory variables. 2014 was chosen as the proxy year for the analysis.

Spatial Analysis

To test Hypothesis 2 (that the conversion of vacant parcels to agricultural use has increased in the city between 2009 and 2014) an overlay analysis was conducted by performing a spatial join with both vacant lot and agricultural business data layers and

mapping them out with separate symbology on one choropleth map. This was done because the two layers could not initially be combined in a data layer to run an OLS regression because the agricultural business data are based on point estimates of actual business addresses. As the vacant plots are polygons, the business data point estimates and polygons do not match up and could not be analyzed. An overlay of both layers was created for visual purposes to map the data to see how they interact. A second OLS regression was run to spatially analyze the relationship of vacant lots to agricultural businesses for the year 2014. Again, data from the spatial join were projected as “North America EquiDistant Conic,” and vacant lots were selected as the explanatory variable with agricultural businesses as the dependent variable.

To test Hypothesis 3 (that new agricultural businesses vary by neighborhood - with neighborhoods with greater land vacancy having higher proportions of agricultural businesses) of this study a visual analysis using choropleth maps was used to analyze neighborhood level changes in agricultural businesses

Chapter III

Results

A scatterplot matrix graph was created to help find key explanatory variables that predict vacant lot counts through multiple regression analysis (Figure 16). From the below scatterplot, the vacant lot counts (“Count”) show a weak negative correlation with the socio-demographic variables (population, black race, white race, median household income, and unemployment).

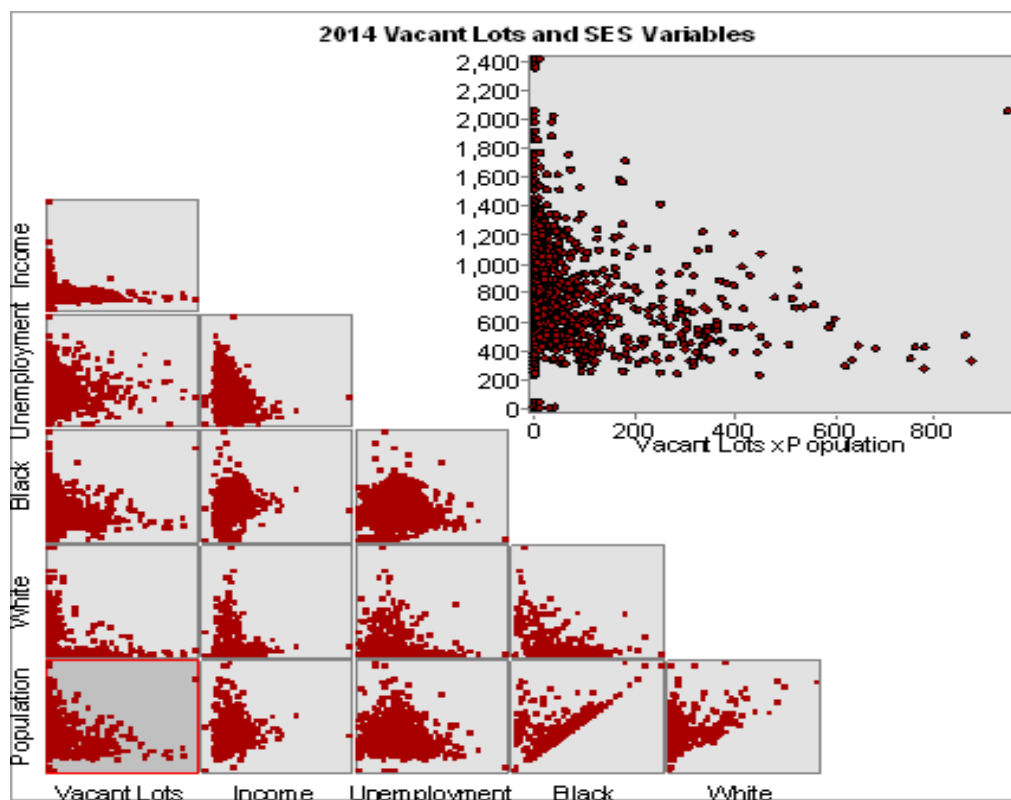


Figure 16. Scatterplot of 2014 vacant lots & SES variables. Data source: Esri, U.S. Census Bureau.

The vacant lots & socioeconomic variables (e.g. income, race, unemployment rate) regression was therefore run with vacant lots as the dependent variable and unemployment rate, black race, white race, and median household income as the explanatory variables. Total population was not included so it would not create redundancy among variables, given the black and white race variables. The results of the regression are displayed as a map of the standard residuals from the predicted values (Figure 17). Red areas are over predicted values, and represent where observed vacant lots were higher than what the model predicted. Blue areas indicate values that were lower than what the model predicted, and yellow areas illustrate values close to the average.

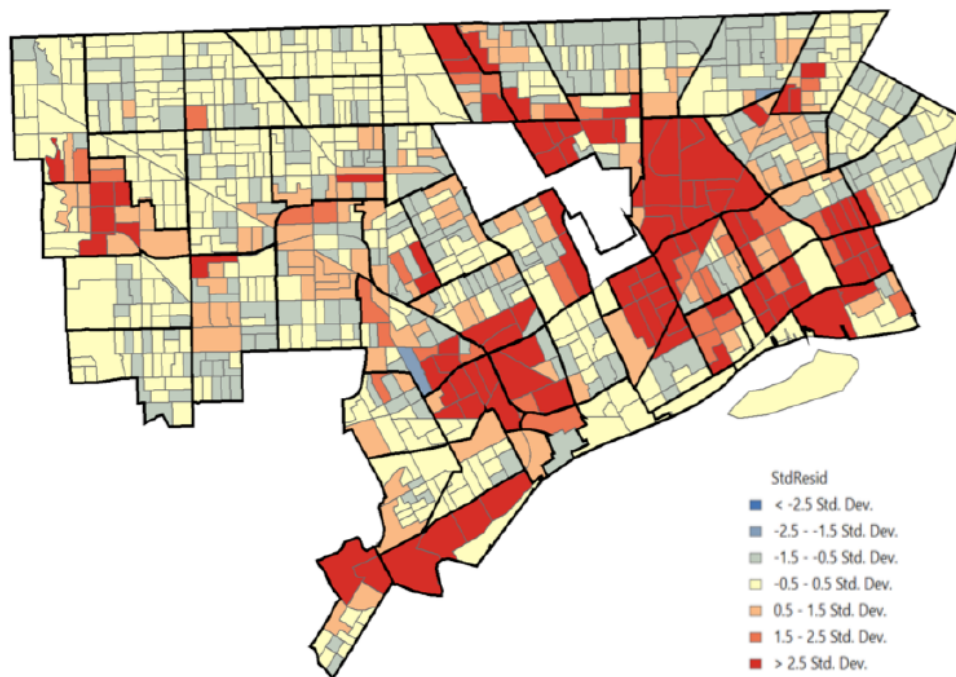


Figure 17. Regression of vacant lots & SES variables (2014). Data source: Esri, U.S. Census Bureau.

Table 3. Statistical results of regression of vacant lots & SES variables.

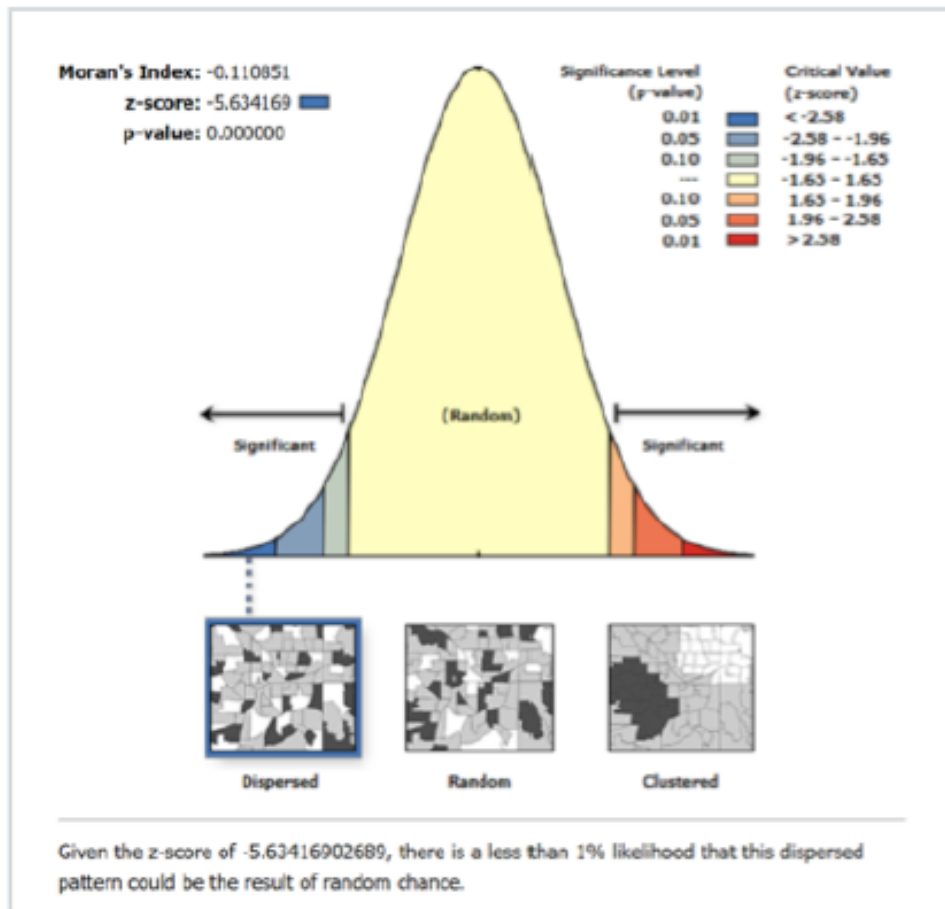
Summary of OLS Results								
Variable	Coefficient	Std. Error	t-statistic	Probability	Robust SE	Robust t	Robust Pr	VIF
Intercept	10.283522	2.735745	3.758947	0.000186*	1.260035	8.161298	0.000000*	-
UNEMP RT CY	1.479585	0.119392	12.392626	0.000000*	0.174449	8.481464	0.000000*	1.441142
WHITE CY	0.008607	0.013417	0.641491	0.521259	0.010489	0.820507	0.411988	1.118051
BLACK CY	0.007740	0.006579	1.176574	0.239471	0.010201	0.758727	0.448074	2.339348
MEDHI NC CY	-0.000510	0.000148	-3.457379	0.000570*	0.000160	-3.184527	0.001482*	2.131246

OLS Diagnostics			
# of Observations	2631	AICc	30881.862414
Multiple R2	0.071262	Adjusted R2	0.069847
Joint F-Statistic	50.373332	Prob (>F), (4.26) degrees of freedom	0.000000*
Joint Wald Statistic	198.669675	Prob (>chi-squared), (4) degrees of freedom	0.000000*
Koenker (BP) Statistic	56.970315	Prob (>chi-squared), (4) degrees of freedom	0.000000*
Jarque-Bera Statistic	102479.069619	Prob (>chi-squared), (2) degrees of freedom	0.000000*

* Statistically significant

With a very low Adjusted R-Squared value of 0.070 the OLS regression results indicate that the socio-demographic variables only explain about 7% of the vacant lot variation that is occurring (Table 3). Looking at the coefficients, the unemployment rate, and white and black race variables all have the expected positive coefficient signs, whereas, median household income has a negative coefficient indicating that the higher the income the lower the number of vacant lots. Looking at the Variance Inflation Factor (VIF) values, we see that there is no redundancy among the explanatory variables because their VIF values are all lower than 7.5. For the test of statistical significance,

asterisks indicate that only the unemployment rate and median household income values were statistically significant with P-values less than 0.01. With a Jarque-Bera Statistic value of less than 0.01 the OLS diagnostics indicate that the model predictions are biased and the residuals are not normally distributed. Next, a spatial correlation autocorrelation test (Global Moran's I Summary) was run to test whether the under and over predicted values of vacant lot residuals are randomly distributed, and to see if there is feature similarity among the block groups. A bandwidth distance of 50 meters was applied as an appropriate neighborhood to allow for the spatial analysis because the default distance of 30 meters was not great enough to capture neighboring values. The Global Moran's I Summary in Figure 18 shows that the predictions were dispersed (not random).



Global Moran's I Summary	
Moran's Index:	-0.110851
Expected Index:	-0.000380
Variance:	0.000384
z-score:	-5.634169
p-value:	0.000000
Dataset Information	
Input Feature Class:	2014OLSNewVacant
Input Field:	STDRESID
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	50.0000 Meters
Weights Matrix File:	None
Selection Set:	False

Figure 18. Spatial autocorrelation report of vacant lot residuals (Global Moran's I Summary). Data source: Esri, U.S. Census Bureau.

Finally, the Koenker (BP) Statistic was evaluated to determine whether a geographic weighted regression model would be a better fit. When this test is statistically significant ($p < 0.01$) it means that the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). Not surprisingly, the OLS regression Koenker Statistic was less than 0.01, indicating that the model results will likely be improved with a geographic weighted regression.

The Vacant Lots and Agricultural Businesses OLS regression was run with agricultural businesses as the dependent variable and vacant lots as the explanatory variable (Figure 19). The OLS regression results above show that the model over predicted many agricultural businesses compared to what was observed in 2014. This is illustrated in the blue areas, indicating block groups where agricultural businesses were lower than what the model predicted. With a negative coefficient of -0.004807, the model indicates that there is an inverse relationship between vacant lots and agricultural businesses. The negative Adjusted R-Squared value of -0.0000116 indicates that the model is a poor fit for the data and there is no predictive value from the regression. This negative value could mean that there are too many vacant lots or predictors compared to the low sample size of agricultural businesses. In summary, the model shows that vacant lots is insignificant as an explanatory variable to predict agricultural businesses on the block group level, and does not support Hypothesis 2 (that the conversion of vacant parcels to agricultural use has increased in the city between 2009 and 2014).

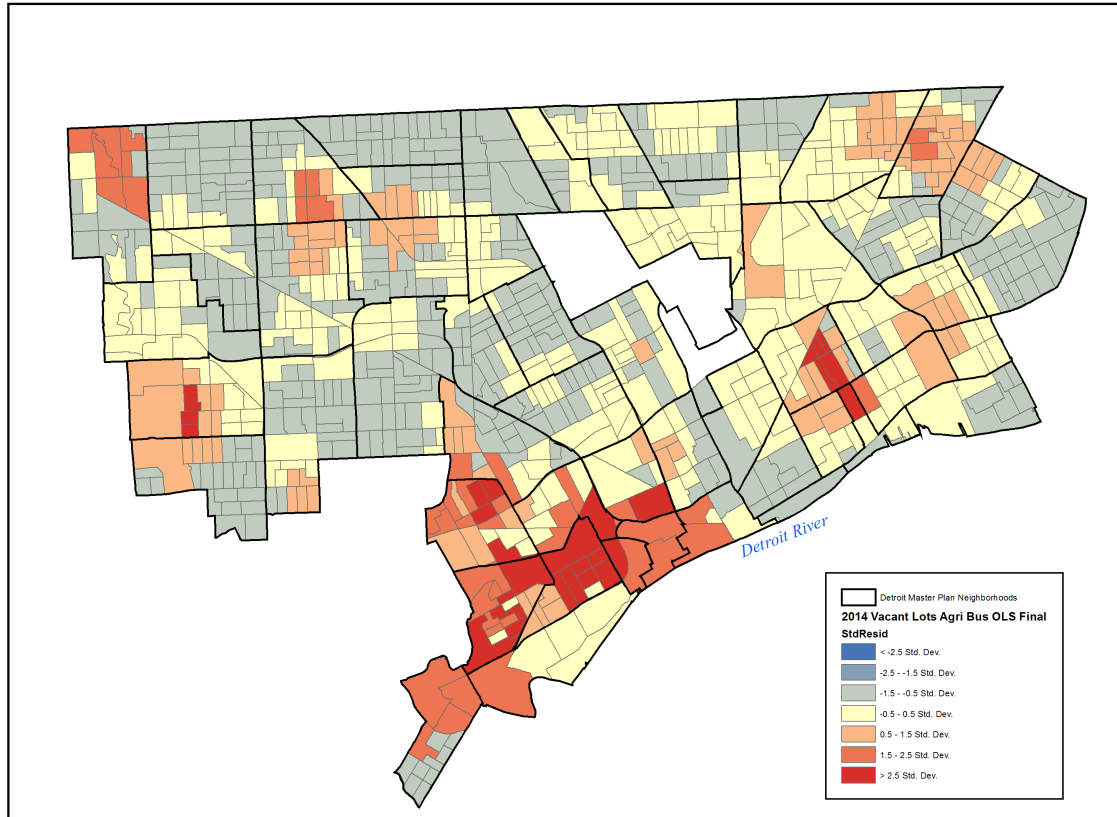


Figure 19. Map of regression of vacant lots & agricultural businesses (2014). Data source: Esri, U.S. Census Bureau.

Table 4. Vacant lots & agricultural businesses regression results.

Summary of OLS Results							
Variable	Coefficient	Std. Error	t-statistic	Probability	Robust SE	Robust t	Robust Pr
Intercept	11.161697	0.822275	13.574164	0.000000*	0.812454	13.738249	0.000000*
Vacant Lots	-0.004807	0.005073	-0.947613	0.343574	0.004510	-1.065833	0.286785

OLS Diagnostics			
# of Observations	877	AICc	7768.576575
Multiple R2	0.001025	Adjusted R2	-0.000116
Joint F-Statistic	0.897971	Prob (>F), (4.26) degrees of freedom	0.343588

Joint Wald Statistic	1.135999	Prob (>chi-squared), (4) degrees of freedom	0.286499
Koenker (BP) Statistic	0.124568	Prob (>chi-squared), (4) degrees of freedom	0.724132
Jarque-Bera Statistic	7540.1808 40	Prob (>chi-squared), (2) degrees of freedom	0.000000*

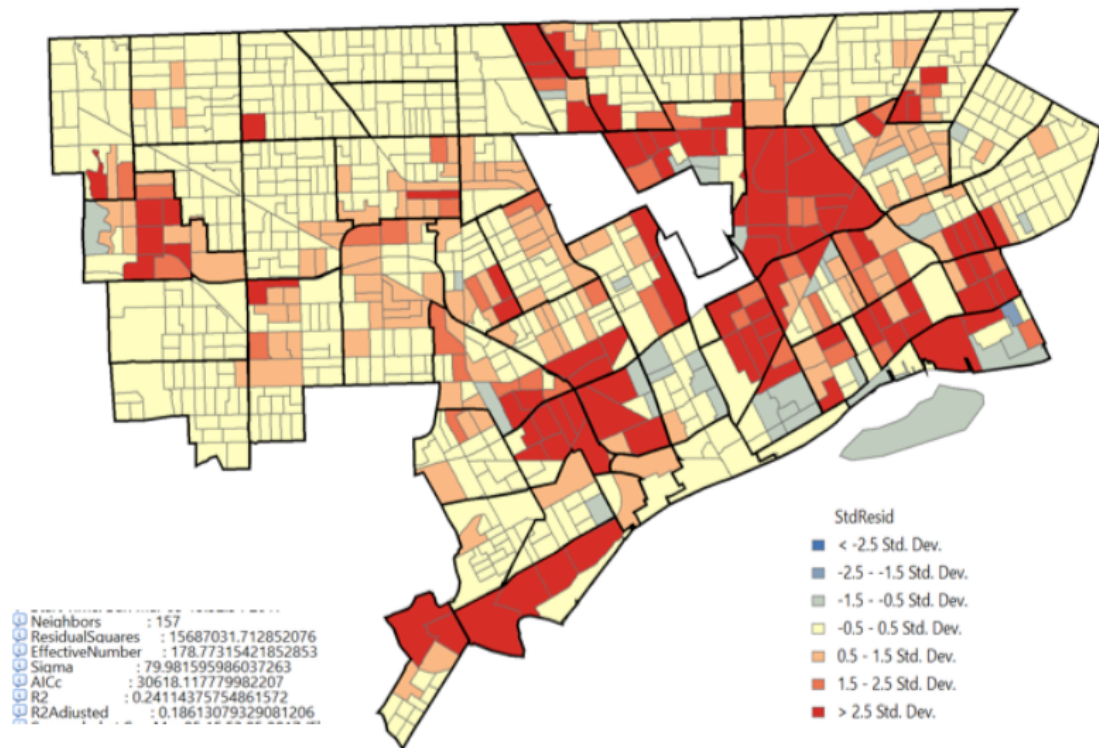
* Statistically significant

Geographic Weighted Regression

The geographic weighted regression (GWR) for the vacant lots and SES variables was performed using only unemployment rate and median household income as the explanatory variables because they were the only statistically significant variables. An Adaptive Kernel type was selected so that the bandwidth (or neighbors) for each local estimation would change according to the spatial density of vacant lots (or input feature class). Here, the bandwidth is calculated as a function of the nearest neighbors so that each local estimation is based on the number of vacant lot features. By calculating a separate regression equation for each feature, the GWR serves as a better way to analyze the spatial relationships between the vacant lots and explanatory variables given the high variation among features.

The GWR had a R-Squared value of 0.24 and an Adjusted R-Squared value of 0.19 (Figure 20). While these values are lower than the optimal value of 0.5 or higher, the values indicate that the GWR model improved the OLS regression. The Adjusted R-Squared value of 0.19 means that unemployment rate and median household income now explain 19% of the vacant lot variation. Like the OLS map of the residuals, the GWR map (Figure 20) shows clustering of the over and under predicted values (red and blue) which indicates that the model is missing at least one key explanatory variable. While the GWR served as a better fit to model the relationship between vacant lots and income and

unemployment, these results do not support Hypothesis 1 (that vacant lots are positively associated with higher unemployment rates, lower median household incomes, predominantly black neighborhoods, and less densely populated block groups). Moreover, it is evident that Detroit's socioeconomic conditions/status are only weakly correlated with the number of vacant lots surrounding them.



Neighbors	157
Residual Squares	15687031.712852
Effective Number	178.773154
Sigma	79.981596
AIcC	30618.117780
R2	0.241143
R2 Adjusted	0.186131

Figure 20. GWR of vacant lots and unemployment rate & median household income (2014). Data source: Esri, U.S. Census Bureau.

Spatial Analyses

Figure 21 is an overlay analysis of the vacant lot and agricultural business data. While there appears to be a visual pattern in the distribution of block groups with lower counts of vacant lots and the number of agricultural businesses; this juxtaposed data, however, can only serve as a visual tool. The results from the OLS regression indicate that there is no statistical relationship between vacant lots and agricultural businesses, and that vacant lots is not a predictor of agricultural businesses. Thus, the spatial analysis does not support the notion that the revitalization of vacant parcels towards urban agricultural use has increased in the city between 2009 and 2014 (Hypothesis 2). What is made evident by the data, however, is that number of vacant lots decreased by 13.5% between 2009 and 2014, and agricultural businesses increased by 165% during this period. This exponential growth in agricultural businesses supports Hypothesis 3 (that new agricultural businesses vary by neighborhood - with neighborhoods with greater land vacancy having higher proportions of agricultural businesses).

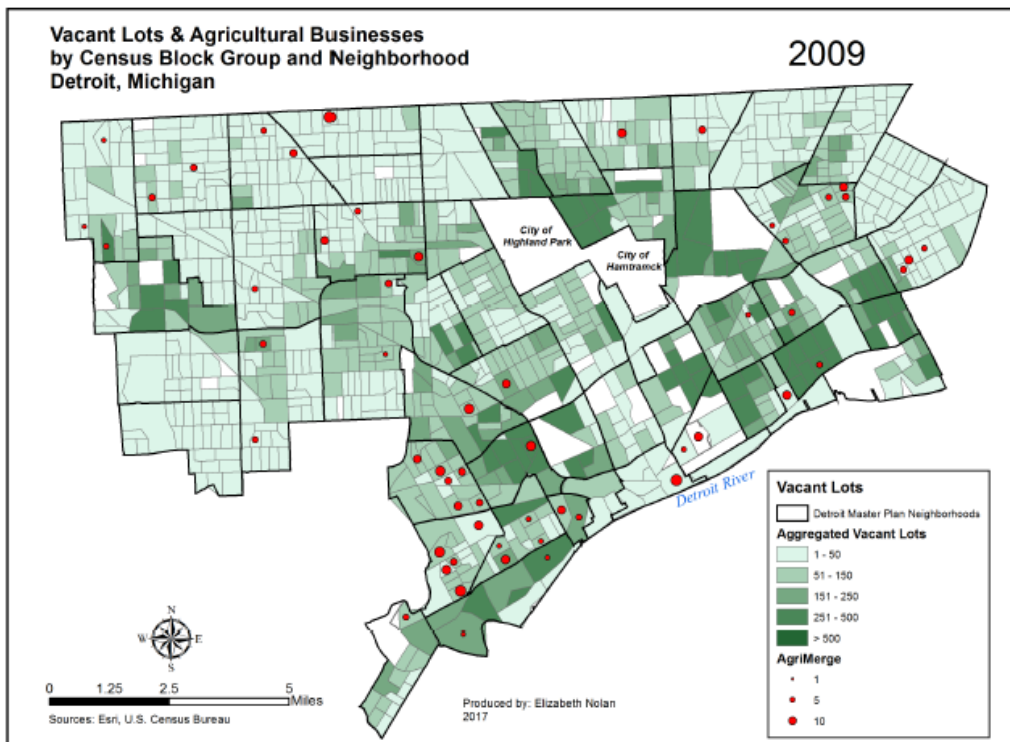
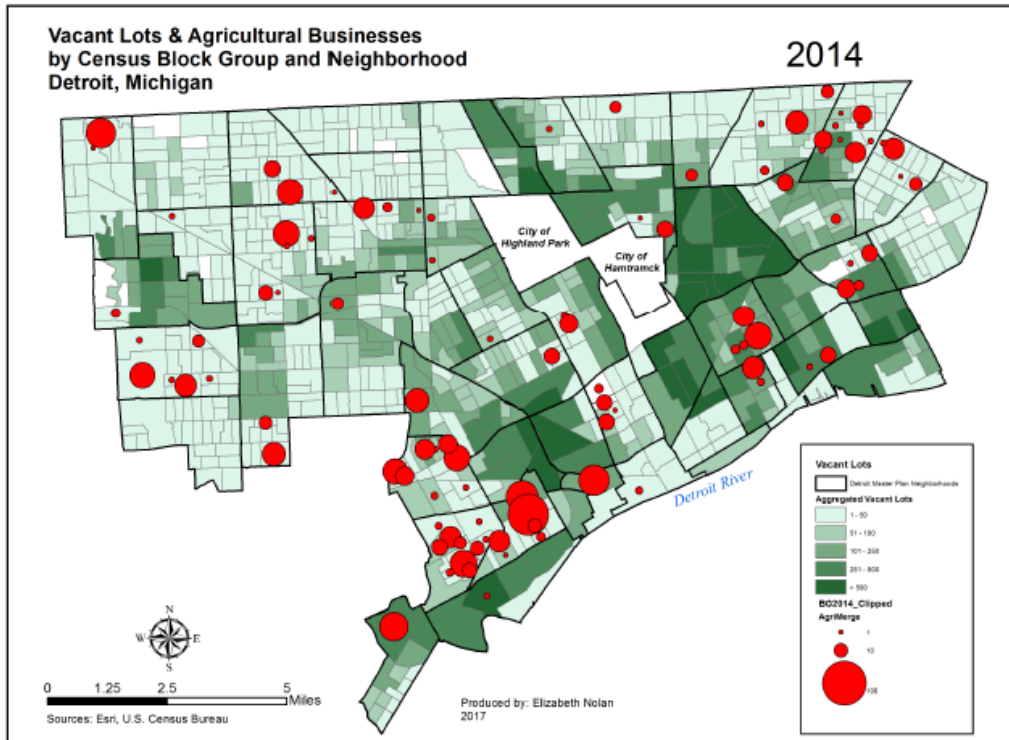


Figure 21. Spatial analysis of vacant lots & agricultural businesses (2009, 2014).
Data source: Esri, U.S. Census Bureau.

Chapter IV

Discussion

The results of the spatial analysis support some of the initial hypotheses, while the regression results indicate that the models only explain some of the variation in vacant land.

Vacant Lots & SES Conditions

The results of the ordinary least squares (OLS) and geographic weighted regressions (GWR) indicate that there is a weak negative correlation between the unemployment rate and median household income across block groups in the city of Detroit. Both models explain very little of the observed variation in vacant lots. Therefore, Hypothesis 1 must be rejected. Given that the number of vacant lots decreased between 2009 and 2014, however, one can infer that the 2009 lots are being reclaimed. Yet, neither model explains the potential mechanism(s) driving these changes across neighborhoods. While the GWR improved the OLS model's fit, it explains well below 50% of the model, and reveals that the explanatory variables do not satisfy the relationship. These results strongly suggest that there are other contributing factors that could explain the high prevalence of vacant land, and the distribution of the same across neighborhoods in Detroit. An alternative hypothesis could be that crime rates, dwindling public services, or relocated businesses are associated with the changes in vacant land across the city. These are all plausible factors that have influenced the migration of people within and outside of Detroit.

Vacant Land & Agricultural Land Use

While results of the choropleth maps of overlapping vacant lots and agricultural business data suggest that there is a trend between block groups with fewer vacant lots and the number of agricultural businesses, the OLS regression indicates that the vacant lots do not predict agricultural businesses. The maps in Figure 21 show that the majority of agricultural businesses are located in block groups that have 100 or fewer vacant parcels. While block groups and neighborhoods with lower counts of vacant lots may correspond to or signify lots are being repurposed as agricultural businesses, this dynamic cannot be assumed.

The census data show that from 2009 to 2014 vacant parcels were revitalized, but their land use purposes are not explained by the agricultural business data. Thus, Hypothesis 2 cannot be supported given the design and parameters of this study. The current model is a poor fit to explain the prevalence of agricultural businesses. An explanatory variable is missing from the equation, and an alternative hypothesis may be that agricultural businesses are flourishing in areas with greater community cohesion, or with better social networks and municipal support.

Agricultural Businesses

The tremendous growth in agricultural businesses between 2009 and 2014 is a testament of Detroit's burgeoning urban agricultural industry. Given the toll of fallow land distressing the entire city, this uptick in agricultural business is a positive move in the right direction. However, the agricultural business choropleth maps illustrate that this

growth is not evenly distributed across the city. In 2009 the majority of businesses were located in southern neighborhoods of the city, whereas by 2014, agricultural establishments had drastically increased in pockets throughout the city. This uneven distribution supports Hypothesis 3, and further begs the question of whether these changes are correlated with socioeconomic conditions across block groups. An alternative hypothesis associating agricultural businesses and block group demographics is explored in Figure 22 below. The scatterplot shows that agricultural businesses (“Agri Businesses”) are not correlated with the socio-demographic variables of this study.

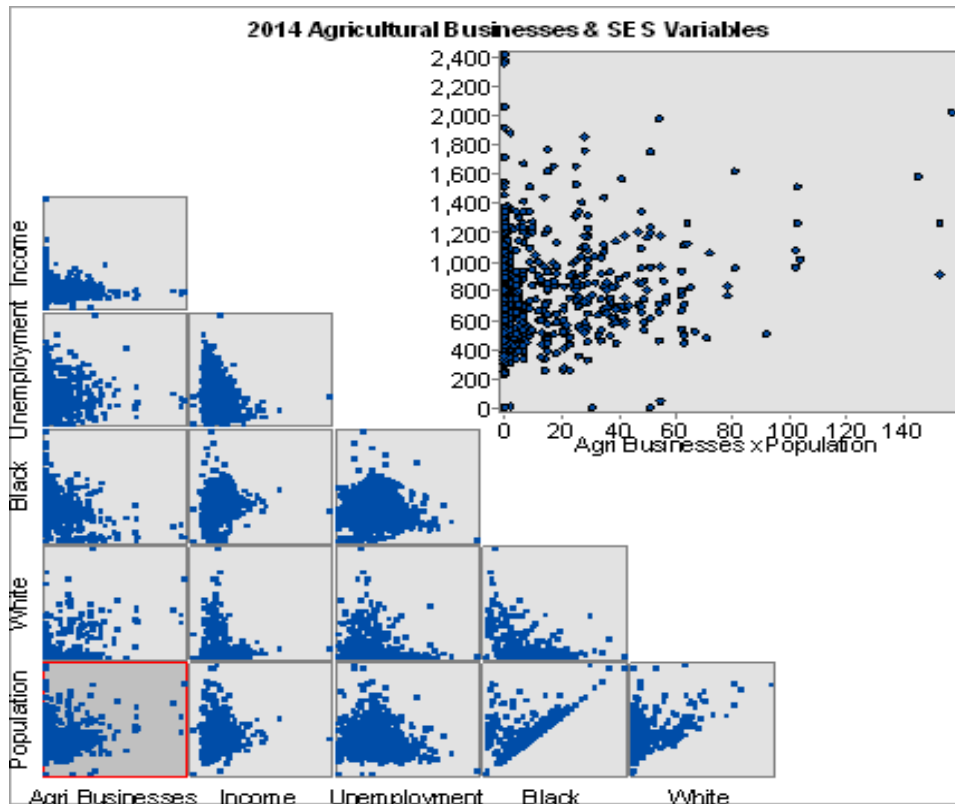


Figure 22. Agricultural businesses & SES variables scatterplot. Data source: Esri, U.S. Census Bureau.

Neighborhood Stabilization

The findings of this study show that there are other factors at play when it comes to Detroit's vacant land. The maps plotting agricultural businesses, vacant lots, and socio-demographic variables indicate that these factors are disproportionately affecting areas of Detroit. While other studies have linked land values to changes in neighborhood socioeconomic status, this study shows that the prevalence of Detroit's devalued vacant land is not attributed to socioeconomic status at the neighborhood level. Nor can the toll of vacant land explain the rise in agricultural businesses across the city between 2009 and 2016. The significance of this is that as the city continues to repurpose vacant plots, policymakers cannot merely focus in less or more affluent neighborhoods with regard to land redistribution. The presence of vacant land is non-discriminating across Detroit's neighborhoods. And yet, the 13% decrease in vacant land over the five-year period suggests that vacant land is being repurposed to benefit Detroit's residents.

Research Limitations

The primary limitations of this study stem largely from the data available for this study. All three datasets used data for the years 2009 and 2014, so any findings only speak to changes for these years, and not the years in between. Also, as the maintained status of a parcel may change more than once in any given year, this change would not have been captured in the land survey data collected at a specific time each year.

Another limitation is that the agricultural business data only reflects established businesses surveyed by the census. It does not include community gardens, homeowners' repurposed side lots, or other grassroots agricultural establishments throughout the city.

This exclusion is likely to underestimate what is really going in the city with regard to urban agriculture and forestry efforts to reclaim fallow land. Moreover, the descriptive data for the agricultural business variable includes agriculture, forestry, fishing, and hunting industries, and denotes farming, fishing, and forestry occupations. Little is known about what type of agricultural businesses are found in the city, hindering efforts to better understand how these businesses are benefitting residents.

Conclusion

The prevalence of vacant land creates an urban planning challenge for the city of Detroit. The mapping of vacant lots illustrates that there is great potential for reclaiming Detroit's green pastures towards sustainable uses, and agricultural uses are merely one way to reincorporate land to help the city better manage vacant land. The exponential growth in agricultural businesses between 2009 and 2014 provide clues as to how the city is reshaping itself after decades of steady depopulation and economic depression. Yet, more research is needed to determine if vacant land is in fact being repurposed for agricultural purposes.

References

- ArcGIS. (2017). *Master Plan Neighborhoods, Detroit*. Retrieved from:
<http://www.arcgis.com/home/item.html?id=a25b7114d233496eaece59a23e31f4b2#overview>
- Bouffard, K. (2015). Census bureau: Detroit is poorest big city in U.S. *The Detroit News*. Retrieved from:
<http://www.detroitnews.com/story/news/local/michigan/2015/09/16/census-us-uninsured-drops-income-stagnates/32499231/>
- Data Driven Detroit. (2015). *About: Mission*. Retrieved from:
<http://datadrivendetroit.org/about/>
- Data Driven Detroit. (2016). *File Metadata: Motor City Mapping, Winter 2014 Certified Results*.
- Data Driven Detroit. (2017). *Open Data Portal: Property & Land Use*. Retrieved from:
http://portal.datadrivendetroit.org/datasets/?group_id=25cbacb151854daba75685f6f1a4a7f2&q=property&sort_by=relevance
- Davey, M., Williams, T. (2014). Detroit Urged to Tear Down 40,000 Buildings. *The New York Times*.
- Detroit Future City. (2012). *Introduction*. Retrieved from:
<http://report.timetoendblight.org/>
- Detroit Land Bank Authority. (2012). Building Detroit – Neighbors Wanted. Rules for Bidding On and Purchasing Properties. Retrieved from:
<http://auctions.buildingdetroit.org/TheRules>
- Esri. (2016). *ArcGIS for Desktop: What is ArcMap?* Retrieved from:
<http://desktop.arcgis.com/en/arcmap/10.3/main/map/what-is-arcmap-.htm>
- Esri. (2016). *Esri Data Fact Sheet*. Retrieved from:
<http://www.esri.com/library/fliers/pdfs/esri-data-fact-sheet.pdf>
- Foo, K., Martin, D., Wool, C., Polsky, C. (2014). The production of urban vacant land: Relational placemaking in Boston, MA neighborhoods. *ScienceDirect*.
- Hackworth, J. (2014). The limits to market-based strategies for addressing land abandonment in shrinking American cities. *Progress in Planning*, 90, 1-37.

- Hartley, D. (2013). Urban Decline in Rust-Belt Cities. *Federal Reserve Bank of Cleveland. Economic Commentary*. No. 2013-06.
- International City/County Management Association. (2013). New Strategies for Revitalizing American Legacy Cities. *ICMA Center for Sustainable Communities*. Retrieved from: http://icma.org/en/BlogPost/1436/New_Strategies_for_Revitalizing_American_Legacy_Cities
- James, P., Banay, J., Laden, F. (2015). A Review of the Health Benefits of Greenness. *Current Epidemiology Reports*, 131-142.
- Kurth, J., MacDonald, C. (2015). Volume of abandoned homes ‘absolutely terrifying.’ *The Detroit News*. Retrieved from: <http://www.detroitnews.com/story/news/special-reports/2015/05/14/detroit-abandoned-homes-volume-terrifying/27237787/>
- Mallach, A. (2014). Who’s Moving to the Cities, Who Isn’t: Comparing American Cities – A Center for Community Progress Research Brief. *Center for Community Progress, Vacant Spaces into Vibrant Places*. Retrieved from: <http://www.communityprogress.net/who-s-moving-to-the-cities--who-isn-t--comparing-american-cities-pages-460.php>
- Merriam-Webster Dictionary. (2015). *Rust Belt*. Retrieved from: <http://www.merriam-webster.com/dictionary/rust%20belt>
- Motor City Mapping. (2016). *Detroit – Overview*. Retrieved from: <https://motorcitymapping.org/#t=overview&s=detroit&f=all>
- NAICS Association. (2017). *NAICS Identification Tools*. Retrieved from: <http://www.naics.com/search/>
- Ogeneva-Himmelberger, Y., Pearsall, H., Rakshit, R.. (2009). Concrete evidence & geographically weighted regression: a regional analysis of wealth and the land cover in Massachusetts. *ScienceDirect*, 29 (4), 478-487.
- Sallis, J., Floyd, M., Rodriguez, D., Saelens, B. (2012). The Role of Built Environments in Physical Activity, Obesity, and CVD. *American Heart Association*. Retrieved: <http://circ.ahajournals.org.ezp-prod1.hul.harvard.edu/content/125/5/729>
- Stoll, M.A. (2005). Job Sprawl and the Spatial Mismatch between Blacks and Jobs. *Metropolitan Policy Program. The Brookings Institution*. Retrieved from: http://www.brookings.edu/~media/research/files/reports/2005/2/metropolitanpolicy-stoll/20050214_jobsprawl.pdf

Thomas, J.M., Bekkering, H. (2015). *Mapping Detroit: Land, Community, and Shaping a City*. Wayne State University Press, Detroit, Michigan.

U.S. Census Bureau. (2015). *State and County Quick Facts: Detroit (city), Michigan*. Retrieved from: <https://www.census.gov/quickfacts/table/PST045215/2622000>

World Population Review. (2015). *Detroit Population*. Retrieved from: <http://worldpopulationreview.com/us-cities/detroit-population/>