Task Deliverable 5: Final Report

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Evaluating Community Building Effectiveness of Transportation Investments: Using Traditional and Big Data Oriented Analytical Approaches

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CHAPTER 1: BACKGROUND

An efficient and well-performing transportation system is the backbone of a nation's economy – an economy that is thriving, competitive, and productive. It is also the prerequisite for future growth. Each year, state and the federal government invest large amounts of money on different transportation projects. These include building a new roadway, extending or improving capacity of an existing roadway, introducing new transit facilities, installing additional stations or stops to expand transit coverage, and installing walk and bike infrastructure. The primary goal of these investments/projects is to facilitate and enhance the movement of people and goods. However, the impact of these investments/projects are not limited to building connections across regions and improving the mobility of the system users. They also impact land use, urban residential location decisions and activity patterns, economic growth, overall quality of life, and community well-being (Andersson et al., 2010) and are therefore a powerful determinant of urban development patterns (Boarnet, 2011). Further, emerging transportation infrastructure (such as connected vehicles and infrastructure, driverless cars, electric cars) and analytics (social media and big data approaches, machine learning methods) are likely to play a major role in transforming existing cities into Smart Cities comprised of Smart Communities. Given the critical role of transportation, it is important to examine the influence of transportation projects on overall community building, quality of life and well-being.

Transportation infrastructure investments include investments in building a new roadway, extending or improving capacity of an existing roadway, introducing new transit facilities, installing additional stations or stops to expand transit coverage, installing walk and bike infrastructure. The impacts of these investments can be classified into two broad categories: transportation system effects that result in direct benefits for system users (drivers, passengers, companies) and community (social and economic) effects that affect the community as a whole. There are well-defined performance measures, based on engineering and economic criteria, for assessing the direct system user benefits. For example, how a new facility leads to reduced journey time or reduced travel cost. On the other hand, such indicators are scarce for assessing the impacts of transportation projects on community.

Academic literature is replete with studies on how these investments result in direct benefits for system users (drivers, passengers, companies). For example, how a new facility leads to reduced journey time or reduced travel cost or how profitable the facility is in terms of generating revenues. However, investigation into the community effects (according to FDOT, "*…address a variety of important community issues such as land development, aesthetics, mobility, neighborhood cohesion, safety, relocation, and economic impacts"*) did not receive priority from the research community and transportation professionals. In recent years, there is growing interest toward evaluating community impacts in the research community and policy makers. To be sure, assessing community impact is complex, qualitative, and subjective. Thus, one single measure is not sufficient to get the overall picture. It has stemmed from the recognition that transportation projects that benefit a subset of users, might create negative externalities for the adjacent community members. For instance, a highway expansion might provide better accessibility and faster travel times between an origin (such as suburbs) and a destination (such as central business district). However, it is likely to expose the residents of the communities adjacent to the highway to increased air or noise pollution or even divide the existing community to reduce access to the amenities (social exclusion). Any evaluation of the impact of the highway expansion has to consider impact on system users and communities affected.

So, what is community impact? Simply put, *"these are the effects that any transportation project or investment has on adjacent neighborhoods and communities."* It includes *"the quality of the local environment as experienced by people who live, work or visit there as a consequence of changes in noise, views, walking environment, land use mix and community cohesion (the quality of interactions among neighbors). Related impacts on property values can also be included, and differential impacts on vulnerable population groups may also be covered"* under this definition (http://bca.transportationeconomics.org/benefits/community-impacts). Clearly, the concept is qualitative and subjective. The influence on community members is far from homogenous. Thus, comprehensive community impact assessments are inherently complex than assessing system user impacts and a single cumulative index or measure is not generally sufficient. Both positive and negative impacts need to be assessed – the positive impacts would certainly give indication of the success of the project while the negative impacts would help formulate mitigating measures to improve community well-being. A general overview of the interaction between system effects and community effects is represented in Figure 1.1.

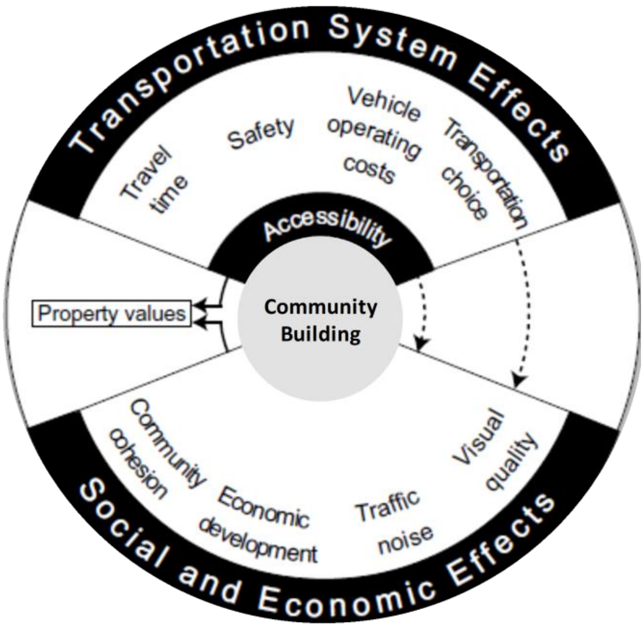


Figure 1.1: Interaction of System and Community Effect (Source: Forkenbrok and Weisbrod, 2001; Figure 1.2)

1.1 CURRENT RESEARCH CONTEXT

According to Florida Chamber of commerce[1], Florida ranks number one in the US in terms of transportation infrastructure rankings. It is the third largest state by population, after California and Texas with a yearly growth rate of more than 1.5%. Orlando is the most thriving city of

[1] http://www.flchamber.com/know-florida-ranked-1-transportation-infrastructure/

the Central Florida region; its growth being bolstered by its job creation rate (1,000 jobs are added per week). The economic and demographic trends suggest that Orlando has an expanding consumer market and these trends are set to drive increased demand for passengers and freight transportation in the coming years. To accommodate the future demand in an efficient and sustainable manner, several small and big transportation projects are underway in the region including second phase of SunRail commuter rail extension, I-4 expansion, pedestrian and bicycling facility installation, and bicycle sharing system (Juice) introduction. The proposed research effort is geared towards examining the community impacts of three transportation infrastructure investment projects: SunRail, I-4 expansion, and JUICE Orlando bikeshare system. Toward that end, we propose five community impact assessment measures or measures of effectiveness (MOE): (1) property value change, (2) changes to job accessibility, (3) commuting time change, (4) land use type change, and (5) changes to travel patterns for zero car households. The development of these MOEs is a data intensive process. These indicators/measures can be developed by collating appropriate data collected from different sources using the ArcGIS platform. In this deliverable, we discuss the data preparation steps, MOE computation process and results of the MOE computation exercise. Chapter 2 provides the details of data preparation. The results for the MOE’s are presented in Chapter 3. Chapter 4 provides details on social media analytics. Finally, Chapter 5 concludes the report.

CHAPTER 2: LITERATURE REVIEW

The importance of the relationship between transportation and land-use development pattern is well documented in history. Unfortunately, the quantity and magnitude are not so well understood. Polzin (1999) presented a three-tiered land-use response to transportation investment (see Figure 2.1). The author postulated that there are three distinct ways transportation investment can influence land use. These are: (1) by providing accessibility, (2) by encouraging complementary investment policies, and (3) by creating momentum or expectations that affect land use. The first is the direct impact of investment while the latter two are labeled as the indirect impact. For example, significant investment in constructing or expanding the physical roadway (for example, the I-4 expansion) suggest a permanence of the system also in the future, in turn, may attract private investment in development of the contiguous areas.

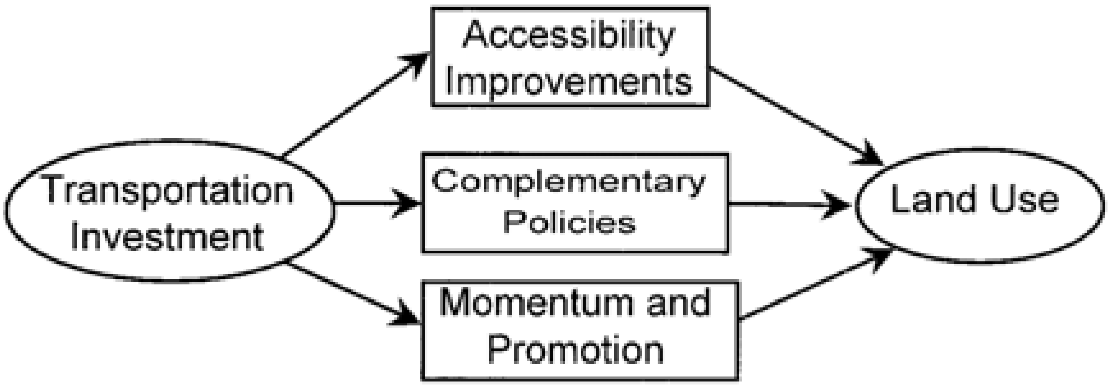


Figure 2.1: Transportation Investment Impacts on Land Use (Polzin, 1999)

There is scarcity of literature that evaluate the community development impact of transportation projects and investments. Our objectives are:

- review and compile contemporary studies on this issue (since the 2000's)
- identify and document the indicators used by previous research efforts
- summarize the results obtained

Towards that end, more than 50 publications were reviewed including published academic research – within and beyond transportation domain (social science, health, urban planning, urban economics, environment), non-academic articles, and published governmental reports. This report provides a complete compilation of reviewed works (attached matrix of studies), and a summary of key findings. To be sure, different projects are aimed at modifying/improving/developing different components of the transportation system. Figure 2.2 identifies the components – Infrastructure, transit facility and non-motorized facility - that we focused our review on.

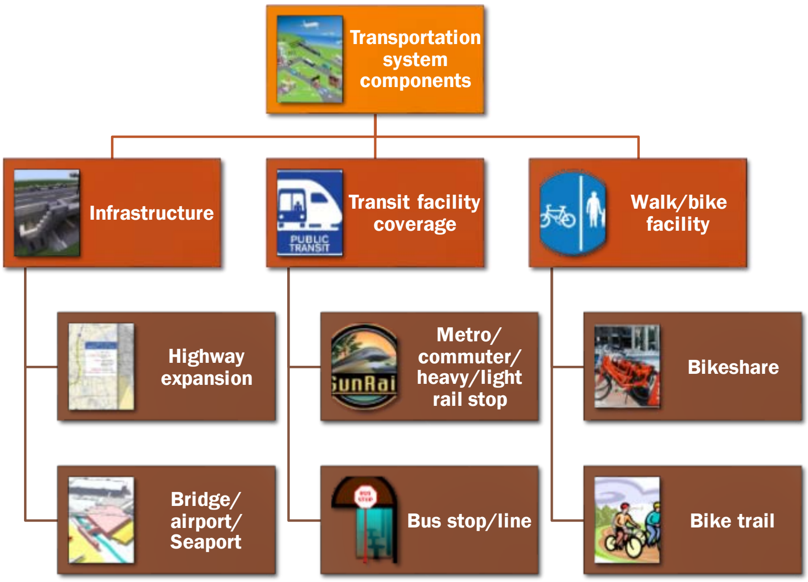


Figure 2.2: Transportation System Components Chosen for Review

As stated in current study, the potential MOEs to be explored in our project falls in three broad categories: (1) land use-impact, (2) economic impact, and (3) transportation impact. Land-use impact includes: (a) property price change, and (b) land use type change; economic impact includes (a) accessibility to employment; transportation impact includes (a) vehicle ownership, and (b) change in commuting time. We will conduct and limit our review along these dimensions only.

2.1 LAND USE

The impacts of transportation facility investments on land development are likely to include both property value increases and accelerated development of land use (Deng & Nelson, 2013). But the impact on property values is likely to occur sooner (Stokenberga, 2014) and changes in land values can act as evidence of a transportation project's larger social, environmental, and economic benefits to society (Higgins & Kanaroglou, 2016). Therefore, it is of paramount importance for planning and policy. As a result, one of the most commonly investigated indicator of community development induced by transportation investments is the land or property value changes of adjacent properties. While there are plenty of studies investigating the price changes for residential property types, limited efforts were devoted to non-residential properties (commercial, retail, office, food, plaza, industrial, and vacant land); presumably due to lack of data. Differences also exist with respect to type of price evaluated. The majority of the studies based their analysis on actual sales price while others have used asking/listing price, assessed value, and offer price. The results reported in the studies are mixed in nature. However, in general, a positive gain in property values, primarily attributable to the increase in accessibility, is reported in vast majority of the studies to date; the change in premiums varying among studies. On the other hand, the two negative externalities that are reported to counter the positive impacts are noise and pollution. There is variation in research design and methodological approach as well. For instance, the studies are mainly cross-sectional. However, a few studies examined repeated sales price data to examine the temporal trend in price change or employed difference-in-difference methodology or conducted before-after analysis.

2.1.1 Investment in Infrastructure

From our review, we have found that there is vast empirical literature on the effects of improved accessibility brought about by new or improved roadway infrastructure (such as roads, bridges, airports and seaports). Table 2.1 lists the studies that we reviewed in this category. Several observations can be made from the table.

- The most commonly investigated indicator of community development is the sales price of properties including residential, commercial, retail, office, food, plaza, industrial, and vacant land as a result of new highway development, expansion of highway, construction/opening of new bridge/tunnel, opening of tolled roads, and expansion of airport facility
- Hedonic regression technique is the most prevalent methodology applied
- The variation in sales price is investigated as a function of proximity (how far the properties are located from the roadway) and the noise level within a certain buffer distance
- The results obtained are mixed. However, the majority of the studies found that increased accessibility brought by the facility increases values of residential properties
- As expected, nuisance from noise negatively impacts property price. The price reduction is of the order of 1-3%. Andersson et al. (2010b) found that road noise has larger negative impact than rail noise
- Hamersma et al. (2017) investigated resident's satisfaction due to new highway construction and found that new residents who moved to the neighborhood after highway construction expressed more satisfaction than the existing residents
- Kang and Cervero (2009) found that conversion of freeway to greenway increases property price

Table 2.1: Literature on Roadway Infrastructure Impact on Property Price/Rent

Study	Region	Evaluated Measure	Property Type	Dependent Variable and Methodology	Result
Levkovich et al., 2016	Netherlands	Proximity (distance from interchange and highway)	Residential	Housing price, Repeat sales/ difference-in-difference	• Positive effect of increased accessibility outweighs the negative effects
Gingerich et al., 2013	Windsor, Canada	Proximity (properties within 800m buffer of highway ramp)	Commercial, retail, office, food, plaza, industrial, and vacant	Sales price, Spatial regression model	• No significant correlation except for a negative impact on price of vacant land
Iacono and Levinson, 2011	Minnesota, USA	Proximity (dummy for location within ¼ -1mi of upgraded highway)	Residential	Sales price, Hedonic regression	• 100-m increase in distance from the nearest access point on an upgraded highway link reduced property price by 0.3% • Proximity to expanded highway's Right of Way (ROW) reduces housing price upto ¼ mile
Blanco and Flindell, 2011	London and Birmingham, UK	Road traffic noise (sound level)	Residential	Offer price, Hedonic regression	• Residents of different geographic region have different willingness-to-pay for lower noise levels
Brandt and Maennig, 2011	Hamburg, Germany	Proximity (dummy for location of house on a wide road) Air and rail traffic noise (sound level)	Residential (condominiums)	Listing price, Hedonic spatial lag regression	• Property prices reduce by 0.23% following a 1 dB(A) increase in road noise
Andersson et al., 2010b	Lerum, Sweden	Road and rail noise (sound level)	Residential (single-family)	Sales price, Hedonic regression	• Road noise has a larger negative impact on the property price than railway noise
Martinez and Viegas, 2009	Lisbon, Portugal	Proximity (distance from network)	Residential	Asking price, Hedonic spatial lag regression model	• Proximity to urban ring roads and radial networks increase property values • Proximity to motorways and roadways with increased office buildings decrease property values
Kim et al., 2007	Seoul, South Korea	Proximity (distance to highway, arterial road, minor arterial) Road traffic noise	Residential	Land price, Hedonic regression	• 1% increase in traffic noise reduces property price by 1.3%

		(sound level)			
Cervero and Duncan, 2002	Santa Clara, USA	Proximity (within ½ mile distance from grade separated freeways or highway interchange)	Office and commercial land	Transaction price, weighted Hedonic regression	• Property location within ½ mile of thoroughfares was associated with lower land values
Hamersma et al., 2017	Netherlands	Highway development	Residential	Residents' satisfaction, Structural equation model	• Residents living in areas closest to highway development has lower satisfaction • Small proportion of the residents perceived an increase in residential satisfaction due to the highway development
Meijers et al., 2013	Netherlands	Construction of a new bridge/tunnel	Residential	Housing price, Hedonic regression	• Increased accessibility increases housing price
	Seoul, South Korea	Freeway replaced by urban stream and linear park	Residential and commercial	Land value, Multilevel hedonic regression	• The conversion resulted in increased land value within 500 meters of the freeway and greenway
Riebel et al., 2008	Los Angeles, USA	Expansion of highway	Residential	Sales price, Combined hedonic spline regression	• Maximum increase in price is observed at a moderate distance from the expanded highway
Theebe, 2004	Netherlands	Expansion of airport and construction of railways	Residential	Sales price, Hedonic regression	• Noise reduced housing price by 3%-10%
Boarnet and Chalermpong, 2003	California, USA	New tolled roads	Residential (single-family)	Sales price, Hedonic regression	• Accessibility benefits created by the new tolled road increase the housing price
Smersh and Smith, 2000	Jacksonville, USA	Construction of bridge	Residential	Sales price, Repeat sales regression	• Differential effects are found at different ends of the bridge

2.1.2 Investment in Transit

We considered rail and bus transit system in our review. The majority of the studies focus on rail transit. Rail transit system comprised of heavy rail, commuter rail, rapid/high speed rail, metro/subway, and/or light rail. Investment in rail transport system is reported to affect local economy at macro-, meso-, and micro-level (Banister and Thurstain-Goodwin, 2011). Macroeconomic studies use aggregate time-series data and examine the linkage between infrastructure and regional growth measured in terms of GDP or employment growth or population growth (Atack et al., 2010). At the meso-level, agglomeration economies, such as how traffic congestion impact productivity in cities and labor market effects are assessed. In micro-level studies, land and property market effects are examined. The findings from these studies provide guidance for the adoption and implementation of transit finance strategies and thus their importance is widely recognized in the transportation economics and planning literature (Ko and Cao, 2013). For the purpose of this review, we focus our attention on micro-level studies. Table 2.2 list the studies that we reviewed in this regard. Several observations can be made from these tables.

- The impact of accessibility benefits of rail facilities is mostly investigated by examining the values of properties sold before and after the opening of the facility. Some researchers have explored pre-opening anticipatory effects of rail transit lines on property values ("announcement effect") as well (Li, 2016; McMillen and McDonald, 2004; Bae et al., 2003) and found that announcement of new facility opening increases property price
- Property values are represented in terms of sales/transaction price, assessed market value, or rental rates. For residential properties, these data are extracted from the assessor's data, parcel data, or multiple listing service (MLS) data while the rental rates were obtained either from self-administered surveys or rental offices of apartment complex
- Controlling for a wide range of other features such as physical attributes of the housing and neighborhood characteristics, the impact of rail system on the residential and non-residential stock has mainly been examined through proxies of rail accessibility, proximity, and service quality measures (Armstrong and Rodriguez, 2006; Debrezion et al., 2011)
- The studies are mainly cross-sectional. A few studies used repeated sales price data (McMillen and McDonald, 2004; Grimes and Young, 2010) or employed difference-in-difference methodology based on openings of stations (Gibbons and Machin, 2005; Li, 2016)
- Hedonic pricing models and its extensions are the most prevalent methodology applied; the functional forms vary from study to study
- While there are plenty of studies investigating the price changes in residential property types, limited efforts were devoted to non-residential properties – lack of data being the major hindrance
- Although the results are mixed, most studies concluded that investment in rail corridors generally increases property prices. According to urban economics, this is the due to the increase in the accessibility of the corridor relative to the whole transportation

network. However, the accessibility benefits seem to be localized and decline with distance, both for residential and non-residential properties (Ko and Cao, 2012). In addition, we also observed that railways stations impact residential and non-residential property types separately. The extent of the impact area of railway stations is larger for residential properties, whereas the impact of a railway station on commercial properties is limited to immediately adjacent areas (Debrezion et al., 2011)

Due to their extensive network, effects of bus transit system on property values and community development is more likely to be regional as opposed to the localized (as it is for rail transit). Table 2.2 lists the studies that we reviewed in this regard. The following observations can be made from these tables.

- Only a few studies attempted to examine the effect of bus transit accessibility. Interestingly, researchers found that proximity to bus stops has no significant association with property price but it negatively impacted apartment rents.

2.1.3 Investment in Walk/Bike Facilities

Given the wide ranging implications of over-reliance of automobiles for personal travel, policy makers are trying to promote non-motorized modes as potential alternatives, at least for short distance utilitarian trips. Recently, governments are investing more in infrastructure facilitating walking and biking to popularize them among the general public. Although the positive impacts of cycling are widely known, there are very few studies that actually studied community impact. Table 2.3 lists the studies that we reviewed in this regard. Several observations can be made from these tables.

- Of the four studies on bike facilities, two are on bikeshare and two on bike trails. Properties in the vicinity of bikeshare stations experience higher prices (El-Geneidy et al., 2015) while bikeshare stations also induce economic and retail activities (Buehler and Humrey, 2015). Interestingly, bike trails negatively impacted housing price in suburban areas (Krizek, 2006)
- Walkability is an important attribute that has been linked to quality of life in many ways. Health related benefits of physical exercise and walking, mental health benefits of reduced social isolation and increased social interaction are a few of the many positive impacts on quality of life that can result from a walkable neighborhood. While the health and environmental implications of walkable communities are being extensively studied, the social benefits have not been investigated as broadly. The few studies that we found, almost all of them reported that increased walkability increases property price. A negative association of mortgage default probability with walkability of neighborhood was found in Rauterkus et al. (2010).

Table 2.2: Literature on Rail Transit Impact on Property Price/Rent

Study	Region	Type of Rail	Effect Evaluated (Measure)	Property Type	Dependent Variable and Methodology	Main Results
Li, 2016	Beijing, China	Metro	Accessibility (distance to the closest station (<1 km))	Residential	List price, Hedonic regression	• 3.8% price increase for properties located within 1 km from the closest station
Ko and Cao, 2013	Minneapolis, USA	Light rail	Accessibility (network distance from station)	Commercial, industrial	Sales price, Hedonic regression	• Price increases non-linearly for properties located within 0.9 miles of stations
Gingerich et al., 2013	Windsor, Canada	Light rail	Proximity (properties within 200/400m buffer of rail line)	Commercial, retail, office, food, plaza, industrial, vacant	Sales price, Hedonic spatial lag regression	• Industrial property price increases with increased proximity • The reverse impact is observed for food and commercial services
Mayor et al., 2012	Dublin, Ireland	Commuter rail, light rail, train	Accessibility, proximity (indicator variables for house location within 250m-2km of stations and Right of Way (ROW))	Residential	Purchase price, Hedonic regression	• Properties within 500m-2km of light rail stations experience 7-17% higher price • Properties within 250m-500m of train stations experience 7-8% higher price
Duncan, 2011	San Diego, USA	Light rail	Accessibility (network distance to the nearest station)	Residential (condominiums)	Sales price, Hedonic regression	• Station proximity with good pedestrian environment increase condo price
Debrezion et al., 2011	Amsterdam, Rotterdam and Enschede, Netherlands	Commuter rail	Accessibility (network distance to the nearest and most frequently used station) Service quality (service quality index)	Residential	Transaction price, Hedonic regression	• Housing price is more affected by the distance from the most frequently used station
Andersson et al., 2010a	Taiwan	High speed rail	Accessibility (network distance to the station)	Residential	Sales price, Hedonic regression	• High ticket price and inaccessible locations results in small or negligible increase in land values
Koster et al., 2010	Netherlands	Passenger rail	Accessibility (network distance to the nearest station)	Residential	Repeated sales price, Hedonic regression	• Property values increase by about 1.5−2% with every km reduction in distance from the nearest railway station

Martinez and Viegas, 2009	Lisbon, Portugal	Metro, light rail	Accessibility (walk time to the station)	Residential	Advertised asking price, Hedonic spatial lag regression	• Proximity to rail facility increases property asking price • Increase amount varies with varying accessibility
Shin et al., 2007	Seoul, South Korea	Subway	Accessibility (distance and walk time to the nearest station)	Residential (apartments)	Actual sales price, Hedonic spatial lag regression	• 1% increase in walking time reduces sales price by 0.017%-0.021% • 1% increase in system wide accessibility reduces sales price by 0.051%-0.076%
Hess and Almeida, 2006	New York, USA	Light rail	Accessibility (straight line and network walk distance)	Residential	Assessed value, Hedonic regression	• Properties within ¼ mile of train stations experience 2-5% higher price • Effects vary in magnitude for different stations in the system – premium is higher in high income area stations
Armstrong and Rodriguez, 2006	Eastern Massachusetts, USA	Commuter rail	Accessibility (network distance from station by foot and by car) Proximity to right-of-way (drive time to the nearest highway interchange and commuter ferry boat)	Residential (single-family)	Sales price, Hedonic spatial lag regression	• Properties within ½ mile buffer of stations experience 9.6%-10.1% higher price • 1-minute increase in drive time, property values decrease by 1.6% • Every 100ft distance from ROW increases property values between $73.21-$289.72
Celik and Yankaya, 2006	Izmir, Turkey	Subway	Accessibility (distance from subway station)	Residential (multi-family)	Asking price, Hedonic regression	• 1-meter additional distance decreases the property values by $4.76
Gibbons and Machin, 2005	London, UK	Subway	Accessibility (distance to the nearest station) Proximity (distance to the ROW)	Residential	Sales price, Hedonic spatial lag regression	• 1-km reduction in distance increase property values by 1.5%
Bae et al., 2003	Seoul, South Korea	Subway	Proximity (distance to the ROW)	Residential (condominiums)	Sales price, Hedonic spatial lag regression	• Distance to ROW impacted sales price prior to the opening of subway line

Clower and Weinstein, 2002	Dallas, USA	Light rail	Accessibility (distance from station)	Office, retail, industrial, residential (single and multi-family)	Assessed value, aggregate change in value	• Price of office properties within ¼ mile of rail station increased by 24.7% • Price of residential properties within ¼ mile of rail station increased by 38.2% • Industrial properties located further away experienced larger gains • Negligible increase for retail was observed
Cervero and Duncan, 2002	Santa Clara, USA	Light rail, commuter rail	Accessibility (distance from station)	Office and commercial land	Transaction price, weighted Hedonic regression	• Commercial parcels within ¼ mile of light rail station experienced 20% higher price • No capitalization premiums for properties in close proximity to commuter rail station
Bowes and Ihlanfeldt, 2001	Atlanta, USA	Heavy rail	Accessibility (distance from station) Proximity (distance from ROW)	Residential (single-family)	Sales price, Hedonic regression	• Properties within ¼ mile of rail stations have their price reduced by 19% • Price increase for houses located within 1-3 miles
Knaap et al., 2001	Portland, USA	Light rail	Accessibility (distance from station)	Vacant residential land	Sales price, Hedonic regression	• Announcement effect on property sale price was observed

Table 2.3: Literature on Bus Transit System Impact on Property Price/Rent

Study	Region	Type of Rail	Effect Evaluated (Measure)	Property Type	Dependent Variable and Methodology	Main Results
Cao and Hough, 2008	Fargo, USA	Bus transit	Proximity (distance from route)	Residential (apartments)	Monthly rent, Hedonic regression	• Apartments located within 1/8 mile of bus routes are $18.41 cheaper than other apartments
Bina et al., 2006	Texas, USA	Bus transit	Accessibility (density of bus stop)	Residential (apartments)	Monthly rent, Hedonic regression	• Bus stop density negatively impacts rent
Celik and Yankaya, 2006	Izmir, Turkey	Bus transit	Accessibility (distance from bus stop)	Residential (multi-family)	Asking price, Hedonic regression	• No significant effect on property values
Cervero and Kang, 2011	Seoul, Korea	Bus rapid transit	Proximity (distance from bus stop)	Residential, non-residential	Land use type, Multinomial logit Land price, Hedonic regression	• Land price increased by 10%
Munoz-Raskin, 2010	Bogota, Columbia	Bus rapid transit	Accessibility (properties within 10 minutes of walking distance of the system)	Residential	Housing price, Hedonic regression	• Price of middle-income properties increase • Reverse impact for low-income properties

Table 2.4: Literature on Walk/Bike Facilities Impact on Property Price/Rent

Study	Region	Type of Facility	Measure	Property Type	Dependent Variable and Methodology	Result
El-Geneidy et al., 2015	Montreal, Canada	Bikeshare (BIXI)	Presence of bikeshare stations	Residential	Repeated sales price, Multilevel longitudinal hedonic regression	• Presence of bikeshare system in a neighborhood increases the property value by 2.7%
Pivo and Fischer, 2011	USA	-	Walkability via Walkscore	Office, retail, apartment, industrial	Market value, income return, capital return, total return, Linear regression	• 10-point increase in walkability increases office, retail and apartment values by 1-9% • No effect on industrial properties
Rogers et al., 2011	New Hampshire, USA	-	Walkability	-	Social capital, Correlation	• Neighborhood walkability is positively linked with community well-being
Rauterkus and Miller, 2011	Alabama, USA	-	Walkability via Walkscore	Residential, commercial	Sales price, Linear regression	• Increased walkability increase land value and the effect is stable over time
Rauterkus et al., 2010	Chicago, Jacksonville and San Francisco, USA	-	Walkability via Walkscore	Residential	Mortgage default, Probit regression	• Walkability is associated with a lower mortgage default probability in high income areas • Mortgage default probability increases with higher walk Scores in low income areas
Krizek, 2006	Minneapolis, USA	Bike trails and lanes	Proximity to bike facilities	Residential	Sales price, Linear regression	• In suburban areas, bike facilities negatively impact home values

2.2 ECONOMIC IMPACT

Given the wide ranging implications of over-reliance of new investments on transportation field, economic impact that interests policy makers to develop the adjacent land. Although the positive impacts of economic impacts are widely known, there are very few studies that actually studied that impact. Table 2.5 lists the studies that we reviewed in this regard. Major observations can be made from these studies, significant impact happens for low wage jobs considering high income jobs.

2.3 TRANSPORTATION IMPACT

In contrast, it was surprising to find that only a handful of studies have investigated the impact of transportation impact on community building (see Table 2.6). Among other effects, researchers have investigated how transportation investments is associated with vehicle ownership, vehicle miles traveled, transit ridership, and health. The major findings regarding these studies are improved rail or metro services reduce vehicle ownership of household. Another finndings from these studies is ridership decreased in other conventional rail corridors where high speed rail stations are not directly accessible.

Table 2.5: Literature on Job Accessibility/Employment

Study	Region	Type of Investment	Measure Evaluated	Methodology	Main Results
Combs, 2017	Bogota, Columbia	Bus rapid transit	Changes in travel pattern (tour frequency)	Count regression	• No substantial impact on lower income households to meet daily mobility needs
Buehler and Humrey, 2015	Washington DC, USA	Bikeshare (Capital Bike)	Economic (Users' willingness to spend, perception of business owner)	Intercept survey of users and business	• 23% of the patrons were likely to spend more due to bikeshare facility • 20% of the business thought bikeshare had a positive impact on sales
Fan et al, 2012	Twin Cities, USA	Light rail	Labor market accessibility	Linear regression	• Significant impact in accessibility to low-wage jobs
Bowes and Ihlanfeldt, 2001	Atlanta, USA	Heavy rail	Commercial development/ Retail employment density	Random effects regression	• No significant impact

Table 2.6: Literature on Transportation Impact

Study	Region	Type of Rail	Measure Evaluated	Dependent Variable	Methodology	Main Results
Shen et al., 2016	Shanghai, China	Metro	Competitiveness as mobility tool	Vehicle ownership	Binary logit/ Nested logit	• High quality rail service can reduce vehicle ownership
Huang and Chao, 2014	Taipei, Taiwan	Metro	Competitiveness as mobility tool	Vehicle ownership	Count regression (difference-in-difference)	• Extending metro coverage with improved level of service can reduce vehicle ownership
Cao and Schoner, 2014	Minnesota, USA	Light rail	Transit use (use of transit for commute and non-commute purpose)	-	Propensity score matching	• Residents who lived in the area prior the line was opened use transit more frequently • 50-80% increase in ridership
Bhattacharjee and Goetz, 2012	Denver, USA	Light rail	Congestion on adjacent highways	Vehicle Miles Traveled (VMT)	Temporal and spatial mapping	• Light rail reduces congestion, but for a short period of time
Senior, 2009	London, UK	Light rail	Transit use (Changes in frequencies of rail and bus use, modal switching)	-	Before and after analysis	• In the rail corridor, in both short and medium term, rail ridership increased while ridership of bus decreased • Higher frequency of rail usage was observed in the rail corridor
Brown and Werner, 2007	Minnesota, USA	Light rail	Health (bouts of activity) Transit use (ridership)	-	Before and after analysis	• Walk to station was associated with moderate activity bouts • After opening of a new stop, the ridership increased by 19%
Lee and Chang, 2006	Seoul, South Korea	High speed rail	Transit use (change in number of passenger trips)	-	Before and after analysis (1 year)	• Ridership increased in the corridor where high speed rail stations are located • Ridership decreased in other conventional rail corridors where high speed rail stations are not directly accessible
Bowes and Ihlanfeldt, 2001	Atlanta, USA	Heavy rail	Commercial development	Retail employment density	Random effects regression	• No significant impact

Combs and Rodriguez, 2014	Bogota, Columbia	Bus rapid transit	Competitiveness as mobility tool	Vehicle ownership	Difference-in-difference	• Reduces vehicle ownership in high income households • Reverse impact for low income households
Merom et al., 2003	Sydney, Australia	Bike trail	Trail usage Walking and cycling activity	-	Before and after analysis (bike count, change in walking and cycling hours)	• Mean daily bike count increased • Trail usage was higher among bike owners living near the trail

CHAPTER 3: MEASURES OF EFFECTIVENESS (MOE) COMPUTATION USING PUBLIC DATA

3.1 TRANSPORTATION INFRASTRUCTURE

Several small and big transportation projects are underway in the Central Florida region including the second phase of SunRail commuter rail extension, I-4 expansion, and bicycle sharing system (Juice) introduction (see Figure 3.1). A brief discussion of each of these three transportation investments is provided below.

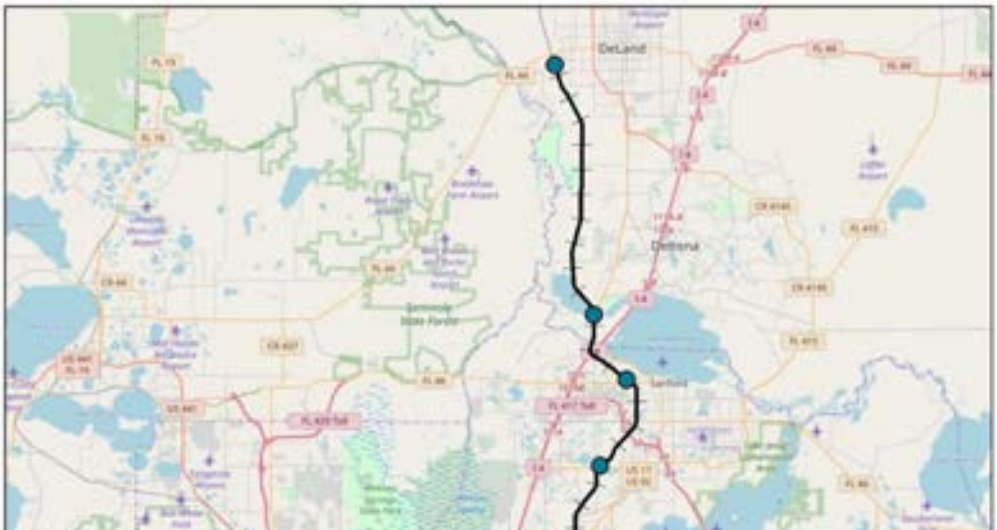


Figure 3.1: Major Transportation Investment Projects (SunRail, I-4 Expansion and JUICE Bikeshare) in Central Florida Region

3.1.1 SunRail

SunRail is the commuter rail system for the Central Florida region inaugurated in Spring 2014 with 12 stations in three counties (City of Orlando, Volusia, Seminole, and Orange). The first phase of SunRail is 32 miles long connecting DeBary road of Volusia County to Sand Lake road of Orange County. In the second phase, the service was planned to expand both in north and south directions with 5 additional stations. The proposed north area is 12 miles long with one station while the south area is 17.2 miles long with 4 stations. The construction of phase-2 stations in the south started in 2016 and these stations became operational in 2018. All of the phase-1 (already opened) and phase-2 SunRail stations are shown in Figure 3.2. While Deland station is not operational, MOEs for this station were computed for the sake of completeness.

Figure 3.2: SunRail Stations

3.1.2 I-4 Expansion

Expansion of the Interstate 4 (I-4) (see Figure 3.3) is the one of the largest and most ambitious interstate road construction projects in Florida transportation history. This long-awaited project involves improving, expanding and reconstructing the 54-year-old "Orlando Expressway", and is termed as I-4 Ultimate. The 21-mile long expansion (west of Kirkman Road in Orange County to east of State Road 434 in Seminole County), started in February 2015 and is expected to be completed by 2021 with four dynamically tolled express lanes. The construction plan is divided into 4 segments of 4-6 miles each: attractions (5.7 miles), downtown Orlando (4.2 miles), Ivanhoe (4.9 miles), and Altamonte (6.4 miles). The Attraction segment starts at west of Kirkman road in Orange County while the Altamonte segment ends east of State Road 434.

Figure 3.3: I-4 Ultimate Route

The interstate renovation will be further extended in the future in both north and south bound direction. The southbound extension is proposed to be 21.2 miles long from Kirkman Road to US 27 in Polk County and the express lanes are proposed to be extended further north from State Road 434 to State Road 472 (19 miles). The project will have substantial short and long-term economic impact in the regions that the interstate will pass through. It will make transportation more efficient - improving regional productivity and mobility, improved traveling experience for tourists visiting Orlando attractions, positively impacting local economies, and enhancing freight movement.

3.1.3 JUICE Orlando Bikeshare

In early 2015, Orlando launched its bike sharing system (BSS) with 20 bikes and 4 stations. Within one-year span, it expanded to 200 bikes with 20 stations. The number of stations has continued to grow and stands at 35 in 2018. Figure 3.4 presents the JUICE Orlando bikeshare stations' location. Bikeshare facilities increase safety and level of social interaction amongst the community residents building community cohesion. Such facilities also enhance the image of bicycle as a mode for travel.

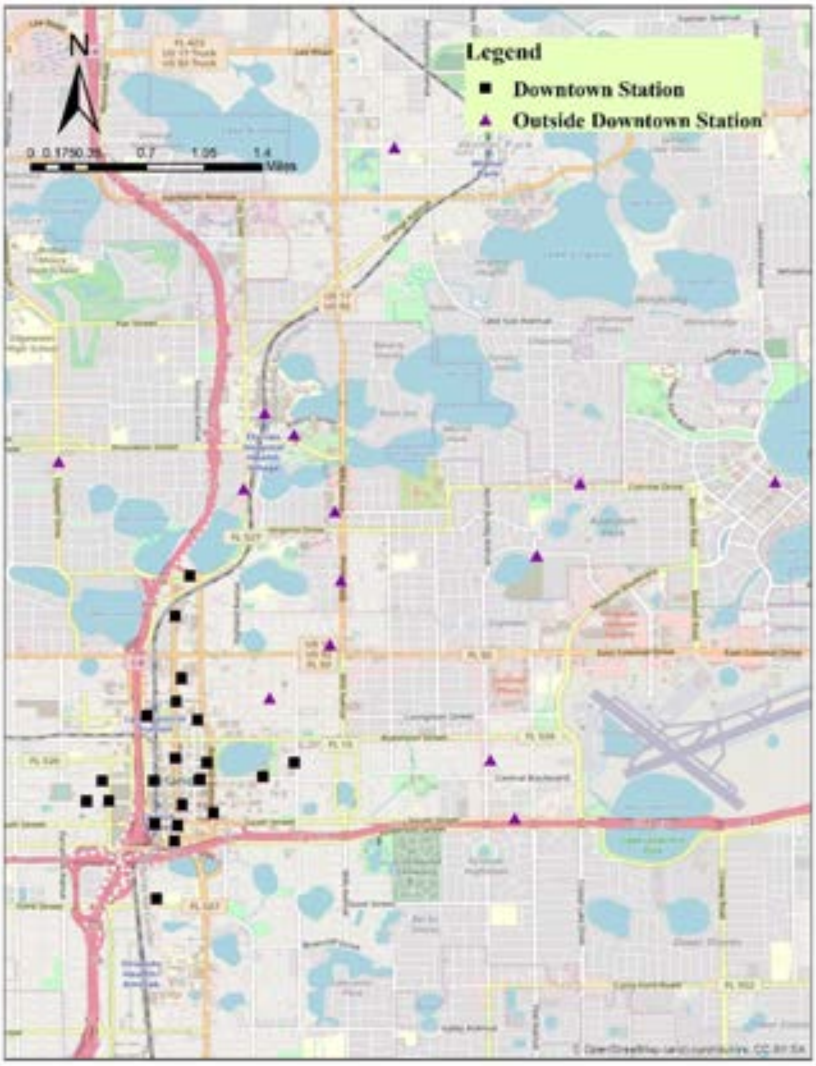


Figure 3.4: JUICE Bike Share Stations

3.2 MOE COMPUTATION

The development of the MOEs is a data intensive process. The process involves collection of appropriate data from different sources, extracting data for the geographic regions under study, and eventually combining layers of data as needed. Informed from the literature review, five MOEs was proposed to evaluate the community building effects of the major transportation investment projects currently underway in the Central Florida Region. The proposed MOEs are:

- Property value change
- Changes to job accessibility
- Commuting time change
- Land use type change
- Changes to travel patterns for zero car households

The proposed changes will be evaluated for the time period 2011-2017. For sake of brevity, the layer preparation steps for the year 2012 was presented. The procedure was repeated for the entire time period of analysis. For job accessibility, commuting time and zero car household pattern based MOEs, data for 2017 was unavailable and the analysis was conducted from 2011-2016.

3.2.1 Property Value by Land Use Type

To capture the change in property value, parcel data (for 2011-2017) obtained from Florida Department of Revenue (FDOR) were utilized. Each parcel is assigned a unique ID (Parcel ID) linking it with equivalent parcel level attribute information such as property/feature value, land value, land area in square feet, land use codes (DOR-UC), owner name, owner address, physical address, physical zip code, building details and so on contained in the Name-Address-Legal (NAL) file.

The transportation infrastructure projects considered in this research passes through four counties: Orange, Osceola, Seminole and Volusia. Hence, the property data layer was prepared by merging the parcel data information for these four counties. Please note that Just Value (land just value, building value, and special feature value) of a property includes: present cash value; use; location; quantity or size; cost; replacement value of improvements; condition; income from property; and net proceeds if the property is sold. The net proceeds equal the value of the property minus 15% of the true market value. This accounts for the cost of selling the property. In calculating the change in property values, Just Value reported by DOR was considered as a surrogate measure for direct property value and in the following sections, this value will be referred to as the property value for simplicity. The preliminary analysis showed that the property value for the majority of the parcels in Volusia and Osceola counties are less than or equal to $50,000/acre. As expected, the largest variation in property values is observed for Orange and Seminole counties.

The purpose of our research is to investigate the property value change across different land use types because the impact of transportation projects may have differential impact on different property types. For example, retail/office space values might be more affected than the residential property values. DOR reports in excess of 100 land use types. For the analysis purpose, the land use categories reported by DOR were consolidated into 12 land use categories. These are Single Family Residential, Multi-Family Residential, Retail/Office, Industrial/Manufacturing, Agriculture, Institutional/Infrastructure, Public, Recreational, Water, Vacant, and Others (see Table 3.1). However, the values for the following 5 out of the 12 categories will be reported: (1) Single family residential, (2) Multiple family residential, (3) Retail/Office area, (4) Institutional, and (5) Industrial. DOR land use types are presented on Appendix A.

Table 3.1: Land Use Category Based on DOR Land Use Codes

Land Use Category	DOR Land Use Code
Single Family Residential	1
Multi-Family Residential	3,8
Other Residential	2,4-7,9
Retail/Office	11-39
Industrial	41-49
Agricultural	50-69
Institutional	71-79, 81, 84
Public	83, 85-91
Recreational	82, 97
Water	95
Vacant	0, 10, 40, 70, 80
Others	92-96, 98, 99, 100, 995, 999

The land use pattern is more heterogeneous in Seminole County and the western part of Orange County. Higher percentage of residential and commercial parcels are also observed in these two counties. On the other hand, land usage pattern is more homogenous in Osceola County – agricultural and industrial being the most predominant land use type. Detailed land use profile for each SunRail station is shown in Appendix B (Figure B.1-B.15).

3.2.1.1 SunRail

Several data preparation steps were followed for developing the first MOE. First, the stations was divided into three areas: (1) Downtown Stations[2] including Lynx Central station, Church Street station, and Orlando Health/Amtrak station; (2) Outside Downtown Stations comprised of DeBary, Sanford, Lake Mary, Longwood, Altamonte Springs, Maitland, Winter Park, Florida Hospital Health Village, and Sand Lake Road stations; (3) Phase-2 stations including northbound DeLand and Southbound Meadow Woods, Osceola Parkway, Kissimmee Amtrak, and Poinciana stations. Second, a 1-mile buffer was created around each of the SunRail stations. Please note that overlapping problem happens for downtown stations' buffer area due to the nearness of the stations. As a result of the overlapping, the same parcel might be part of two different stations' buffer areas. ArcGIS proximity tool (Near Generate Table operation) was used to assign a parcel to a unique station. More specifically, the straight line distances

[2]Downtown Stations are fixed based on the downtown area projected at 'I-4 Ultimate Project' construction map at https://i4ultimate.com/construction-info/construction-map/#constructionAlerts

from each parcel to the nearest station was computed and the parcel was assigned to the station which was the nearest (Hess & Almeida, 2007). Figure 3.5 demonstrates an example of the station overlapping problem in the downtown area. Third, the property value evaluation was carried out for the parcels within the 1-mile buffer. These parcels are referred to as Case parcels. Figure 3.6-3.9 presents the result. Fourth, the average property value (per acre) for all parcels for each station by 5 land use types were computed as mentioned before (see Table 3.2).

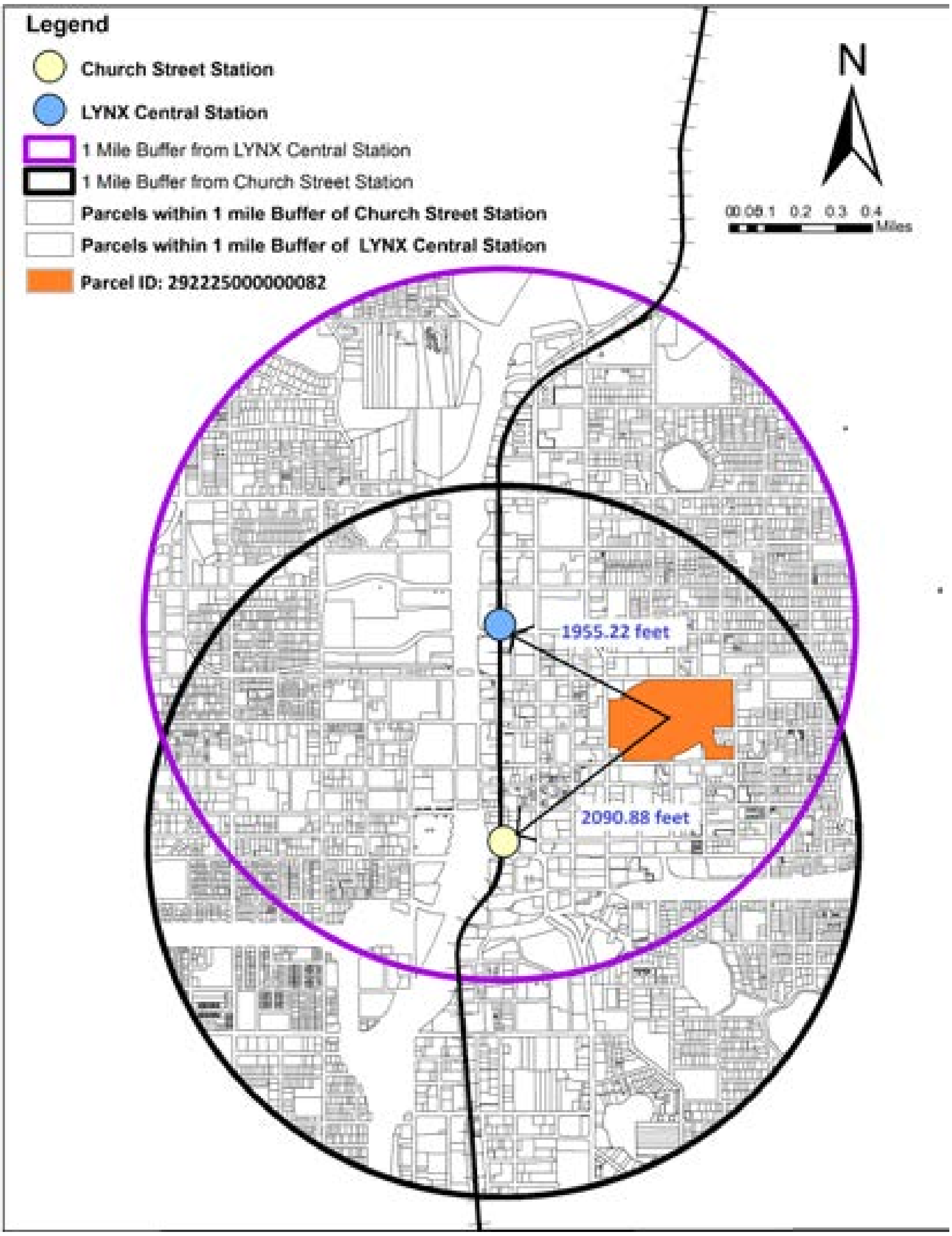


Figure 3.5: Example of Overlapping Buffers and Proximity Analysis

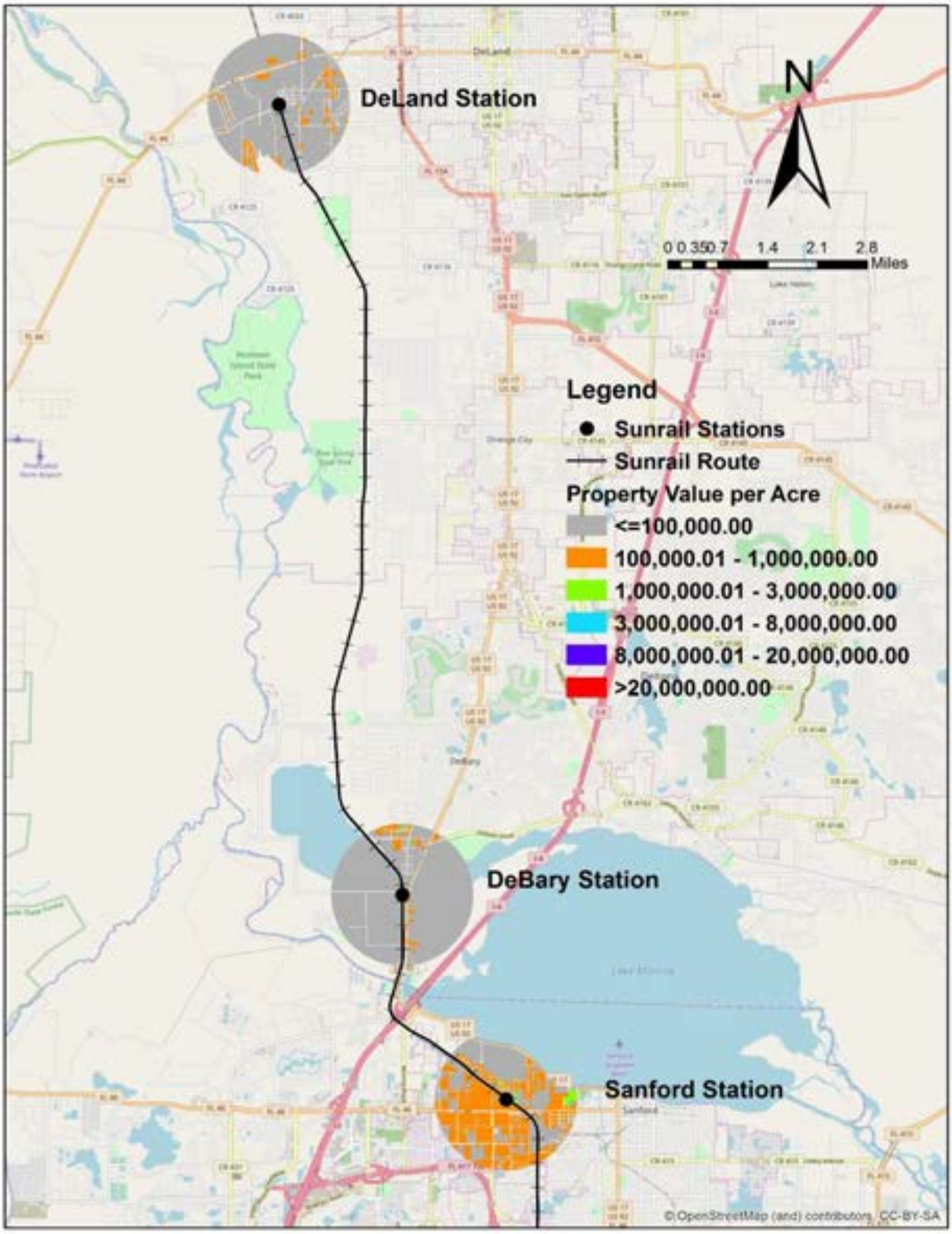


Figure 3.6: Average Property Value (DeLand, DeBary and Sanford Station)

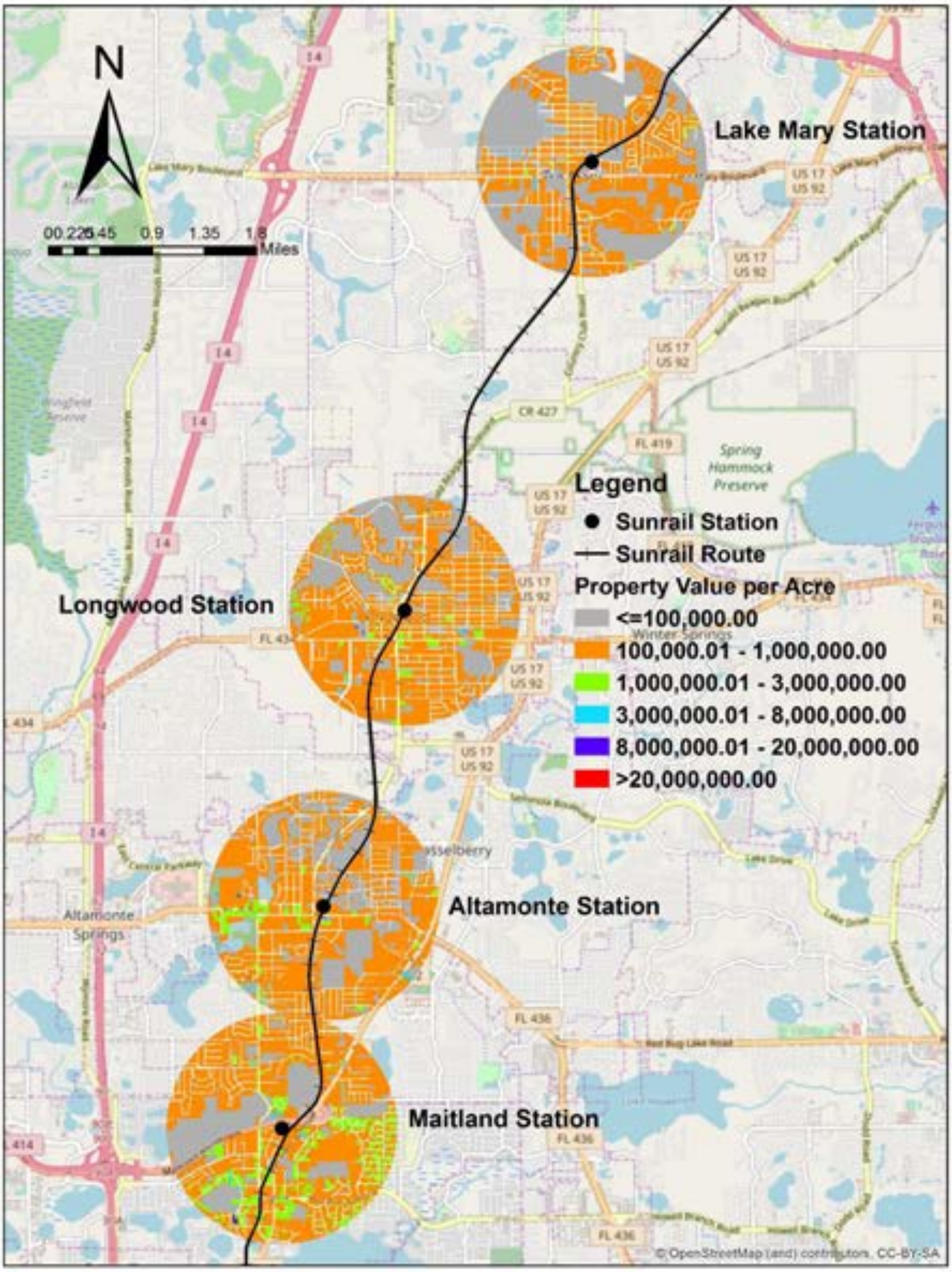


Figure 3.7: Average Property Value (Lake Mary, Longwood, Altamonte Springs and Maitland Station)

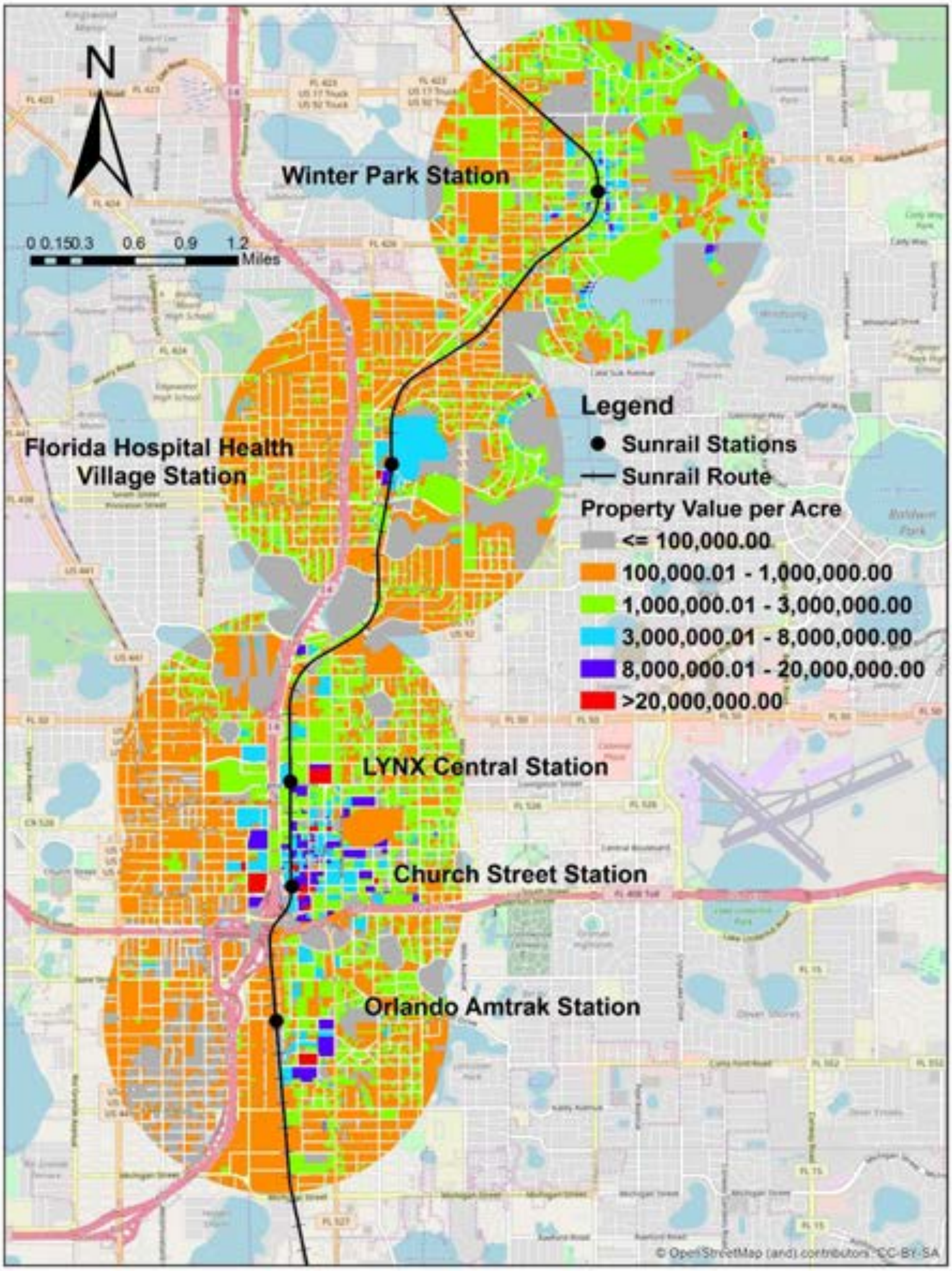


Figure 3.8: Average Property Value (Winter Park, Florida Hospital Health Village, LYNX Central, Church Street and Orlando Amtrak Station)

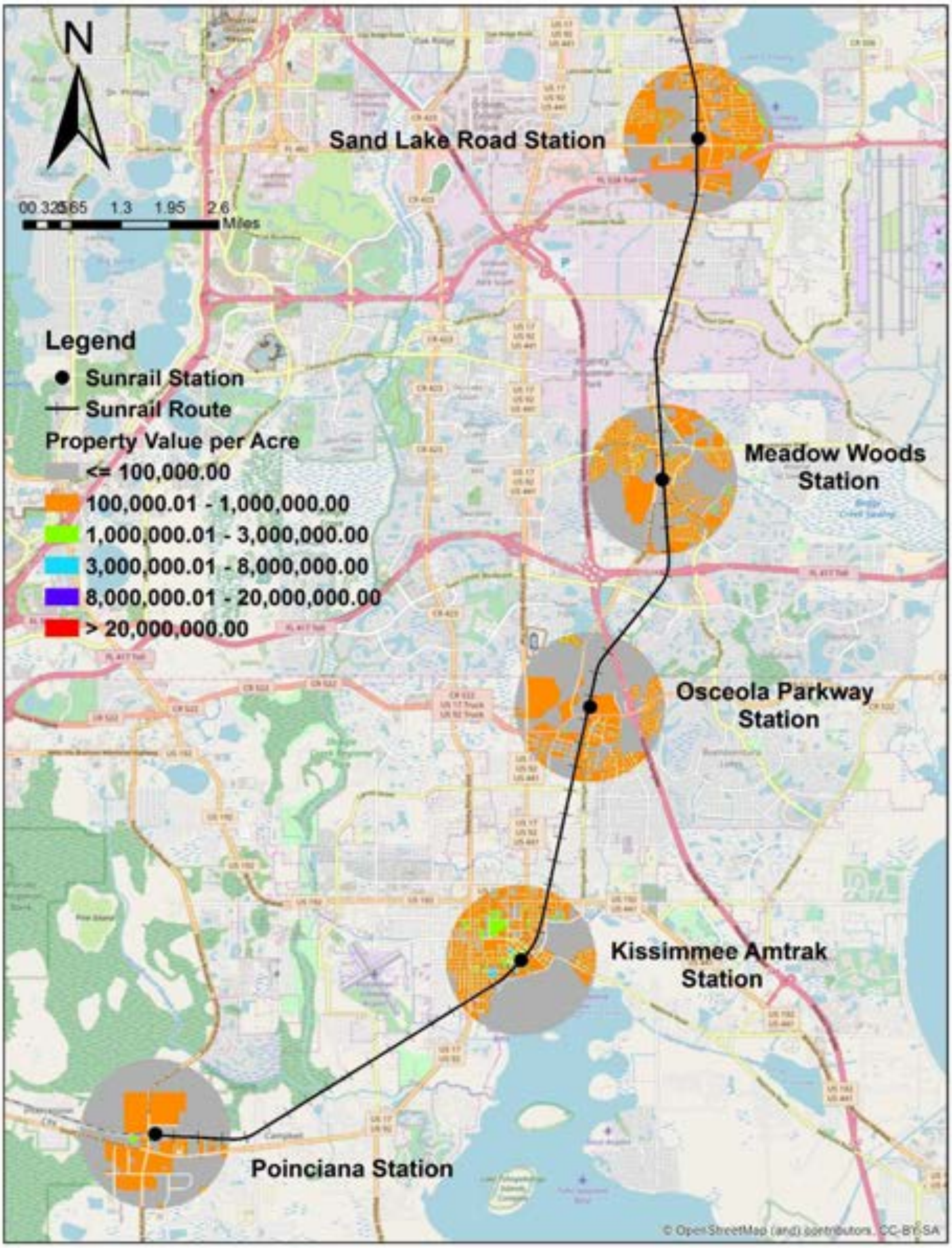


Figure 3.9: Average Property Value (Sand Lake Road, Meadow Woods, Osceola Parkway, Kissimmee Amtrak and Poinciana Station)

As expected, property prices in downtown and near downtown area stations are the highest. More specifically, among the downtown stations, property value for multi-family residential, retail/office, and institutional land use types are the highest for Church Street. On the other hand, the values for single family residential and industrial land use categories are the highest for the Winter park excluding downtown stations. Please note that the construction of southern Phase-2 stations did not begin until 2016.

Table 3.2: Average Property Value per Station by Land Use Type for 2012

Station	Single Family Residential (USD)	Multi-Family Residential (USD)	Retail/Office (USD)	Industrial (USD)	Institutional (USD)
Downtown Stations					
LYNX Central Station	906,590	988,491	1,790,503	630,578	1,462,136
Church Street Station	981,280	2,401,727	5,214,377	281,022	4,683,842
Orlando Amtrak/Sligh Blvd Station	625,409	474,380	1,159,111	419,089	1,492,057
Phase-I Outside Downtown Stations					
DeBary Station	49,601	--	136,409	225,568	181,761
Sanford Station	401,223.	570,141	254,061	361,616	400,609
Lake Mary Station	288,673	337,571	673,920	--	81,433
Longwood Station	345,402	344,385	599,405	413,580	564,793
Altamonte Springs Station	295,864	373,609	829,133	429,185	653,548
Maitland Station	632,226	903,955	708,436	430,167	569,418
Winter Park Station	1,393,663	1,353,358	1,601,312	789,060	1,449,902
Florida Hospital Health Village Station	918,072	626,616	1,208,935	724,904	1,083,417
Sand Lake Road Station	456,825	363,302	405,738	256,050	280,571
Phase-II Stations					
DeLand Station	111,661	86,914	56,488	71,328	108,124
Meadow Woods Station	534,753	351,368	75,014	387,552	159,837
Osceola Parkway Station	414,276	245,964	272,880	204,007	161,955
Kissimmee Amtrak Station	255,253	406,806	693,784	317,913	1,034,599
Poinciana	173,863	--	129,603	379,231	175,979

The average property value per land use type for downtown, outside downtown, and Phase-2 stations were computed. The values are presented in Figure 3.10. As expected, property price for all land use categories around downtown stations are the highest.

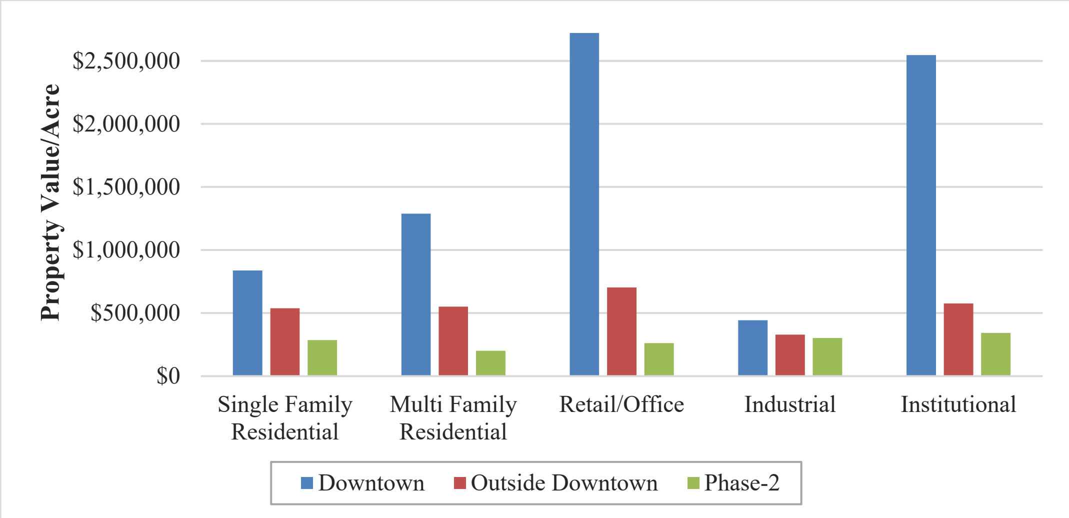


Figure 3.10: Average Property Value across Downtown, Outside Downtown, and Phase - 2 Stations

<u>Control Area Selection</u>

The change in property values in the vicinity of the stations might not be attributable only to SunRail construction without examining the changes in the other parts of the urban region. To determine if the changes in property values is truly influenced by SunRail's development, control areas were systematically selected. Figure 3.11 shows the candidate control areas for the SunRail Stations.

The following procedure has been adopted for selecting the control areas. First, 2 mile and 8 mile buffers were created respectively around the stations. The parcels located in the intersection of the two buffers (area beginning from the circumference of the 2 mile buffer) were selected to be the candidate control areas. Next, based on similar land use type and property value range (within 15% of the mean property value found for each land use type for case areas), control areas for analysis were identified. The same number of control parcels were selected for each land use type for each station. Second, the control parcels were assigned to a unique station by using the nearest distance analysis. Third, the same procedure as case area is followed to estimate average property price per land use category type for downtown, outside downtown, and Phase-2 stations. The values are presented in Figure 3.12.

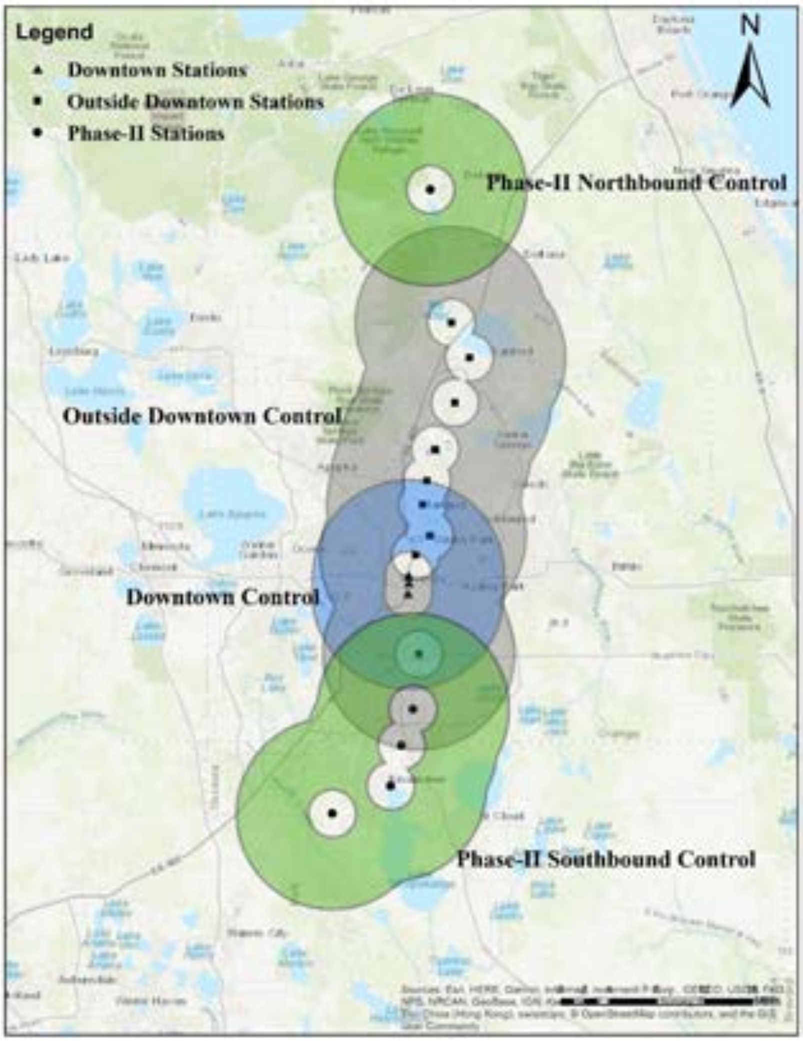


Figure 3.11: Candidate Control Areas for SunRail Stations

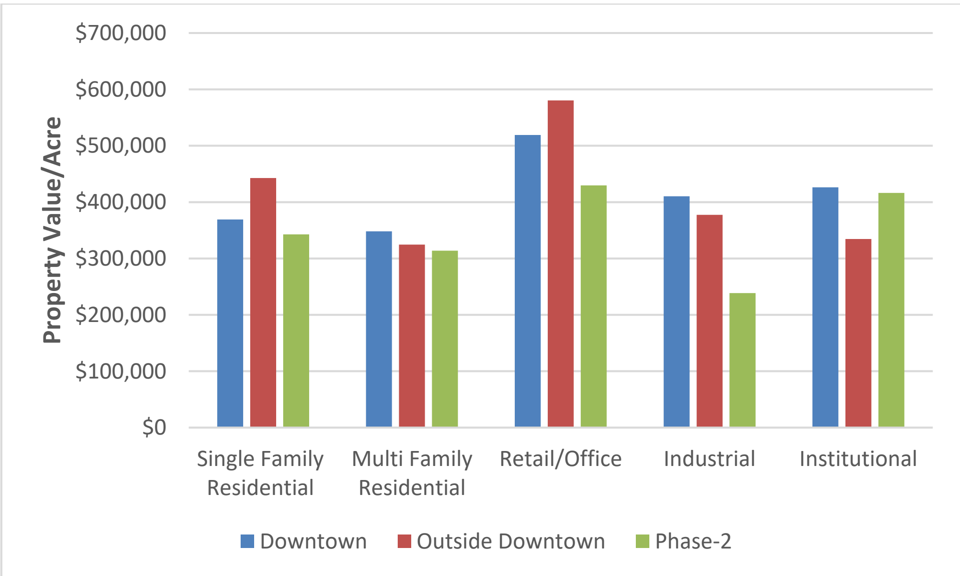


Figure 3.12: Average Property Value across Downtown, Outside Downtown, and Phase - 2 Stations for Control Area

3.2.1.2 I-4 Expansion

The data preparation steps for I-4 expansion are as follows:

- First, a 1-mile buffer was created around the I-4 site. The parcels within this buffer are the case parcels. Variation in property value per acre area within the parcels is presented in Figure 3.13 and land use profile is presented in Figure 3.14.
- Second, overlapping parcels were assigned to a particular I-4 segment (Attraction, Downtown, Ivanhoe and Altamonte) by estimating straight line distance from each parcel to the nearest roadway section. The parcel nearest to the segment was assigned to that particular segment.
- Third, the average property value for each area by land use category was estimated following the same procedure described in 3.2.1.1. Figure 3.15 presents the average property value by land use category for all four segments. The average property value for commercial and institutional parcels is the highest in the downtown segment while property value of industrial parcels is higher in the Ivanhoe segment. No significant variation in single family and multi-family parcels could be observed among the four segments.
- Fourth, similar work was carried out for other years as well.

<u>Control Area Selection</u>

The control areas are selected following the same procedure described for the SunRail Stations. Figure 3.16 shows the candidate control areas for the I-4 expansion segments. Also, the same procedure employed for estimating average property value per land use category type for case segments is used for similar computation for control segments for Attraction, Downtown, Ivanhoe and Altamonte control buffer areas. The values are presented in Figure 3.17.

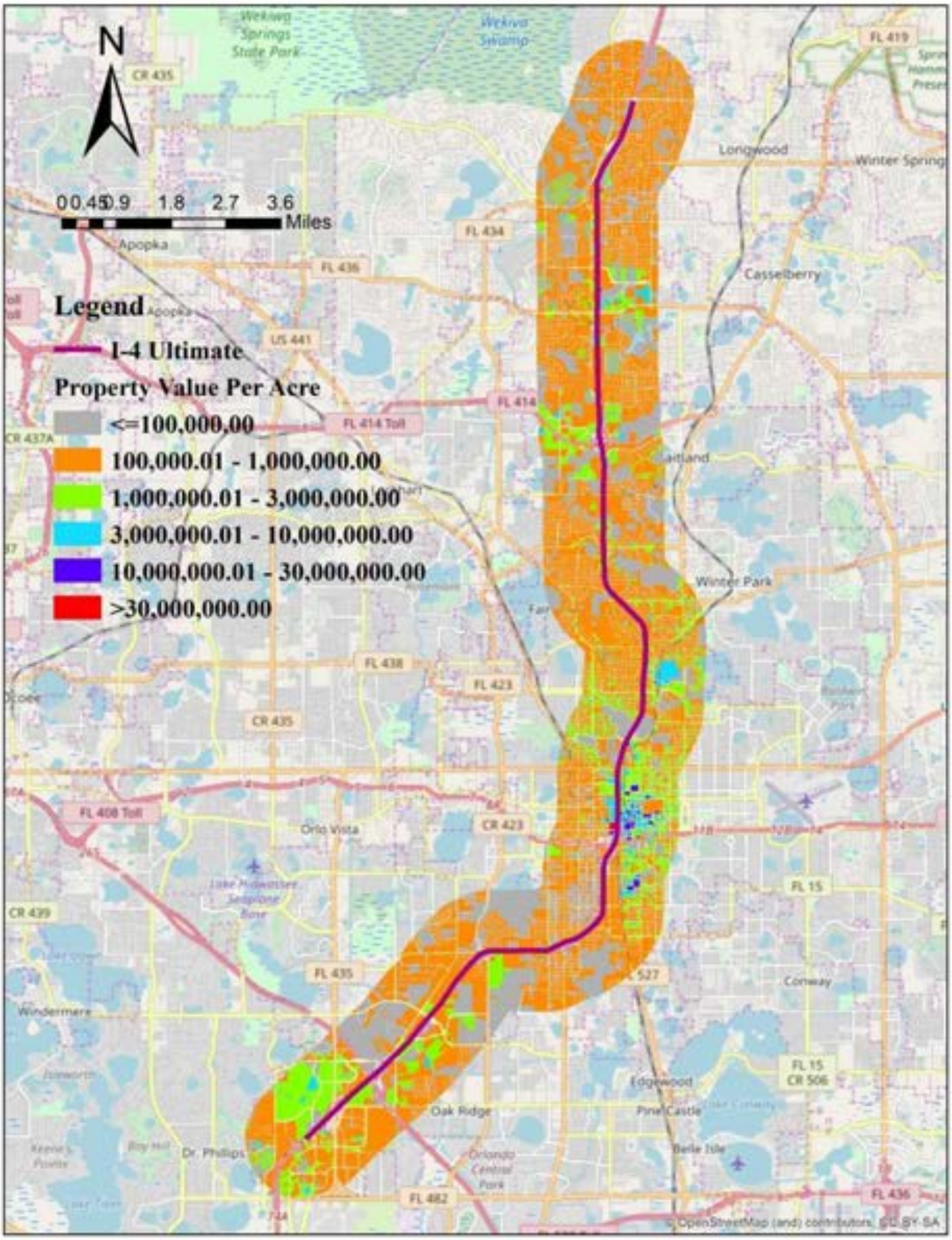


Figure 3.13: Property Value Around 1-mile Buffer of I-4 Expansion Route

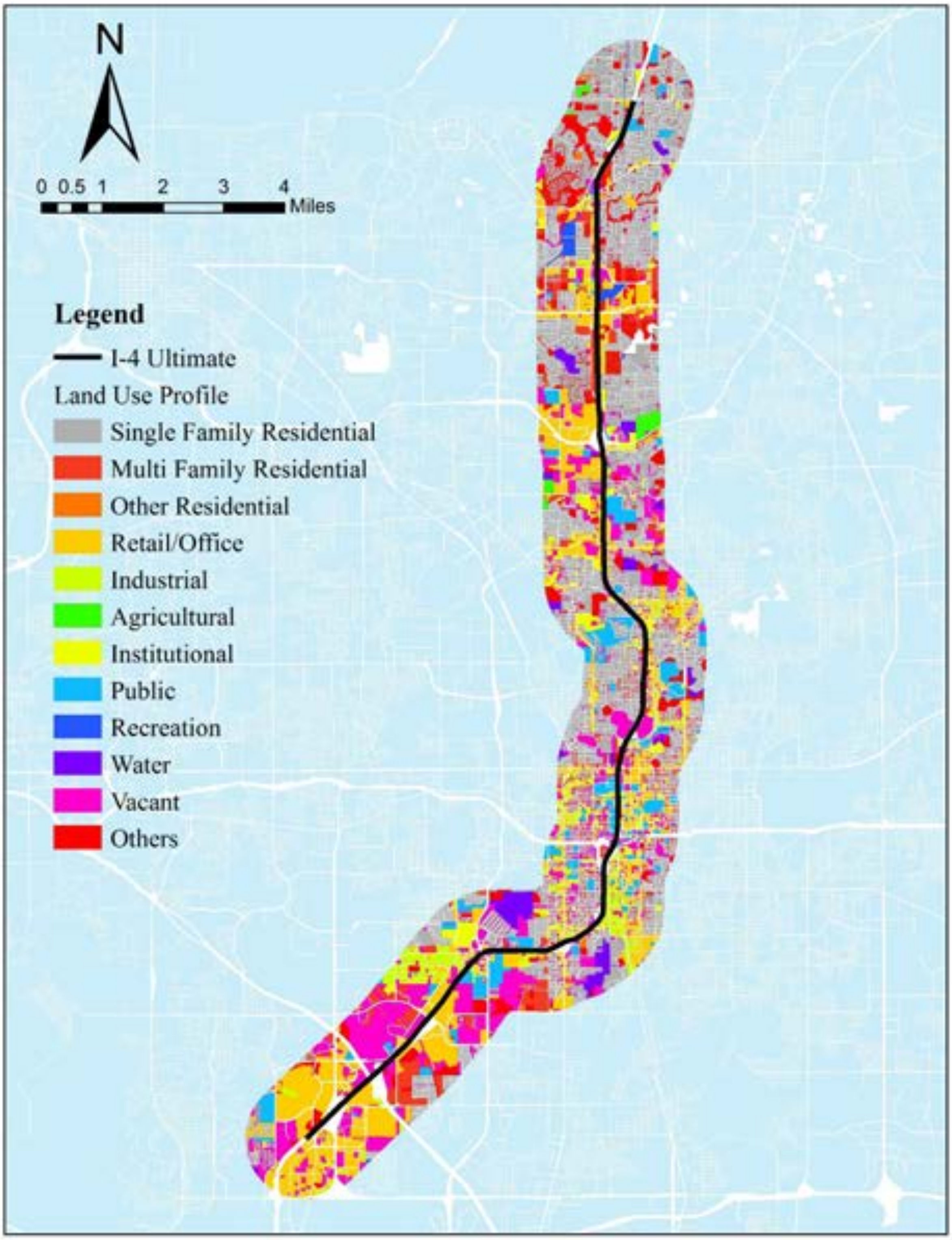


Figure 3.14: Land Use Profile Around 1-mile Buffer of I-4 Expansion Route

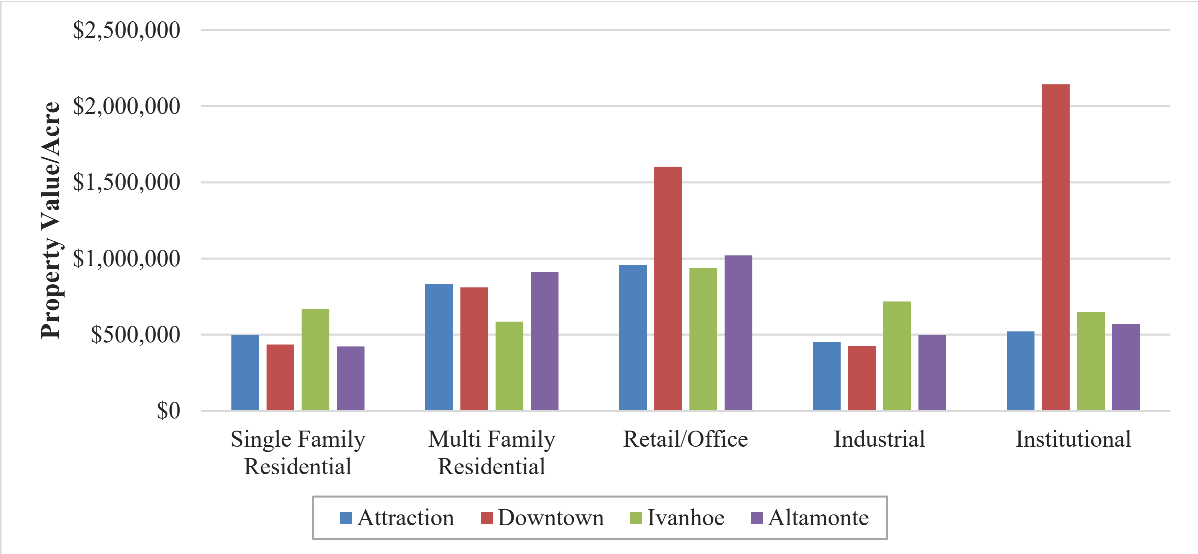


Figure 3.15: Average Property Value across I-4 Expansion Stretches

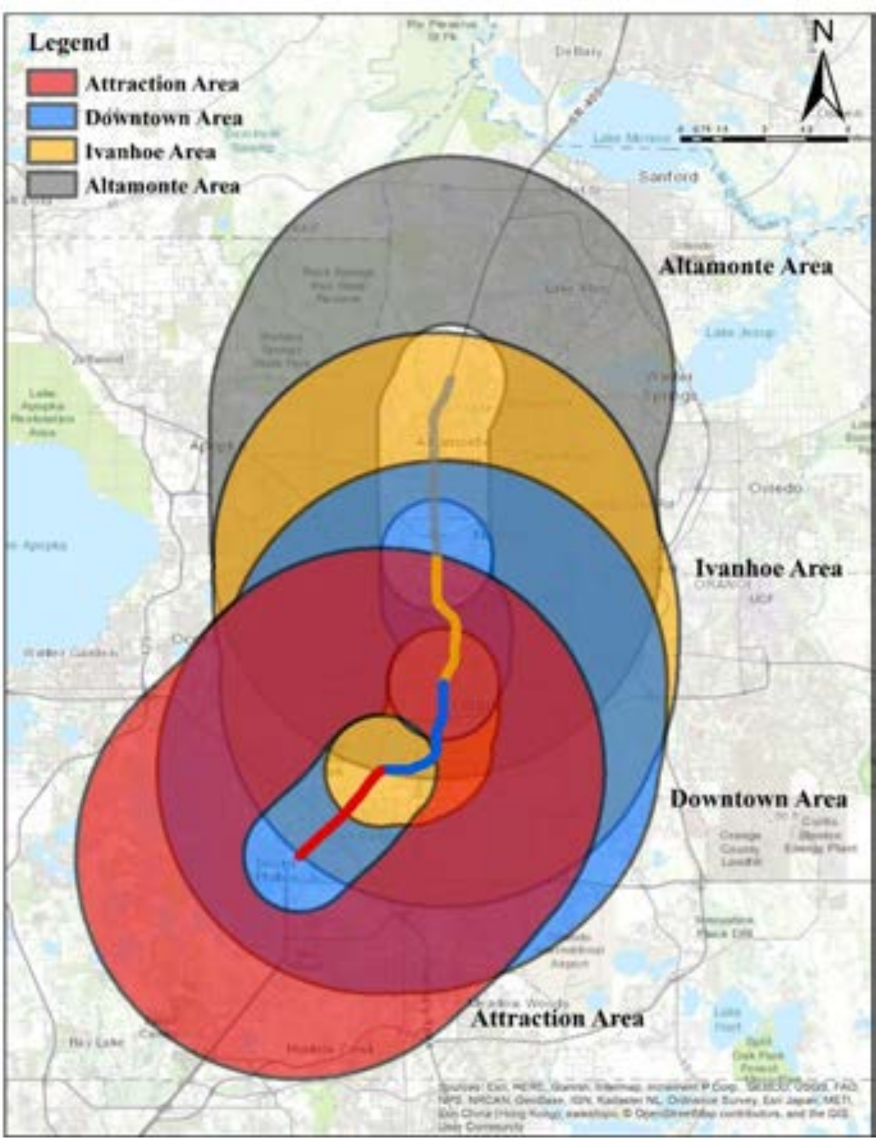


Figure 3.16: Candidate Control Areas for I-4 Expansion

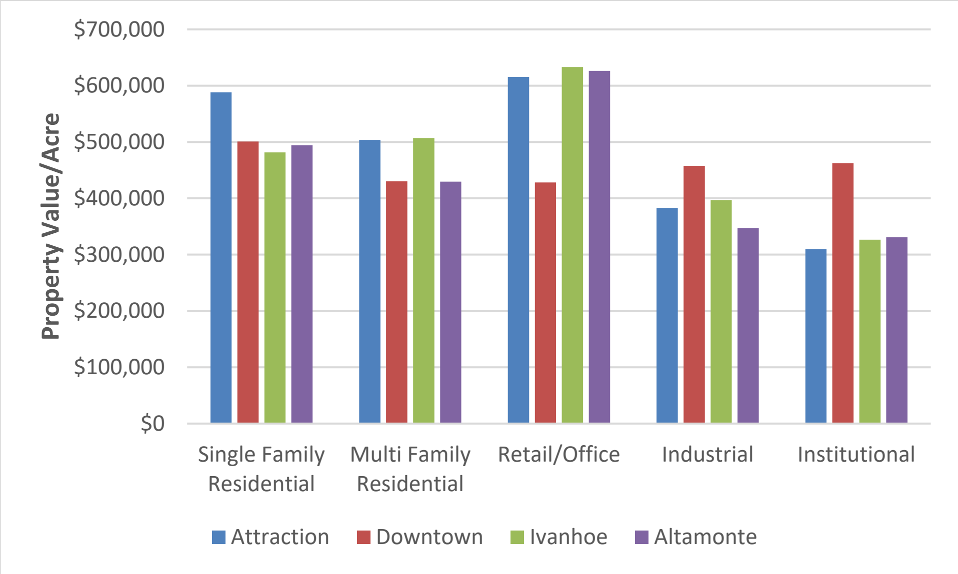


Figure 3.17: Average Property Value across I-4 Expansion Control Stretches

3.2.1.3 JUICE Orlando Bikeshare

Given the spatial reach of the Juice system is quite small in relation to the region it was not possible to identify a viable control data sample. Hence, to illustrate the changes in MOEs due to Juice stations, the stations were classified as downtown and non-downtown stations. The analysis of MOEs was conducted as a comparison of two case samples to illustrate the differences across measures due to Juice stations. For the analysis, the downtown area was created using the following procedure. First, using the downtown zip code (32801), a shapefile was created by clipping it from the tiger shapefile of census tracts. Second, this shapefile was merged with the Downtown development board area (DDA) shapefile downloaded from the City of Orlando website. DDA is the core area for the overall development planned around downtown by Downtown Development Board (DDB). Figure 3.18 represents the merge of Downtown zip code area and DDA.

The data preparation steps for bikeshare stations are as follows:

- First, a 250-meter buffer was created around each bikeshare station. A 250 meters buffer around each station was selected based on earlier research investigating bikeshare systems (Faghih-Imani et al., 2014). The parcels within this buffer, obtained by clipping the DOR parcel shapefile. The stations not part of downtown were classified as non-downtown stations. Variation in property value per acre area within the parcels is presented in Figure 3.19 and land use profile is presented in Figure 3.20.
- Second, overlapping parcels to were assigned to a unique station by estimating straight line distance from each parcel to the nearest station. The parcel nearest to the station was assigned to that particular station.
- Third, average property value for each area by land use category was estimated following the same procedure described before. Figure 3.21 presents the average property value comparison across downtown and non-downtown stations. The property value is consistently higher in the downtown area for all land use type except industrial land usage, but the margin is very small. From Figure 3.21, it is clearly seen that multi-family residential, office and institutional land use type have the higher property price than others in downtown.

- Fourth, similar analysis was repeated for other years as well.

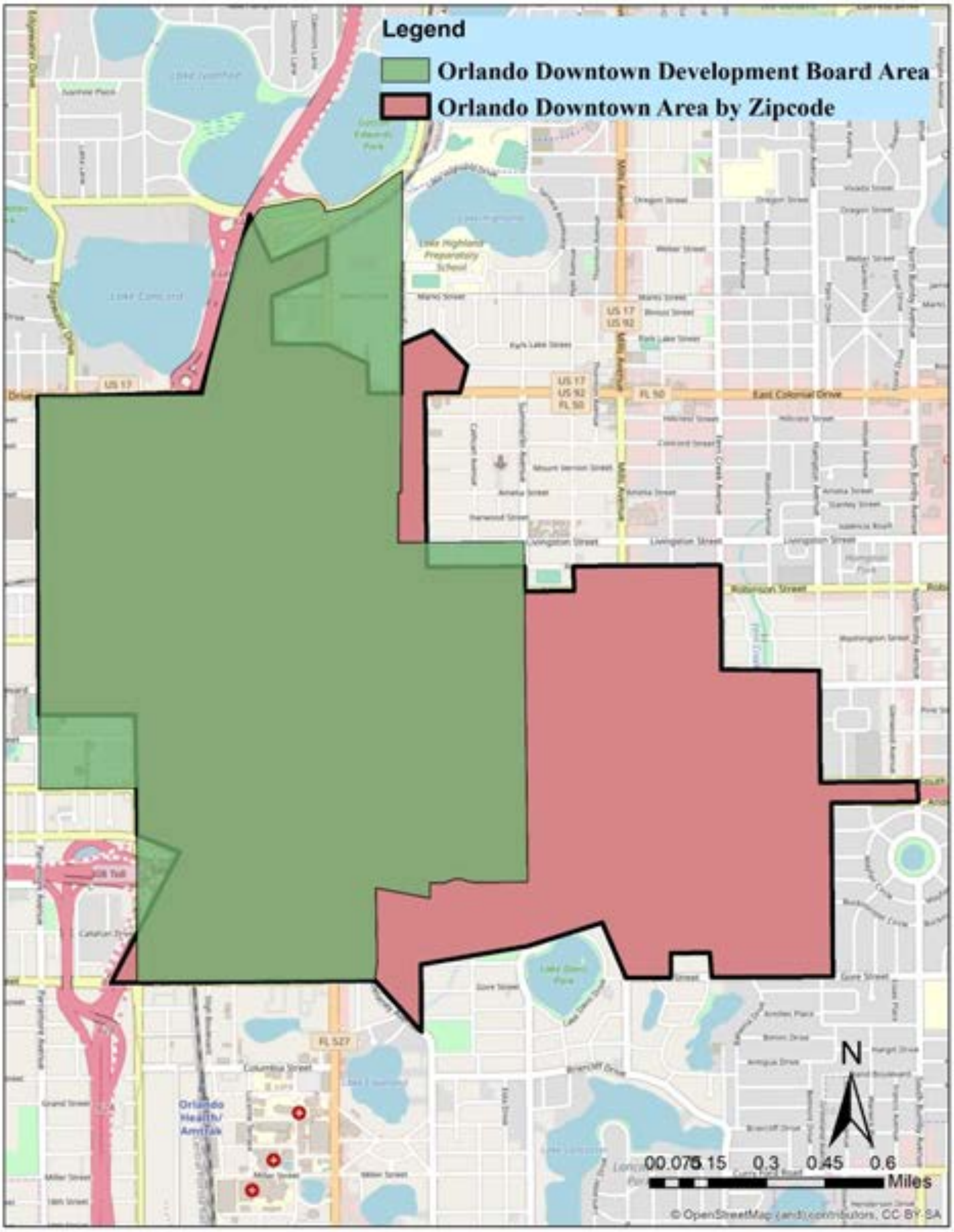


Figure 3.18: Orlando Downtown Area

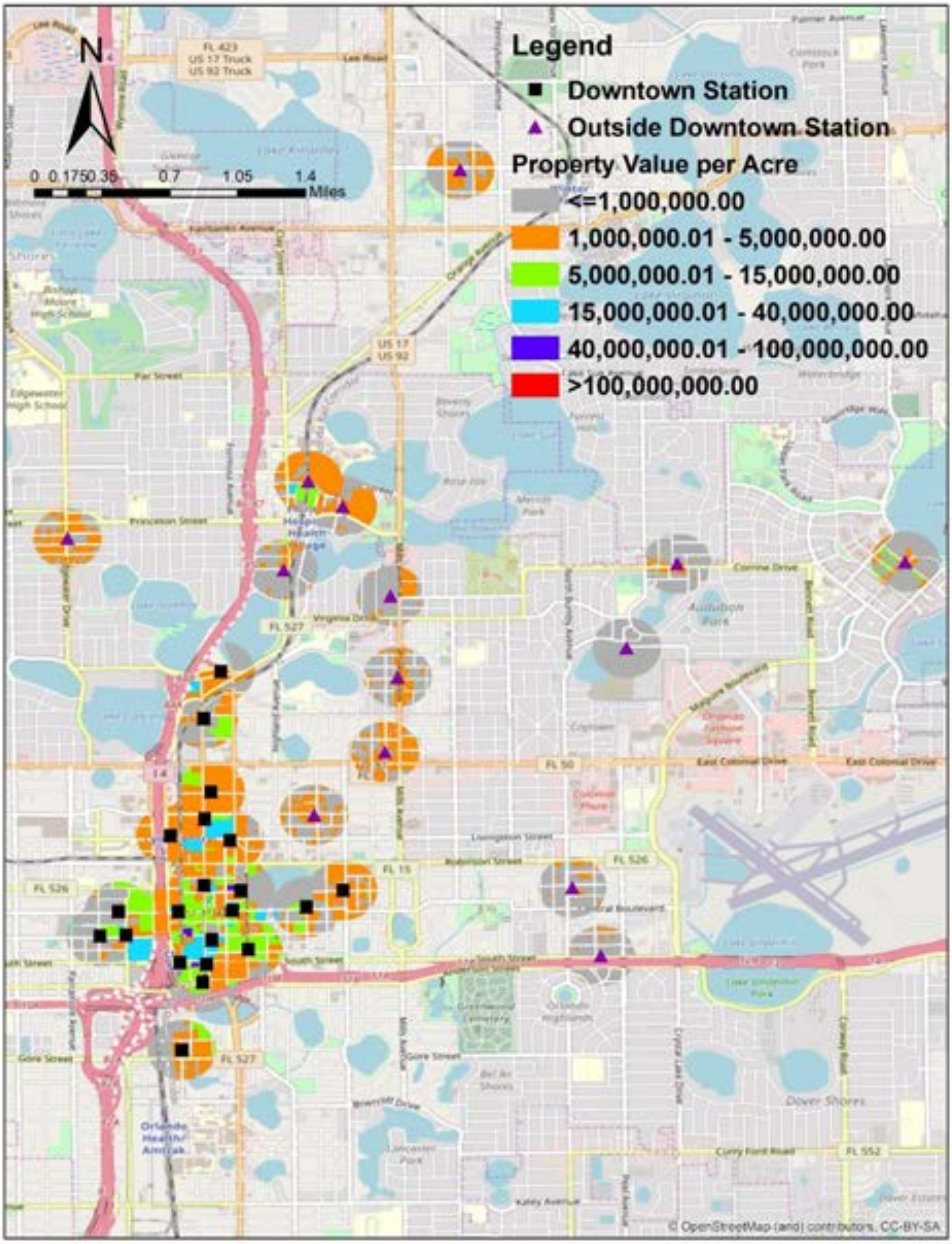


Figure 3.19: Average Property Value Around 250-meter Buffer of Bikeshare Stations

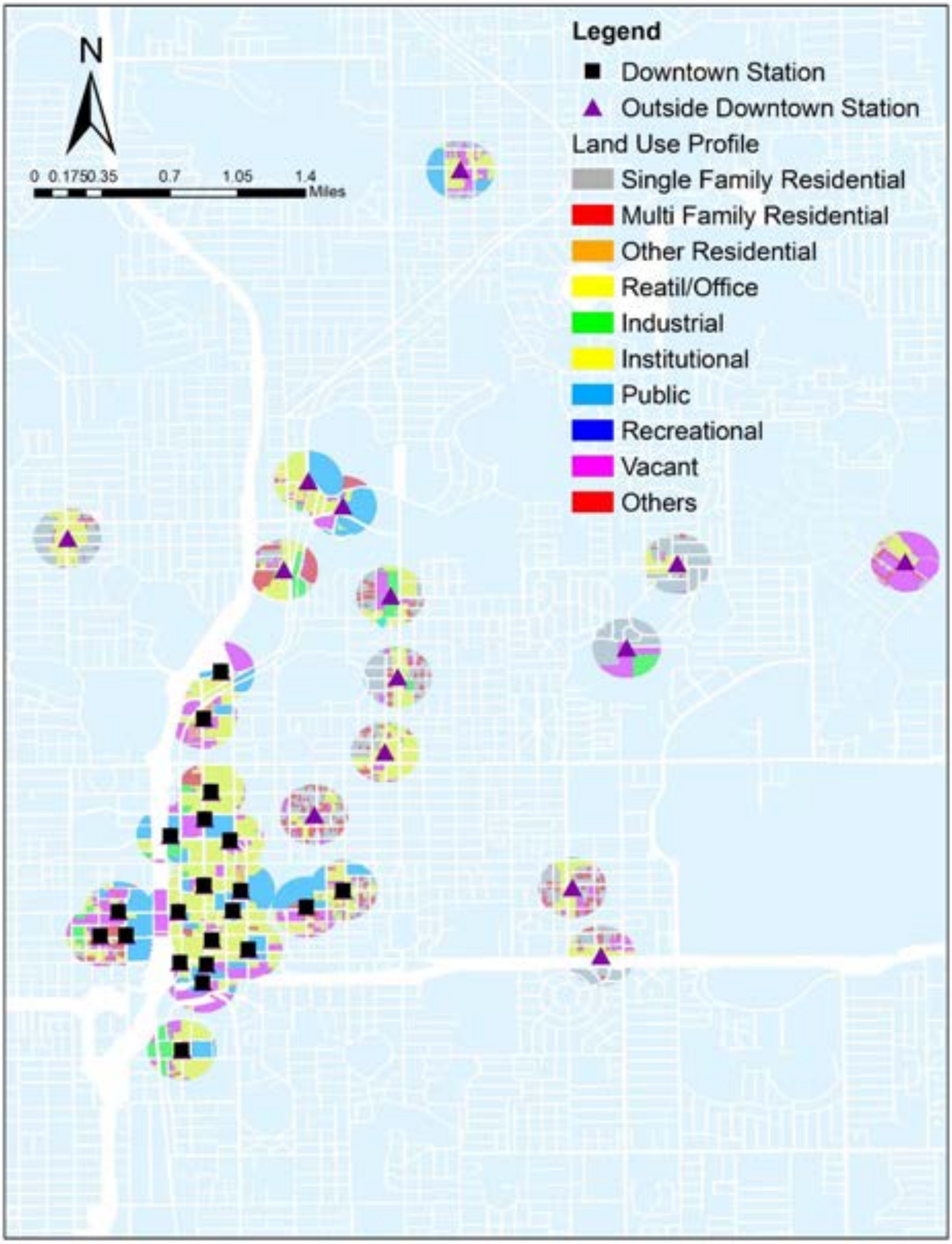


Figure 3.20: Land Use Profile within 250-meter Buffer of Bikeshare Stations

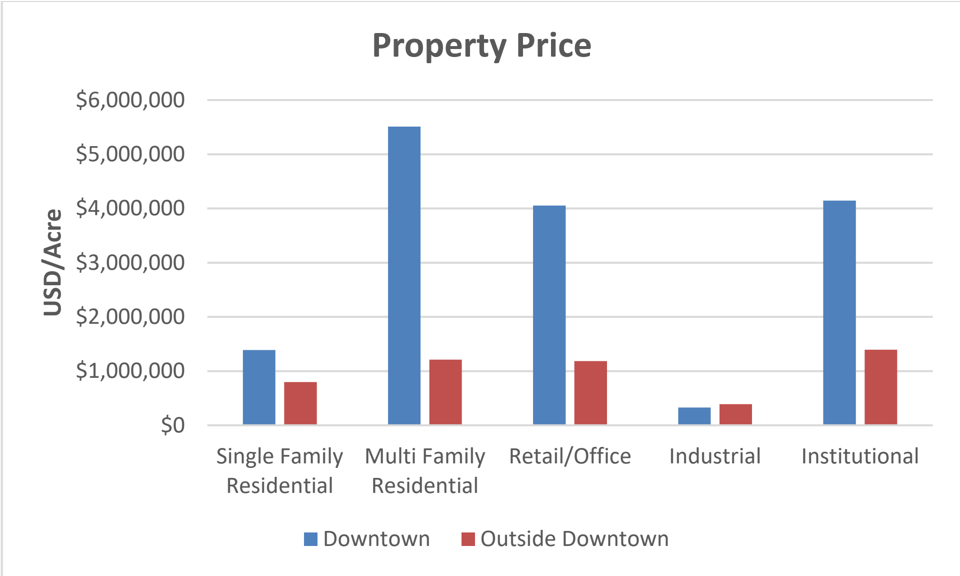


Figure 3.21: Distribution of Average Property Value between Downtown and Non-downtown Bike Share Stations

3.2.2 Accessibility to Employment

Job accessibility can be defined as number of jobs accessible from a desirable point. To capture the change in number of jobs around the chosen investment projects, the employment (number of workers in the labor force) data for the years 2011-2016 was drawn from American Community Survey (ACS). This data contains information on total employment of individuals aged 20 through 64 years. These data were merged with the Florida census tract shapefile using the unique ID created by concatenating county and census tract IDs. Figure 3.22 represents the distributions of total number of employed persons working across the census tracts of Florida. As expected, the highest concentration of number of employed persons can be observed in the Central Florida region.

<u>Driving Network Area</u>

In this study, job accessibility was computed using jobs accessible within a particular driving distance. Several travel time values are potentially used in literature to identify job accessibility (Fan et al., 2012, Manaugh et al., 2010). In this study, 10 minutes' drive time in car was used from the origin of interest as the appropriate threshold. For example, if a person uses SunRail, their accessibility to jobs has been expanded to a 10-minute drive around each station.

Street network of Florida has been used to draw driving area for both driving time and driving distance. 2011-2016 street network of 'NAVSTREET' data was used. To estimate driving time, speed limit of the corresponding street is needed. A fixed speed was defined for a street from variable called 'Speed Category'. Conversion of speed from defined speed limit range is shown in Table 3.3.

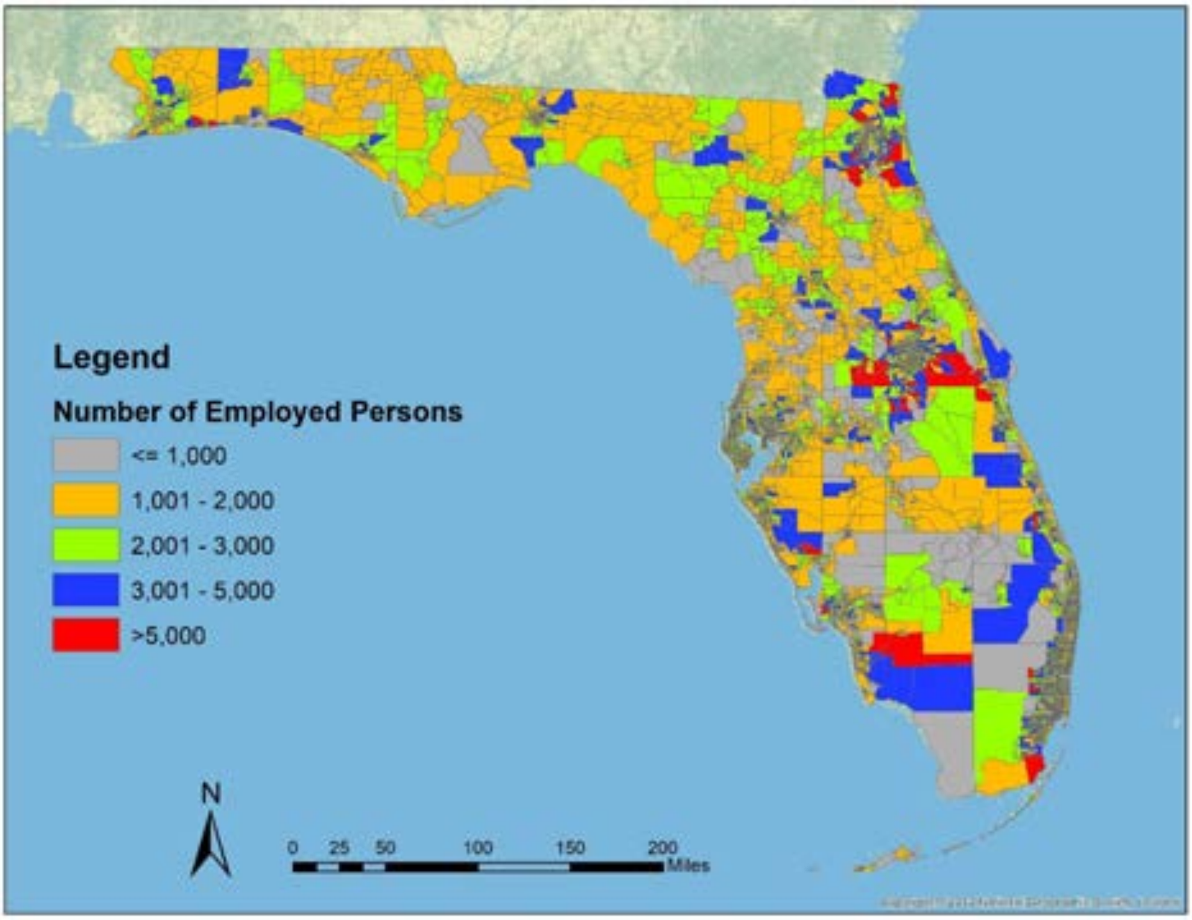


Figure 3.22: Distribution of Number of Employed Persons across Census Tracts in Florida

Table 3.3: Speed Definition

Speed Category	Definition (MPH)	Speed, V (MPH)
1	Above 80	80
2	65-80	70
3	55-64	60
4	41-54	50
5	31-40	40
6	21-30	30
7	6-20	20
8	Below 6	6

Travel time (in minutes) needed to travel the corresponding street was estimated by using equation, T = (L/V) *60 where T is travel time needed to travel the total length of street in minutes, L is total length in miles and V is speed in mph (as mentioned Table 3.3).

3.2.2.1 SunRail

The data preparation steps for SunRail stations are as follows: First, 10 minutes driving area has been selected from each SunRail station from street network of Florida by using network analyst tools in GIS. Case group areas (census tracts) within first 10 minutes driving network area were selected. Figure 3.23 presents 10 minutes car driving area across SunRail stations. Second, each census tract of the driving area zone was assigned to one station. Then total number of jobs for those census tracts was accumulated for each station. Note that, all possible jobs that are accessible from each SunRail station were captured, so it is quite possible that the same job is counted in multiple stations' buffer. Figure 3.24 represents the number of jobs available in the census tracts that coincide with case driving area of SunRail stations. Third the average employment counts across stations of downtown, Phase-1 other stations, and Phase-2 stations were computed. Figure 3.25 presents the count of employed persons within the station's threshold area. As expected, employment concentration is higher around the downtown stations while phase-II stations have much lower concentration. The highest concentration is observed for Church Street station followed by Orlando Amtrak Blvd. station (Downtown) and Florida hospital station (Phase-I outside downtown).

Control Area Selection

To examine the economic impact of SunRail commuter system with respect to number of employed persons, control areas were selected using following procedure: First, a 10 minutes car driving area around the stations was drawn. For this study, travel time between the 20 to 30 minute car driving time was selected as control threshold. Second, the census tracts located within this 10 minute threshold area (at least 20 minutes away and within 30 minutes) were selected to be the control parcels. Figure 3.26 represents the control area for SunRail stations.

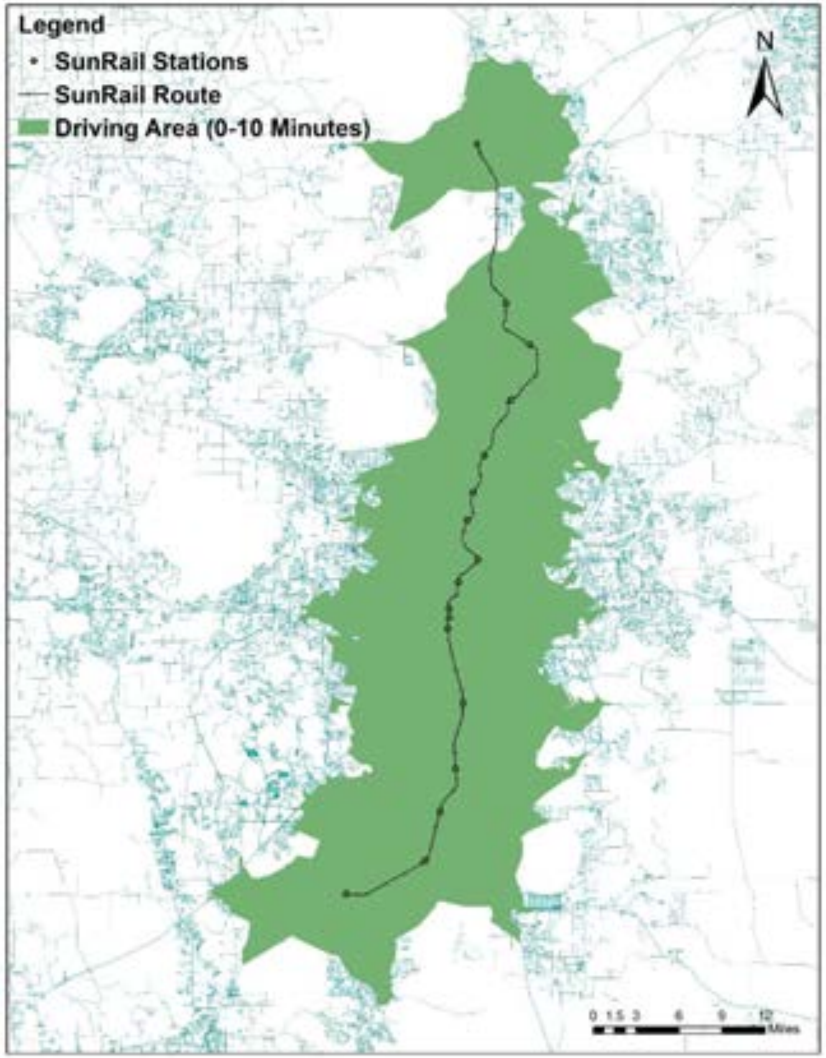


Figure 3.23: Driving Network Area Across SunRail Stations

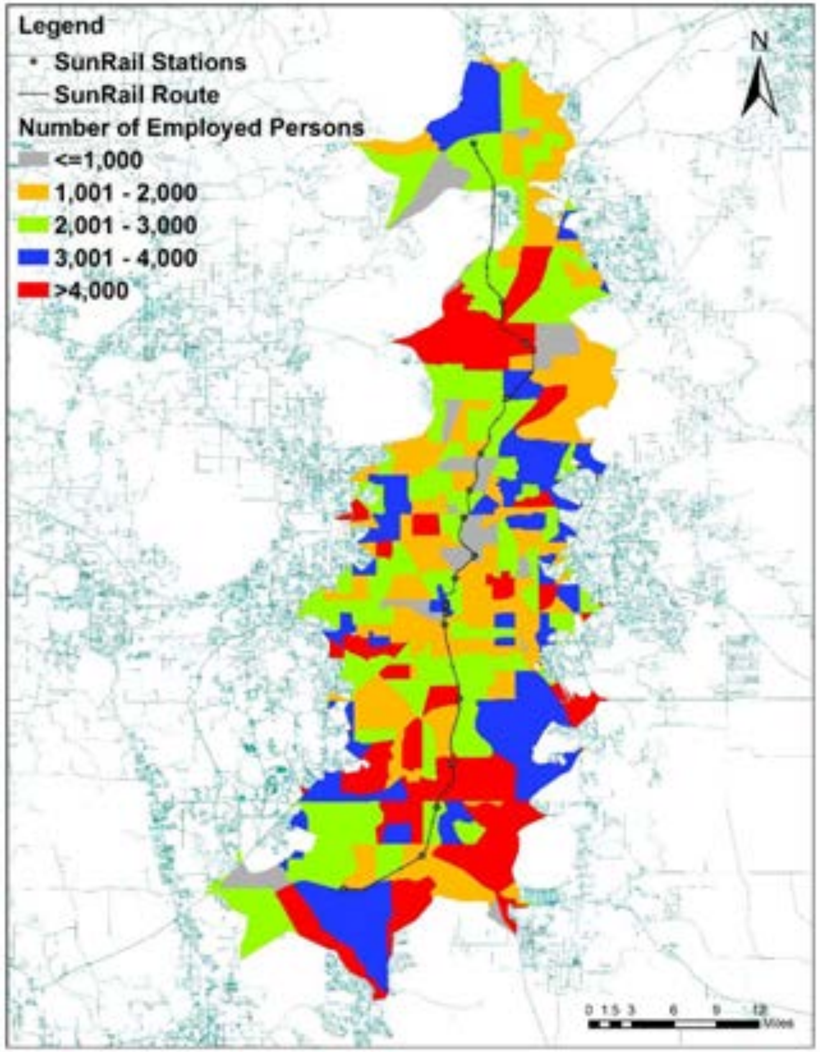


Figure 3.24: Accessible Number of Jobs Across SunRail Stations

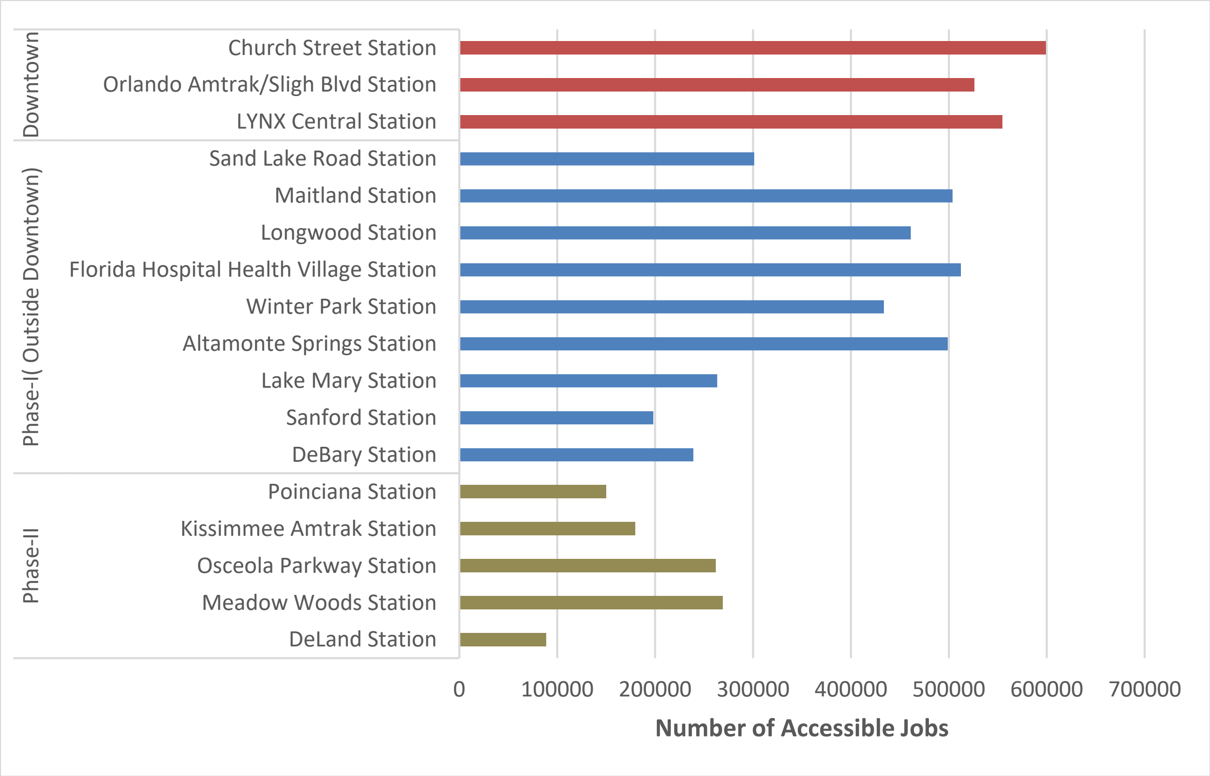


Figure 3.25: Comparison of Number of Accessible Jobs across Downtown, Non-downtown and Phase-II Stations

Figure 3.26: Control Area Across SunRail Station

3.2.2.2 I-4 Expansion

The same procedure as used for SunRail in 2.2.1.4 is applied for generating the count of employed persons for I-4 expansion areas. First, to create a car driving area around I-4 expansion, midpoint for each of four segments (Attraction, Downtown, Ivanhoe and Altamonte) was created. Second, a 10 minute driving area has been selected from each I-4 segment's midpoint by using same technique as for SunRail stations. Figure 3.27 presents a 10 minutes car driving area across I-4 expansion.

The distribution of number of employed persons is presented in Figure 3.28. The accessible employment counts across the four I-4 expansion segments are presented in Figure 3.29. It can be seen that employment concentration is higher in the downtown zone followed by Altamonte and Ivanhoe. For other years same procedure will be followed to capture the changing trend around I-4 expansion.

<u>Control Area Selection</u>

The control areas are selected following the same procedure described for the SunRail Stations. A 10 minute (in between 20-30 minutes) car driving time were selected for control area. Control area for I-4 expansion is shown in Figure 3.30.

Figure 3.27: Driving Network Area across I-4 Expansion

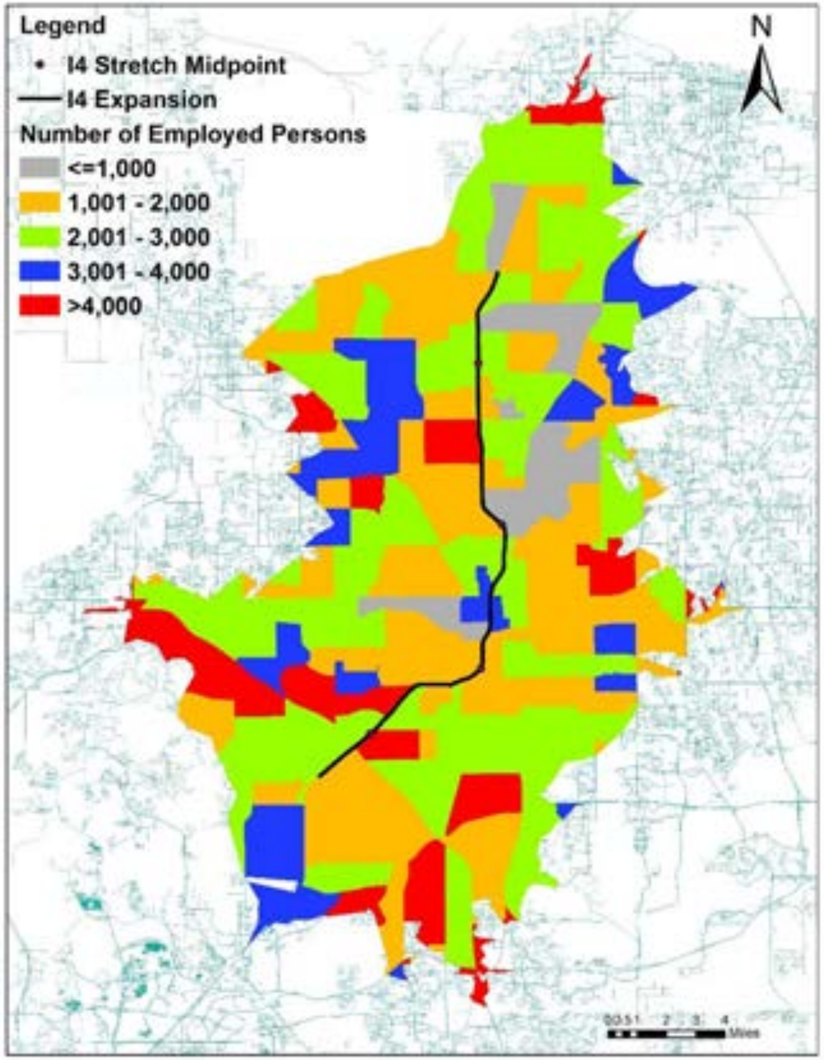


Figure 3.28: Number of Accessible Jobs Across I-4 Expansion

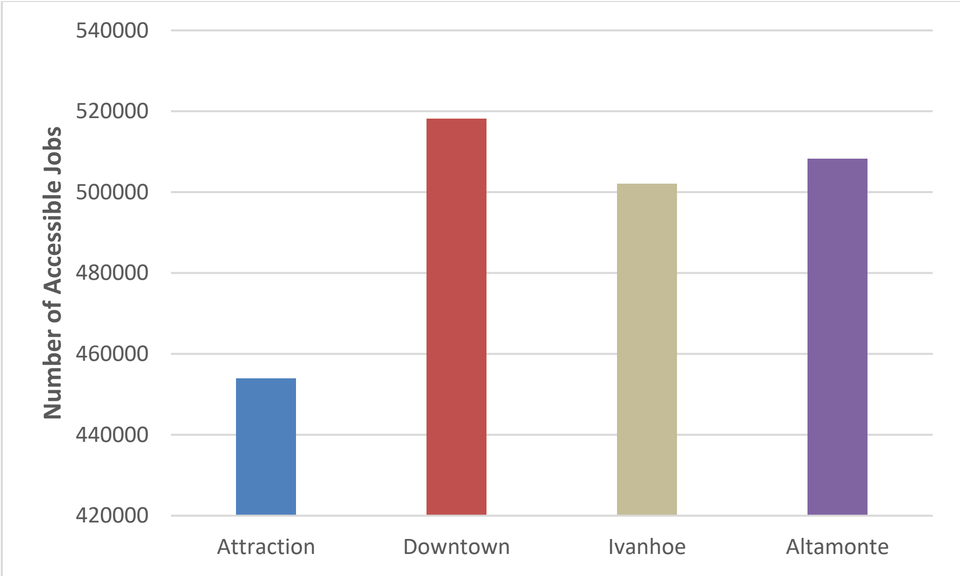


Figure 3.29: Average Number of Accessible Jobs per I-4 Expansion Stretch

Figure 3.30: Control Area Across I-4 Expansion

3.2.2.3 JUICE Orlando Bikeshare

The count of employed persons around bikeshare stations is computed similar to the approach described earlier with a minor change. Instead of using a 10 minute driving distance, a 2 mile distance band is considered. For a flat, paved road in good condition 20 km/h or 12.4 mph is considered as average biek speed. With average speed of 12.4 mph, a bicyclist can travel 2.067 miles[3] in 10 minutes. Figure 3.31 represents the 2-mile area considered for each bikeshare station of downtown and outside downtown area.

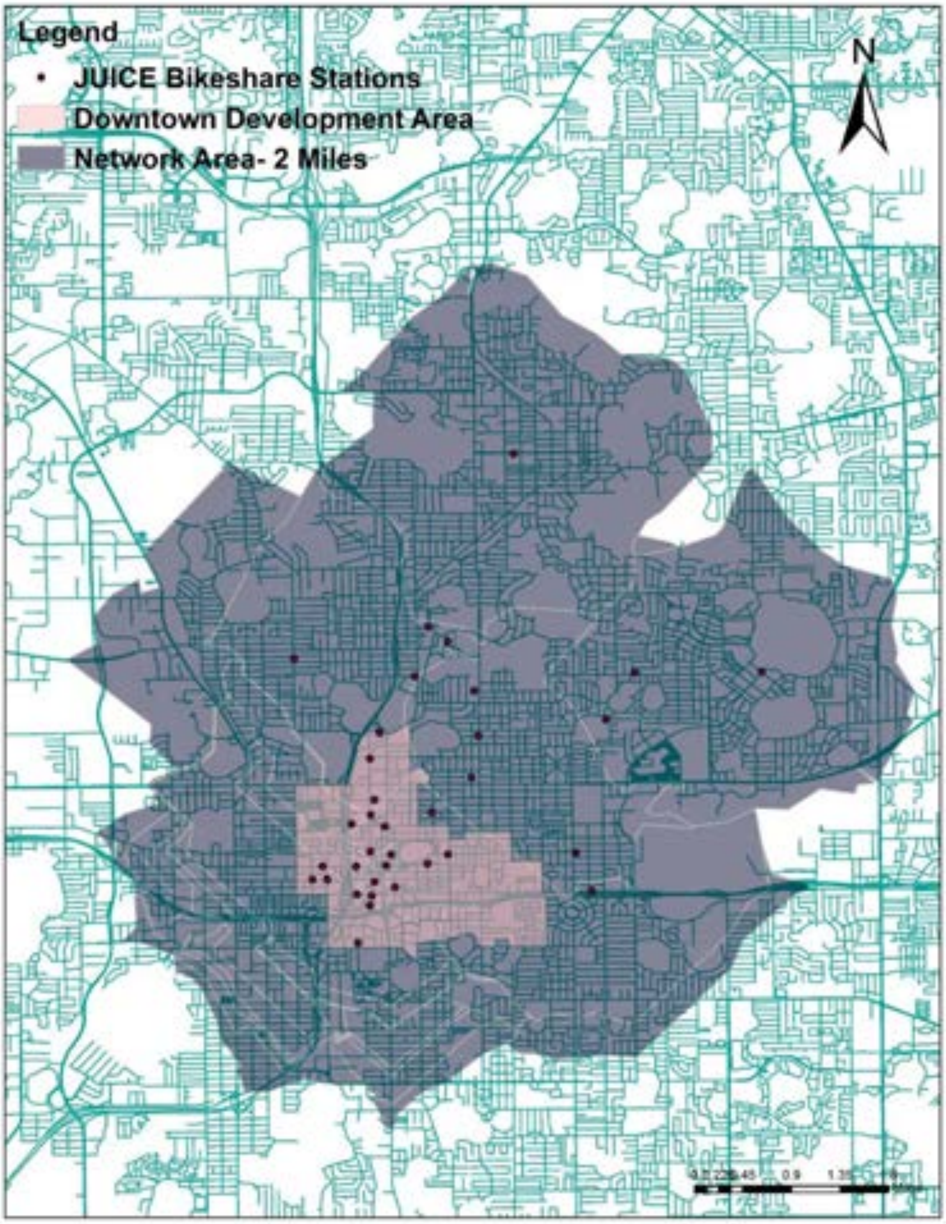


Figure 3.31: Driving Network Area Across JUICE Bikeshare Stations

[3] With 12.4 mph speed a bicyclist can travel in 10 minutes = 12.4*10/60 = 2.067 miles

The job accessibility estimation procedure across JUICE bikeshare stations follows two steps. First, total number of jobs accessible was estimated from census tracts that fall within case areas for each station. Then job counts were computed for two areas; downtown and outside downtown. Second, average employment counts were calculated dividing total job counts for downtown and outside downtown areas with the corresponding number of stations respectively. As described earlier, for Juice system we resort to comparison across two case samples – downtown and non-downtown stations. The comparison of average employment counts between downtown stations and non-downtown stations are shown in Figure 3.32. Downtown stations have higher average job counts per station than outside downtown as expected. Using the same procedure, the employment accessibility layers were prepared for other years as well.

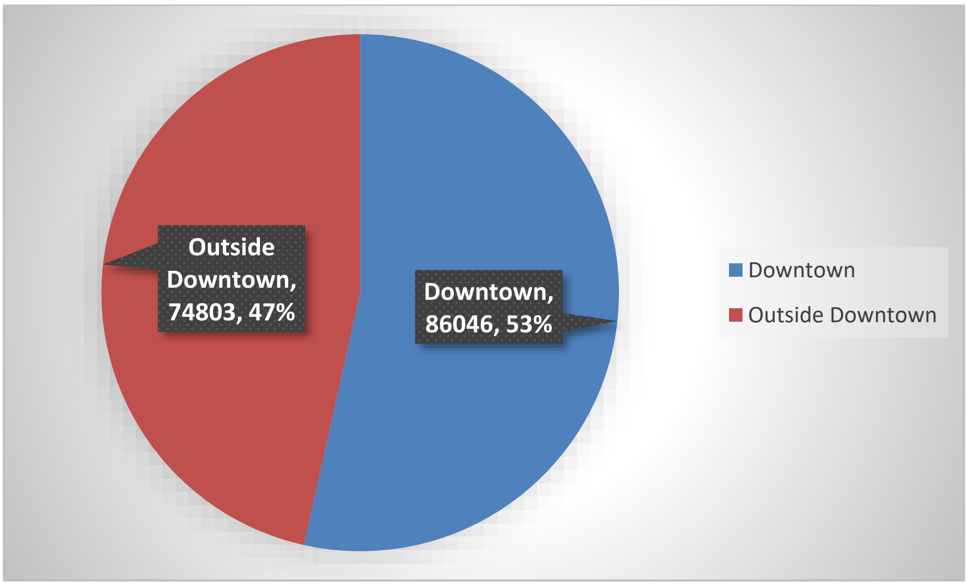


Figure 3.32: Average Number of Accessible Jobs per JUICE Bikeshare Case Areas

3.2.3 Commuting Time

Average commuting time data (journey to work in minutes) per census tract of Florida for 2011-2016 was extracted from American Community Survey (ACS) data. Then commuting data and Florida census tract level shapefile based on a unique ID created from concatenating County and Census Tract was merged for further analysis. Figure 3.33 shows the average commuting time distribution across the Florida census tracts. From the Figure, it can be seen that the average commuting time in the Central Florida region is around 20-30 minutes.

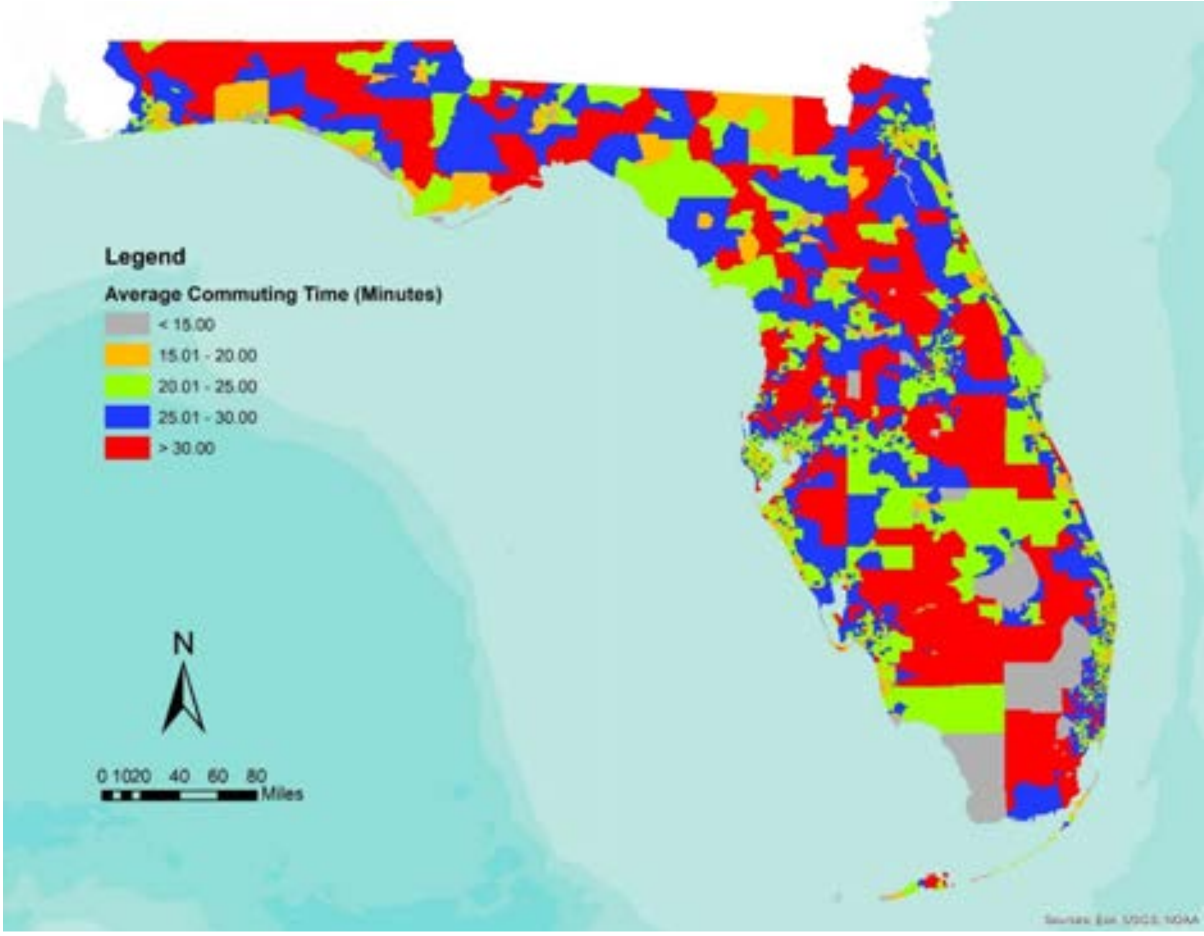


Figure 3.33: Distribution of Average Commuting Time across Census Tracts of Florida

3.2.3.1 SunRail

The data preparation steps for SunRail stations are as follows: First, case group areas (census tracts) within 1-mile radius of the station buffers were selected. Second, using proximity analysis as described in 3.2.1.1, each census tract was assigned to one unique station. After assigning all census tract to a unique station, the average commuting time for each station was computed (See Figure 3.34). It can be seen from the Figure that downtown station areas have commuting time of around 16 to 22 minutes.

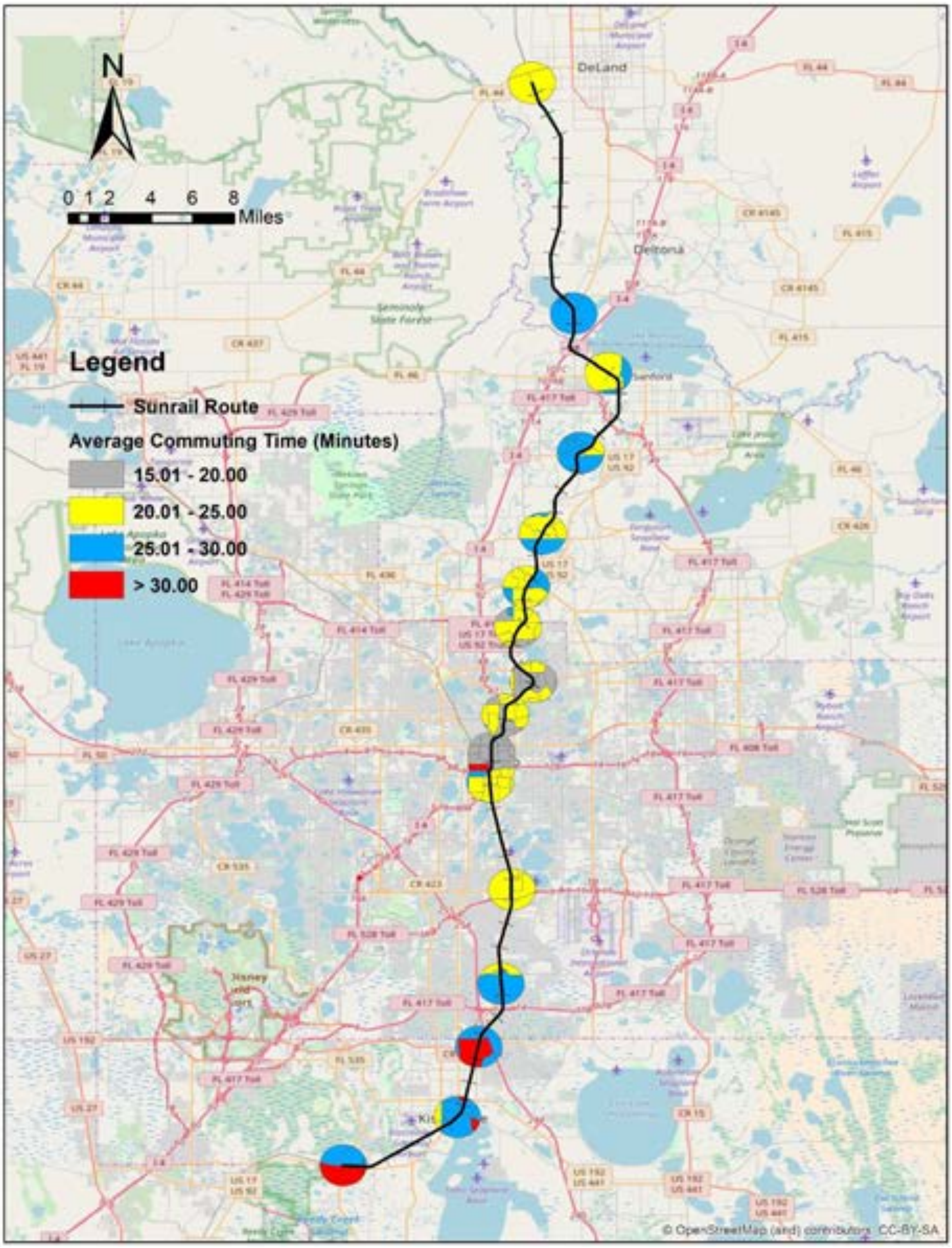


Figure 3.34: Distribution of Average Commuting Time around SunRail Station Buffers

Control Area Selection

The procedure for identifying the control census tract within SunRail Station buffers is as follows: First, a 2 mile and 8 mile buffer respectively was created around the stations. The census tracts located within that common 6-mile buffer were selected to be the candidate control areas. Second, based on the similarity of population density and percentage of mode shares (with a range of 15% of the mean population density and area within the case parcels), control areas for analysis were identified.

3.2.3.2 I-4 Expansion

The same procedure (using 1-mile buffer) for SunRail is applied for the average commuting time within I-4 expansion segment buffer (see Figure 3.35). Analysis results indicated that downtown segments had the lowest range of commuting time (around 17 to 22 minutes).

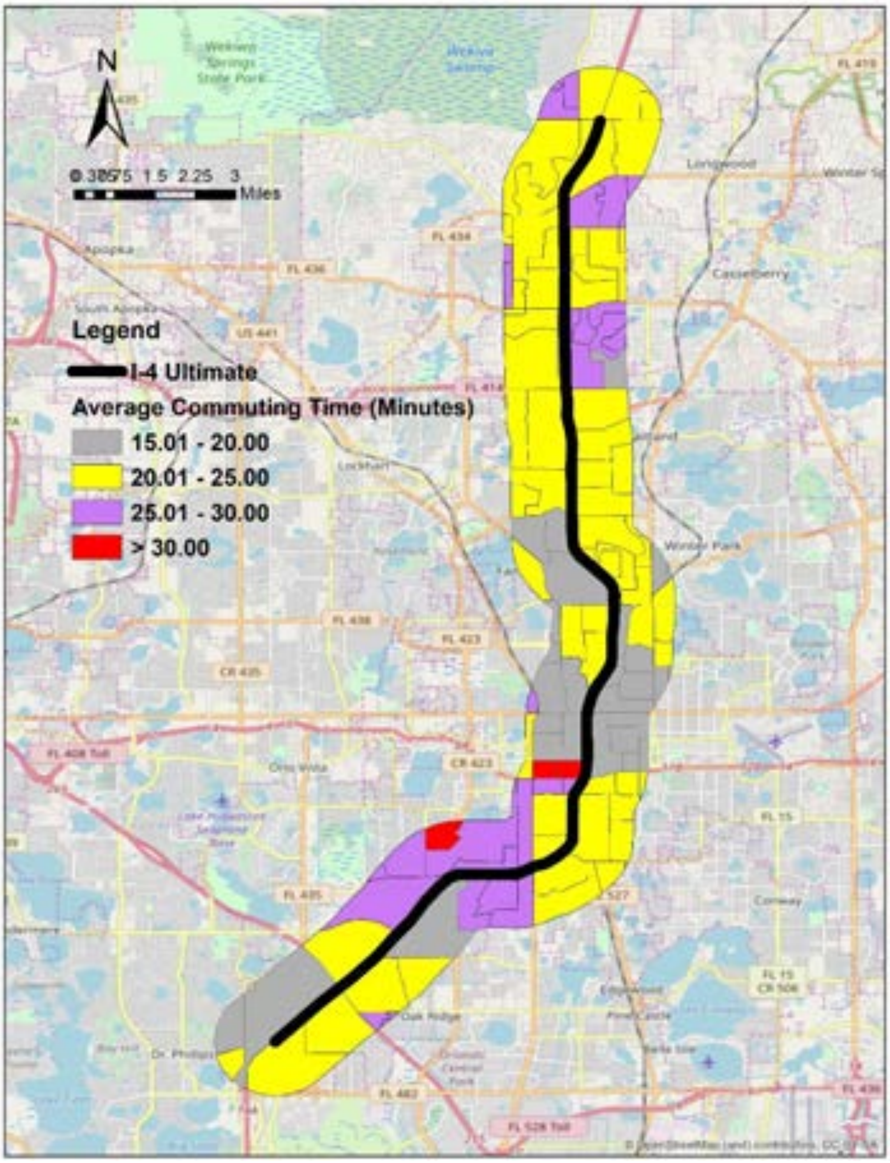


Figure 3.35: Distribution of Average Commuting Time within I-4 Expansion Buffer

Control Area Selection

Same control area selection procedure described in 3.2.3.1 were followed.

3.2.3.3 JUICE Orlando Bikeshare

A procedure similar to job accessibility has been used for estimating average commute time within the bikeshare station buffers (250-meter). The numbers are generated for downtown and non-downtown stations. The results are presented in Figure 3.36. From analysis results it is found that downtown area stations have average commuting time of 17 to 21 minutes.

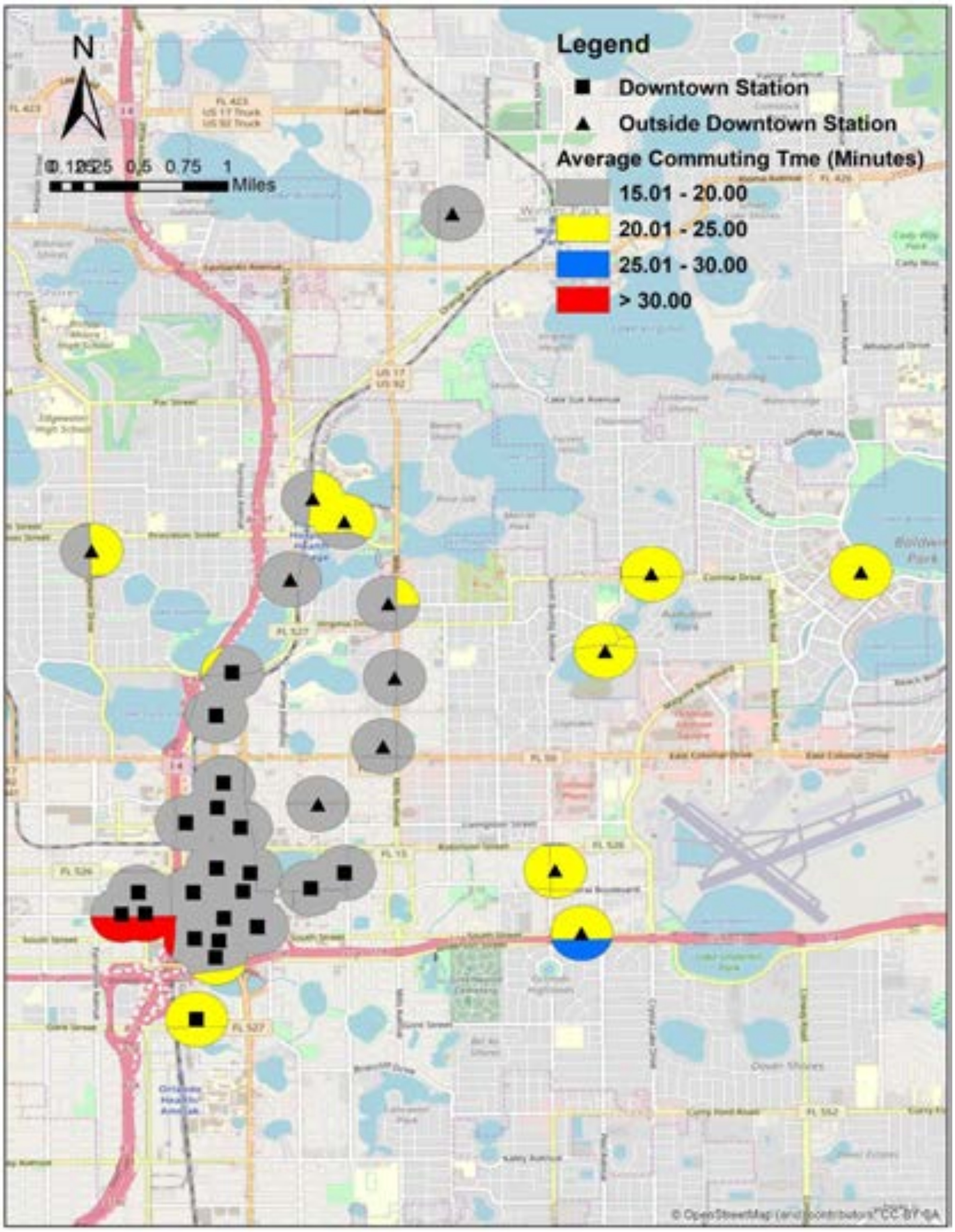


Figure 3.36: Distribution of Average Commuting Time within Bikeshare Station Buffers

3.2.4 Land Use Change

The parcel level data collected from FDOR was used for investigating land use change. 12 land use categories based on DOR based land use code as described in Table 3.1 was created. After creating the land use category, parcel ID within county shapefile was merged with DOR based parcel level land use information.

3.2.4.1 SunRail

The data preparation steps for SunRail stations are as follows: First, case group areas (census tracts) within 1-mile radius of the station buffers were selected. Then, each parcel was assigned to a particular station by estimating straight line distance from each parcel to the nearest station. Second, the vacant parcels for the years 2012 and 2013 was identified (see Figure 3.37 and Figure 3.38). Next, the vacant parcels that changed from vacant to other land use categories in 2013 was identified (see Figure 3.39). It is observed that changes from vacant is minimal at downtown stations. No conversion of any land use type occurred at Church Street station buffer area. Third, the area of the transformed parcels by land use type for each station were aggregated. The results are presented in Table 3.4. Largest change from vacant to single family residential land use could be observed at Lake Mary Station's buffer area (5.75 acre) while around 36-acre area converted from vacant to commercial area at Sand Lake Road station's buffer area. Major portion of conversion around Sunrail stations occurs mainly from vacant area to commercial area which is clearly shown in Figure 3.40. Fourth, the procedure was repeated for creating layers for other years.

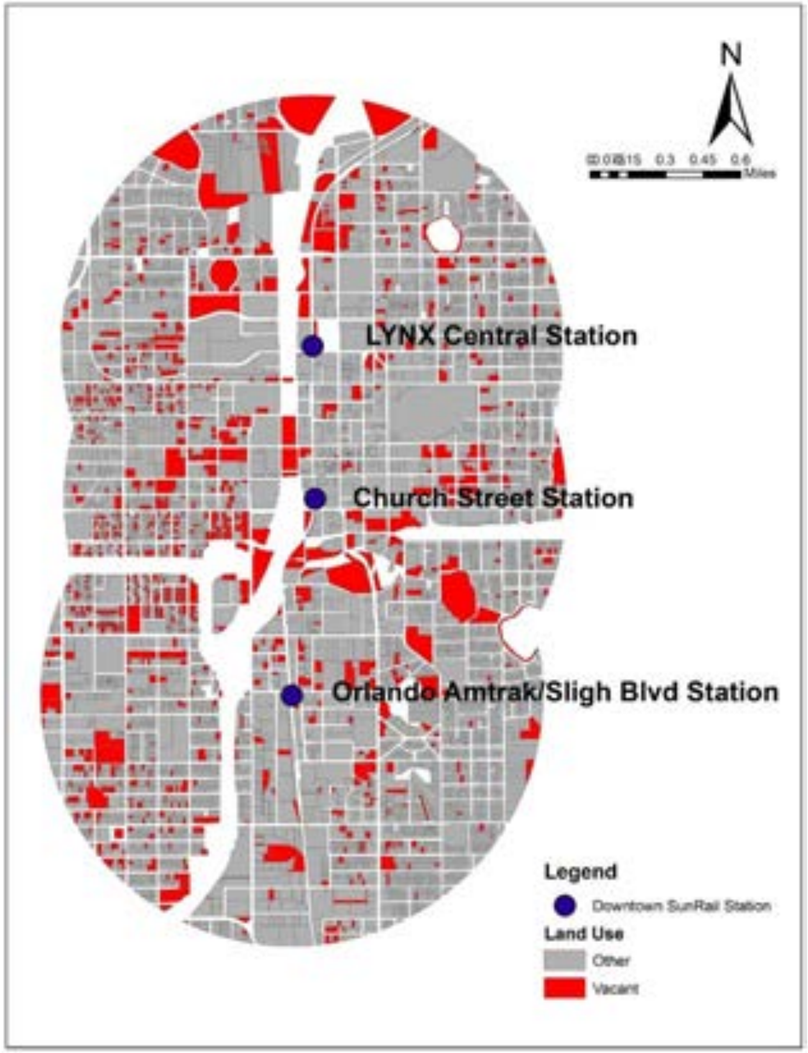


Figure 3.37: Vacant Parcel Area Around Downtown SunRail Station's 1-mile Buffer in 2012

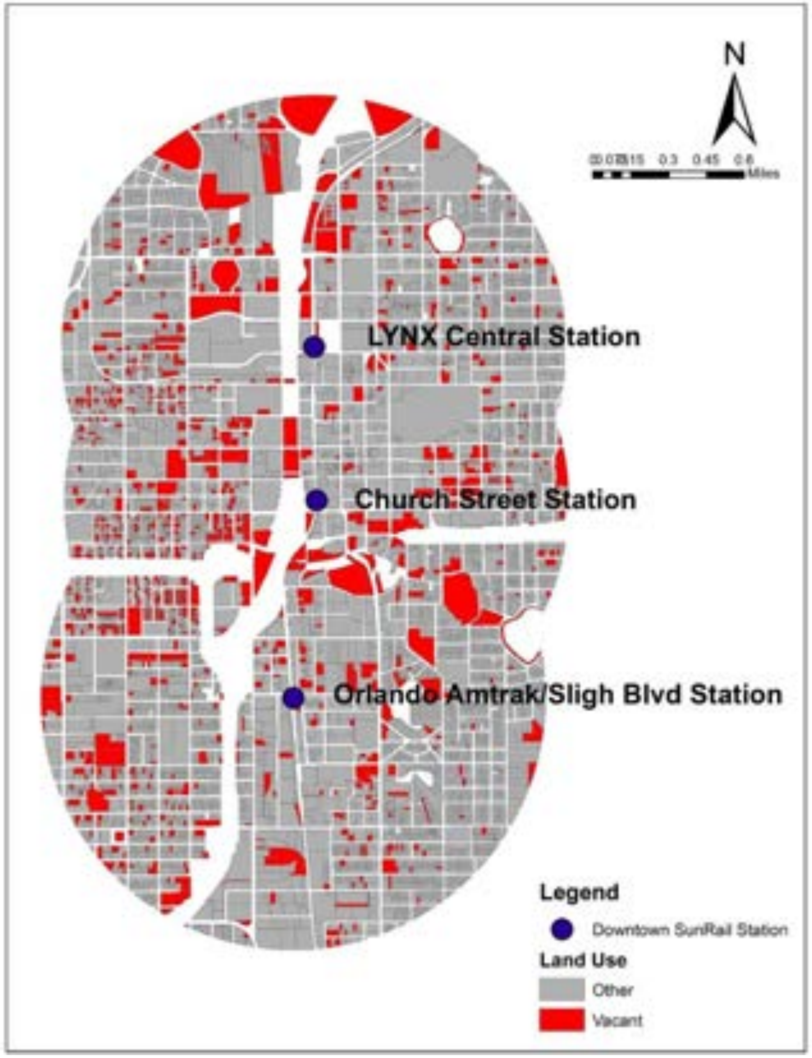


Figure 3.38: Vacant Parcel Area Around Downtown SunRail Station's 1-mile Buffer in 2013

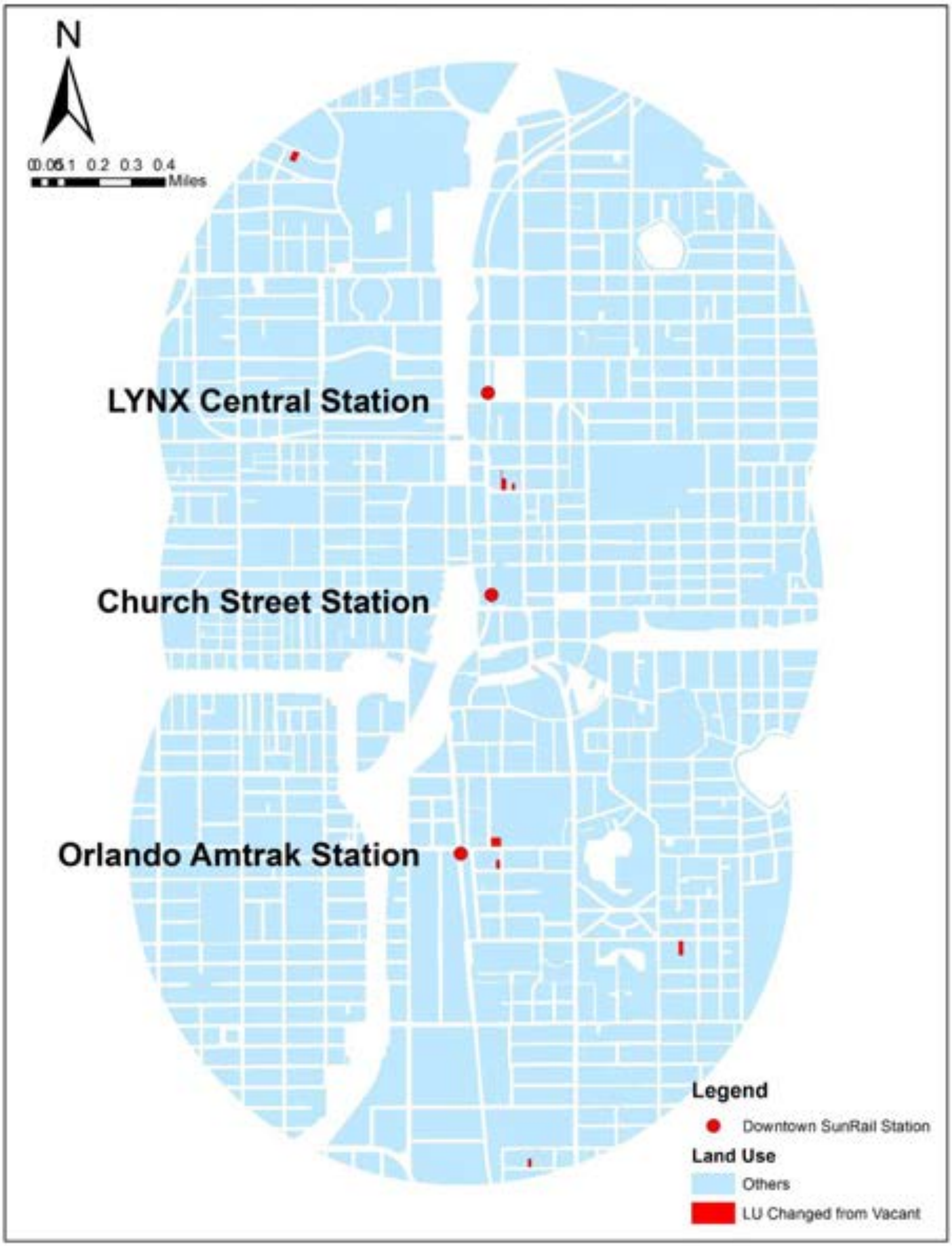


Figure 3.39: Vacant Parcel Area Conversion Around Downtown SunRail Station's 1-mile from 2012 to 2013

Table 3.4: Land Use Change (Acres) from Vacant Area at SunRail Stations from 2012 to 2013

Station		Single Family Residential	Retail/Office	Industrial
Downtown	LYNX Central Station	0.38	0.48	0
	Orlando Amtrak/Sligh Blvd Station	0.37	0.73	0.15
	Church Street Station	0	0	0
Outside Downtown	DeBary Station	0	0	3.27
	Sanford Station	2.39	1.02	0
	Lake Mary Station	5.75	0.28	0
	Altamonte Springs Station	0.7	1.19	0
	Winter Park Station	2.76	1.1	0
	Florida Hospital Health Village Station	1.4	2.44	0
	Sand Lake Road Station	0	36.39	0
	Longwood Station	0	0.47	0.31
	Maitland Station	0.87	0.43	0
Phase-II	DeLand Station	0.52	0	0
	Meadow Woods Station	0.42	0	3.86
	Osceola Parkway Station	0.15	1.75	0
	Kissimmee Amtrak Station	0	11.59	0
	Poinciana Station	0	0	0

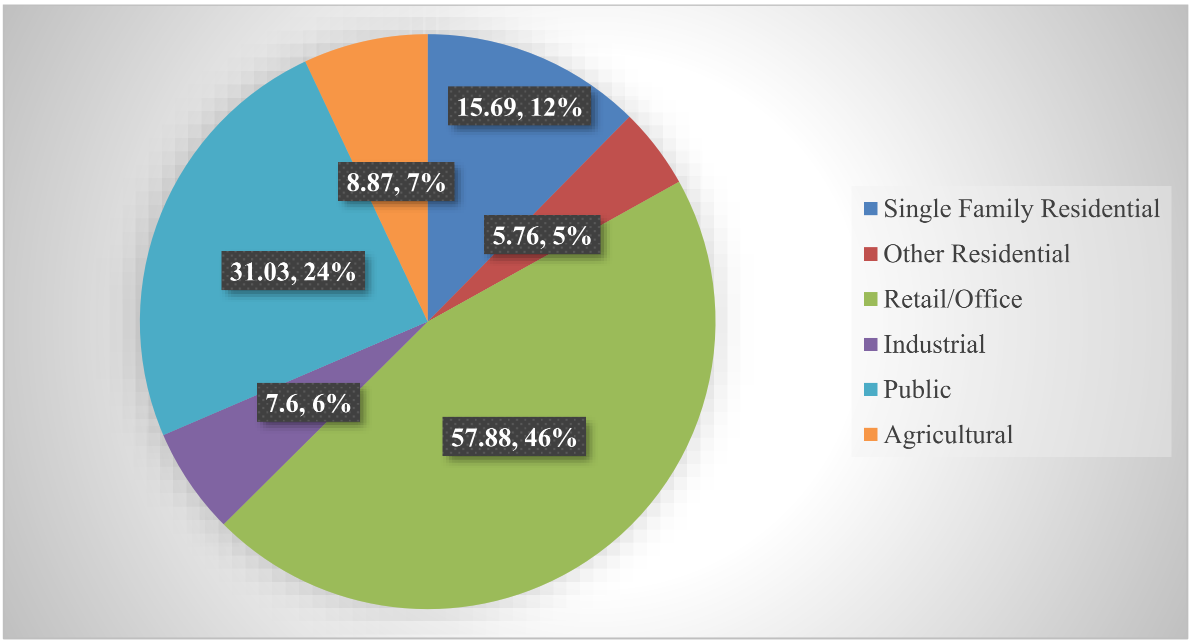


Figure 3.40: Land Use Change from Vacant Area (Acres) to Other Land Use Type within SunRail Station Buffers

Control Area Selection

The method for detecting the control parcels within SunRail Station buffers is as follows: First, 2 mile and 8 mile buffer was created respectively around the stations. The census tracts located within that 6-mile buffer were selected to be the candidate control parcels. Second, each parcel was assigned to the nearest station using similar procedure as case parcels.

3.2.4.2 I-4 Expansion

The same procedure (using 1-mile buffer) for SunRail is applied for the land usage change within I-4 expansion area buffer (see Figure 3.41, Figure 3.42, Figure 2.43).

The results from Table 3.5 clearly shown that major change occurred near the Attraction segment in 2012-2013. Except the Downtown segment, around 6-acre area converted from vacant to single family residential type for other three areas around I-4 expansion. Figure 3.44 represents the total area (acres) changes around I-4 expansion considering all areas and found that retail/office area change was higher than the change for other land use types.

Control Area Selection

The same procedure employed for SunRail control buffer was used for I-4 ultimate area control buffer.

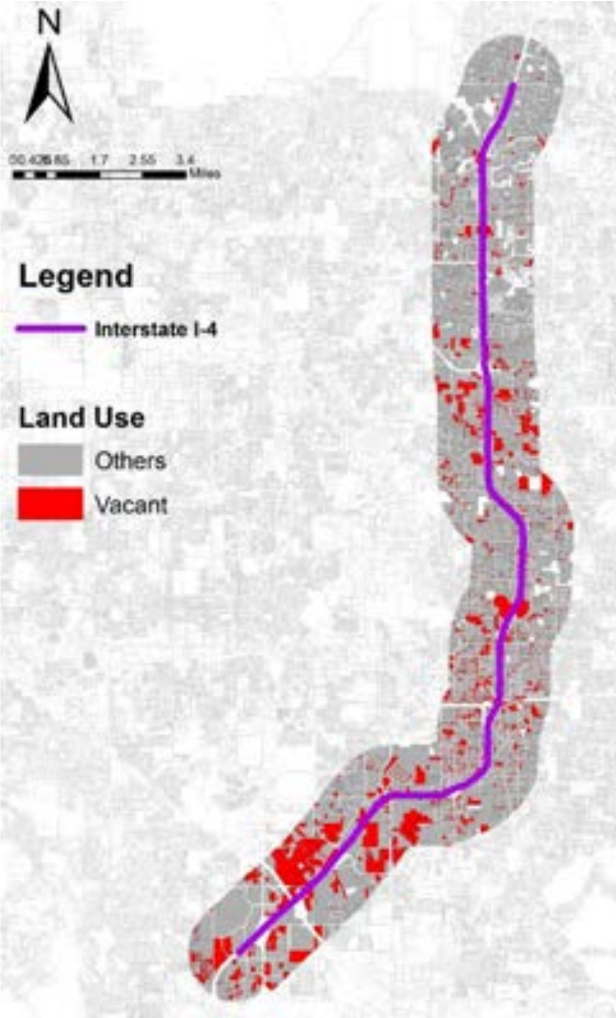


Figure 3.41: Vacant Parcel Area Around I-4 Expansion's 1-mile Buffer in 2012

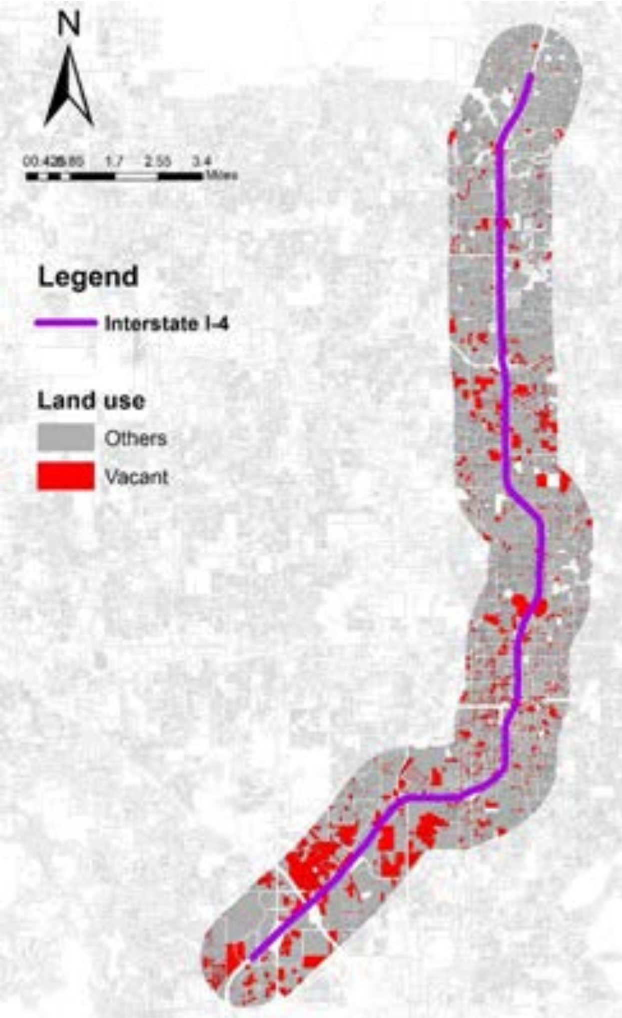


Figure 3.42: Vacant Parcel Area Around I-4 Expansion's 1-mile Buffer in 2013

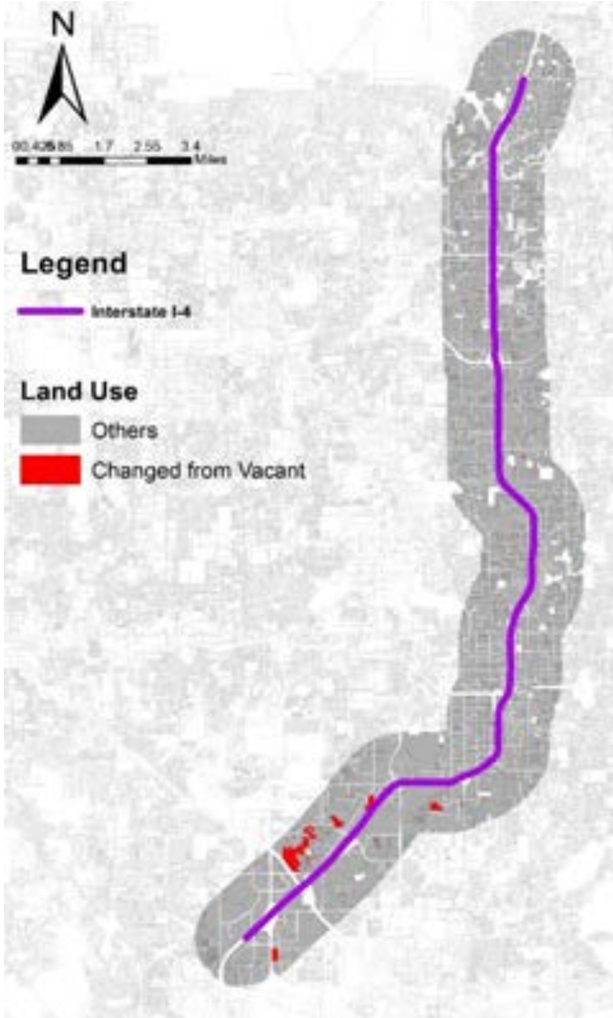


Figure 3.43: Vacant Parcel Area Conversion Around I-4 Expansion's 1-mile Buffer from 2012 to 2013

Table 3.5: Land Use Change (Acres) from Vacant Area at I-4 Expansion Area from 2012 to 2013

Area	Single Family Residential	Retail/Office	Industrial	Institutional
Attraction	6.60	80.02	0.00	0.00
Downtown	0.56	2.80	0.15	0.86
Ivanhoe	6.10	2.76	0.00	0.00
Altamonte	6.84	0.50	0.00	0.00

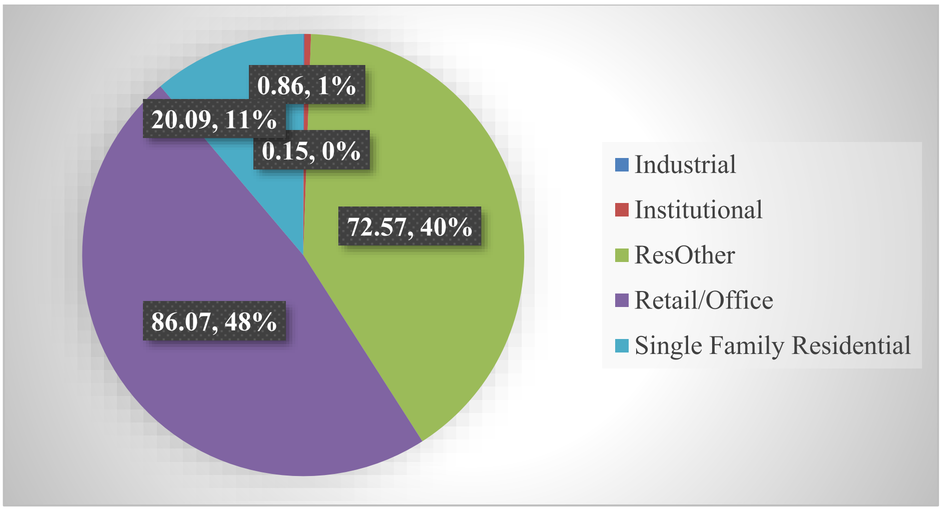


Figure 3.44: Land Use Change from Vacant Area (Acres) to Other Land Use Type at I-4 Expansion Buffer

3.2.4.3 JUICE Orlando Bikeshare

A procedure described in 3.2.1.3 has been used for estimating the change in land usage type within the bikeshare station buffers (250-meter) for downtown and non-downtown stations. The results are presented in Figure 3.45. As the buffer size is small, the change from vacant to other land use type is not very discernible. Moreover, bikeshare stations are installed mainly at and nearby downtown Orlando area. Hence, the changes from vacant to developed are likely to be small.

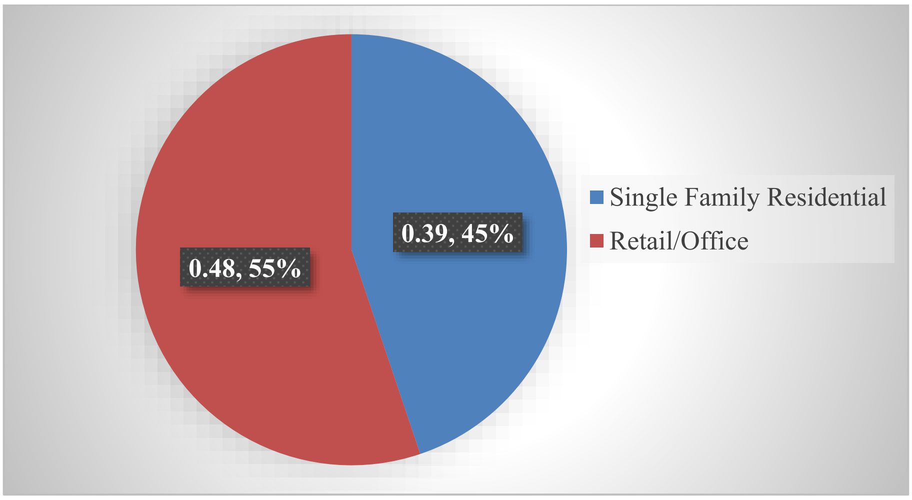


Figure 3.45: Land Use Change from Vacant Area (Acres) to Other Land Use Type within Orlando Bikeshare Station Buffers

3.2.5 Travel Pattern for Zero Car households

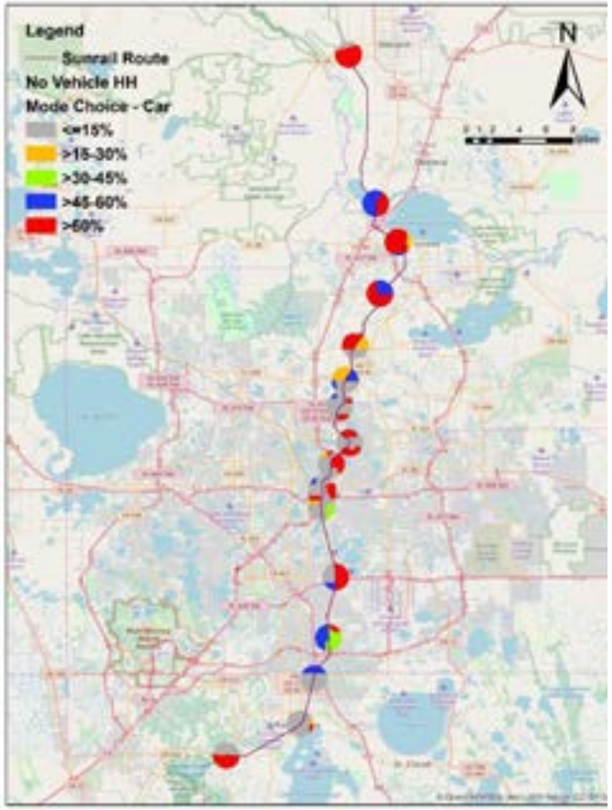
As part of this MOE, the emphasis is on understanding travel patterns of zero car households. Annual changes to travel pattern data was only available for work travel. Hence, the means of transportation to work by household vehicle fleet size data at the census tract level for 2011-2016 was extracted from American Community Survey (ACS) data. Specifically, the principal mode of travel that the worker usually used to get from home to work during the reference week based on vehicle availability on the households was employed. The reported mode choice data were merged with Florida census tract level shapefile based on a unique ID created from concatenating County and Census Tract for further analysis. This data contains information on type of conveyance by number of workers for their commuting purpose with vehicle availability in the household. The alternatives provided for mode choice are Car, truck, or van - drove alone (including office or company cars excluding taxicabs), car, truck or van - carpooled, public transportations (bus or trolley bus, streetcar or trolley car, subway or elevated, railroad, or ferryboat), walk, taxicab/bike, motorcycle and worked from home. These choice categories were compiled for no vehicle, one vehicle, two vehicle and three or more vehicle household. The proportion of zero vehicle households amounted to about 3% for all years of 2011-2016. For zero vehicle households, the percentage of choosing various modes was estimated. It is important to note here that a reasonable sample of work trips made by households with 0 cars involved Drive alone mode. This was counter intuitive; however, on further investigation, it was found that ACS does not consider “office/business” provided vehicles as owned by the household. Thus, individuals using office/business provided vehicles are considered as 0 car households. There is no way of identifying such households to identify truly zero car households in the data. Hence, the results from the exercise need to be reviewed with caution.

3.2.5.1 SunRail

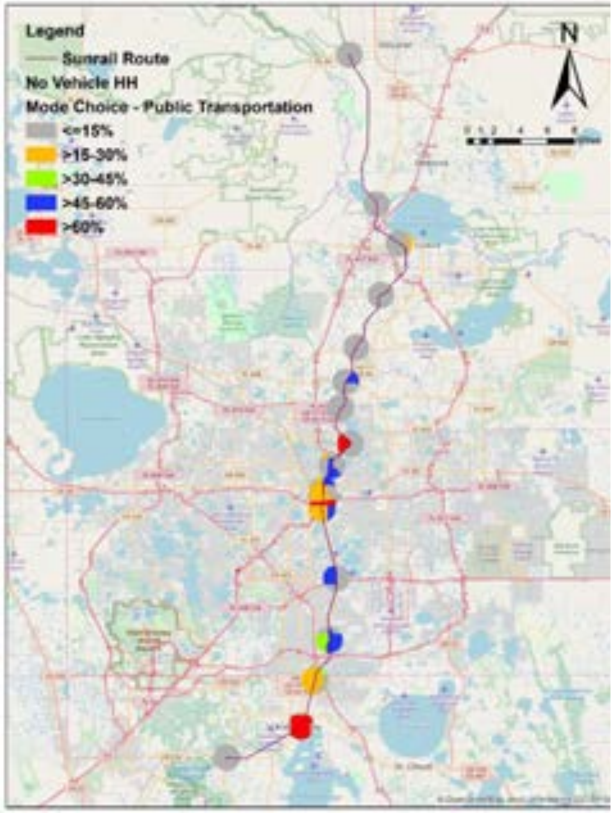
The data preparation steps for SunRail stations are as follows: First, case areas (census tracts) were selected by using similar procedure as described in 3.2.3.1. Second, the average percentage of each mode used by workers of zero vehicle households for each station was computed. In Figure 3.46, mode choice ratio (in percentage) for each mode category is shown. It can be seen from the Figure that downtown station areas are likely to consider mixed mode systems while non-downtown station areas are predominantly car reliant.

<u>Control Area Selection</u>

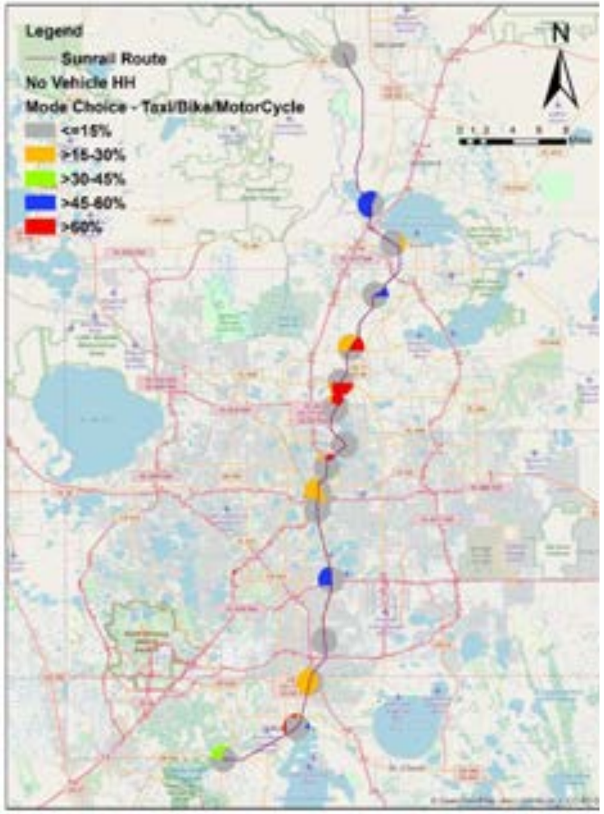
The selection procedure of control area around SunRail Stations is similar to procedure used for commuting time (see 3.2.3.1).



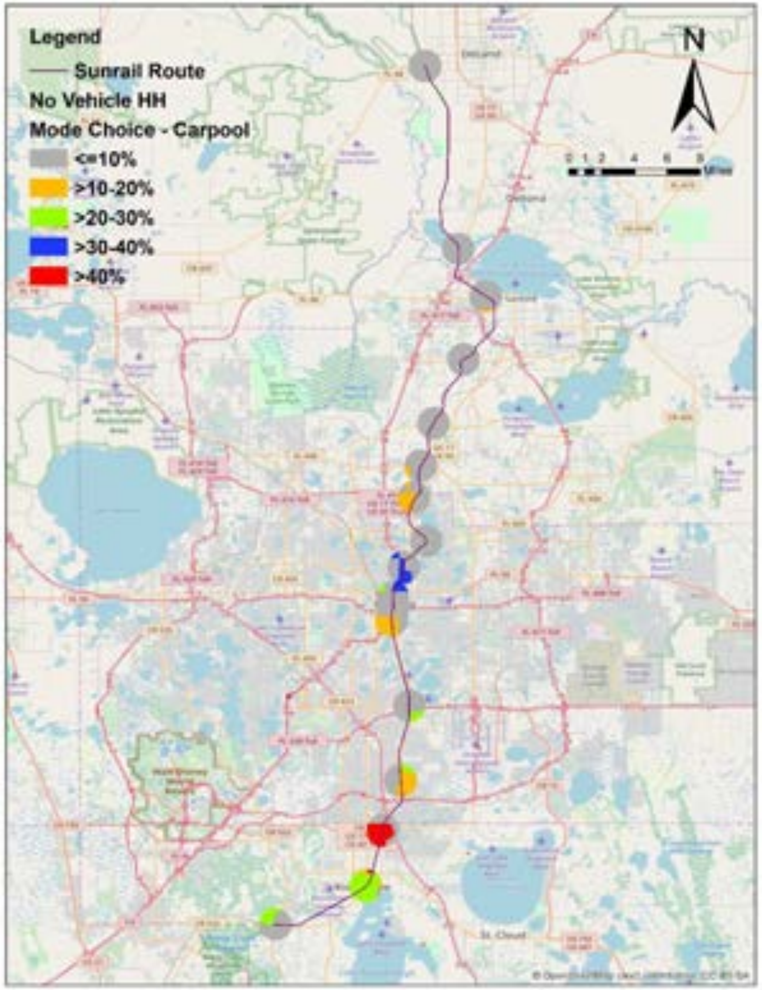
(a) Car- Drive Alone



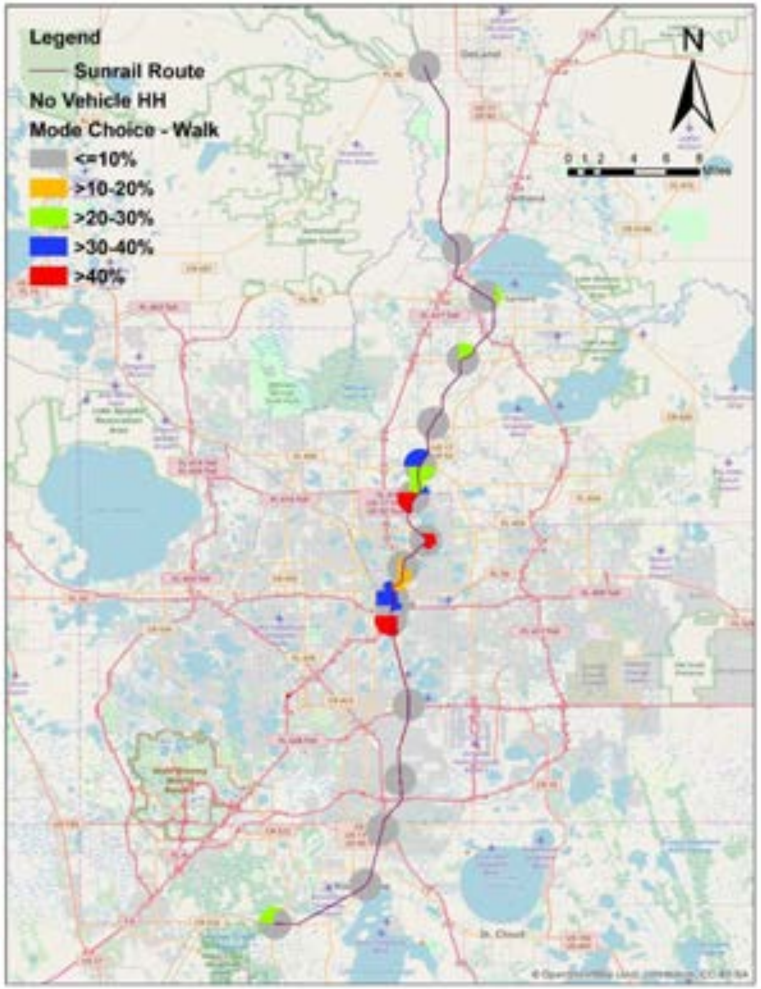
(b) Public Transportation



(c) Taxicab, Bike or Motorcycle



(d) Carpool



(e) Walk

Figure 3.46: Distribution of Mode Choice for No Vehicle HH Workers around SunRail Station Buffers

3.2.5.2 I-4 Expansion

The same procedure of using 1-mile buffer around SunRail stations is applied for I-4 expansion area buffer for four different segments (Attraction, Downtown, Ivanhoe and Altamonte). The mode distribution of zero vehicle households for commuting purpose is represented in Figure 3.47. The analysis indicated that downtown area had the variation on mode choice distribution while other areas are car reliant.

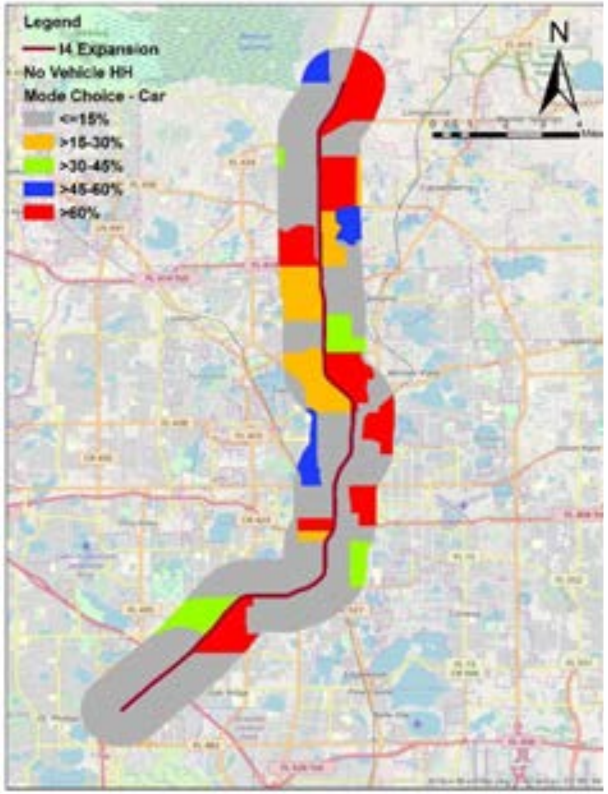
<u>Control Area Selection</u>

Similar control area selection procedures described in 3.2.3.2 were followed.

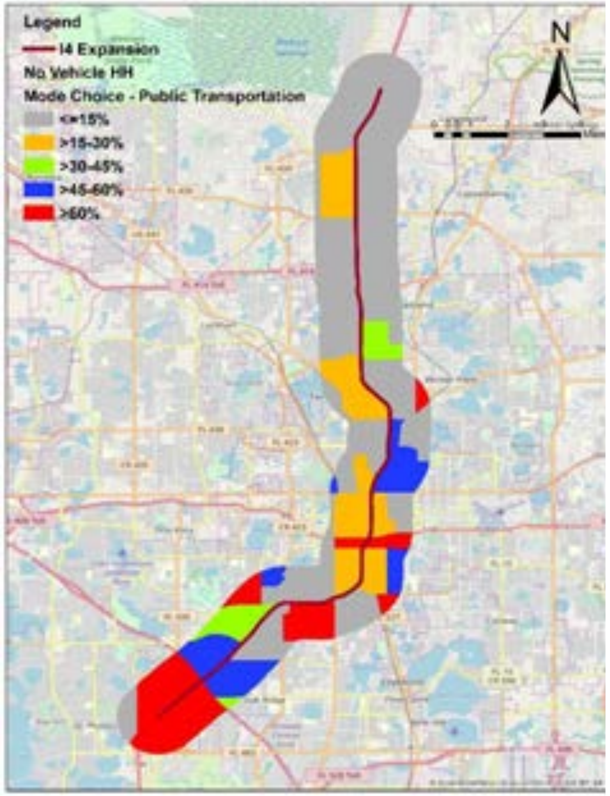
3.2.5.3 JUICE Orlando Bikeshare

A 250-meter buffer was created for estimating average mode distribution within the bikeshare station. Since the majority of the bikeshare stations are located in and around the downtown areas, it is very difficult to choose control census tracts. To overcome this issue, decision has been made to limit the analysis to comparing the changes between downtown and non-downtown stations as described in 3.2.1.3. The various mode distribution around JUICE bikeshare stations (Downtown area and Outside Downtown area) are presented in Figure 3.48. Note that, both downtown and non-downtown stations are showed in the same figure for easier comparison.

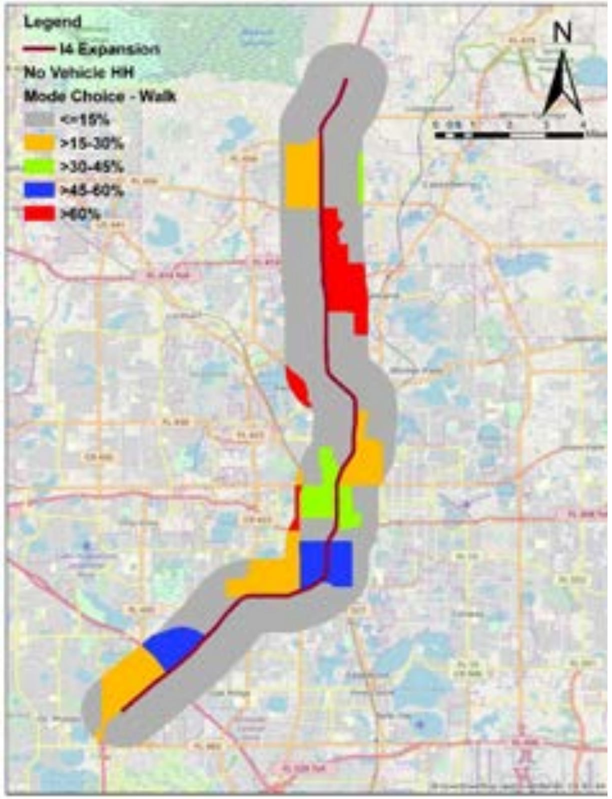
From the figure, downtown and outside downtown areas exhibit higher usage of public transportation relative to other modes. The results also highlight about 20% share has been distributed among walk and taxi/bike/motorcycle category for both groups. So, these results clearly highlight that public transportation is the preferred mode for zero car household workers.



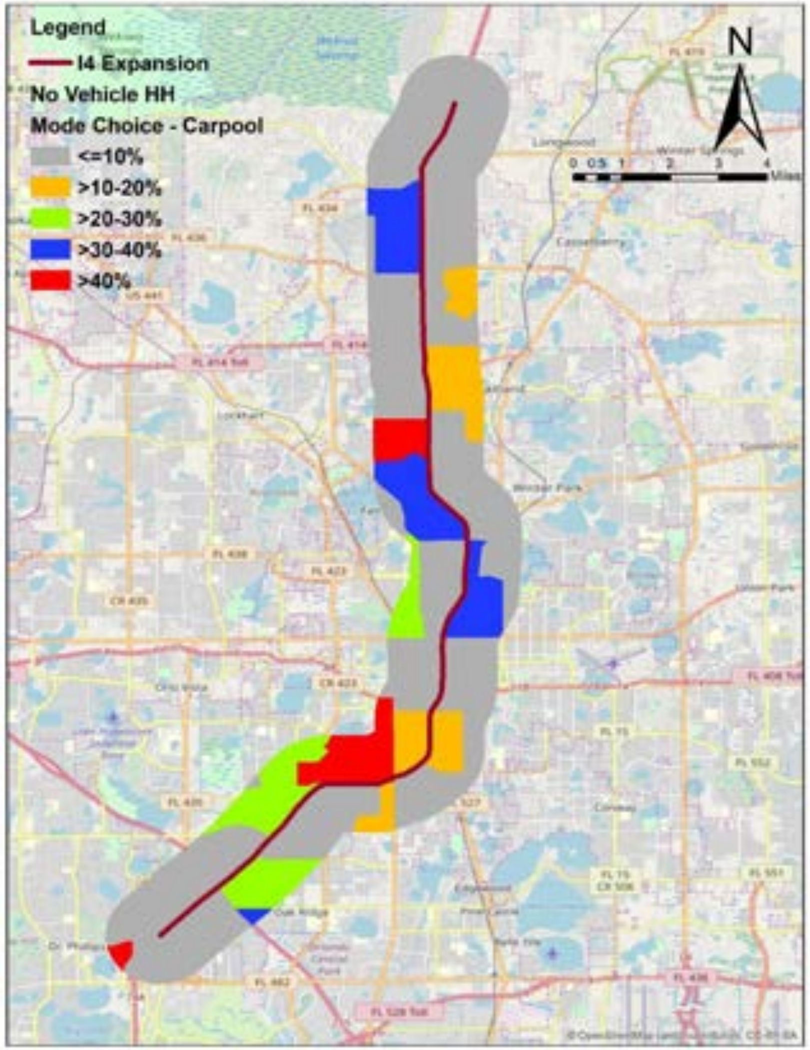
(a) Car- Drive Alone

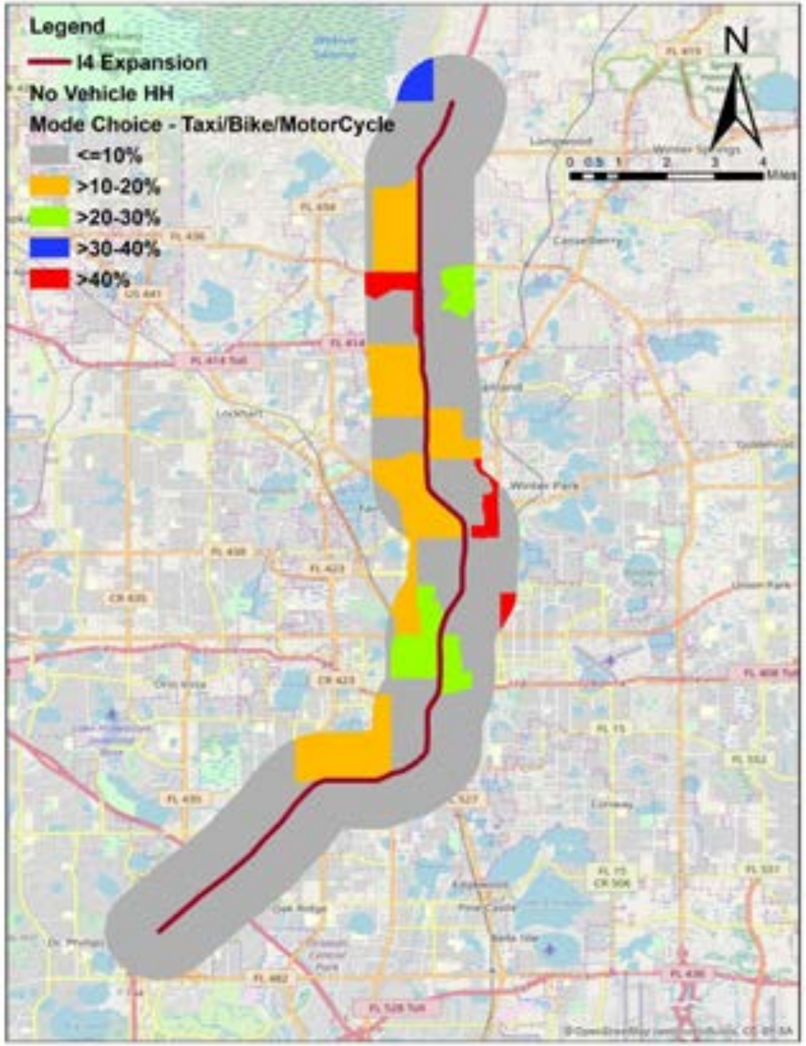


(b) Public Transportation



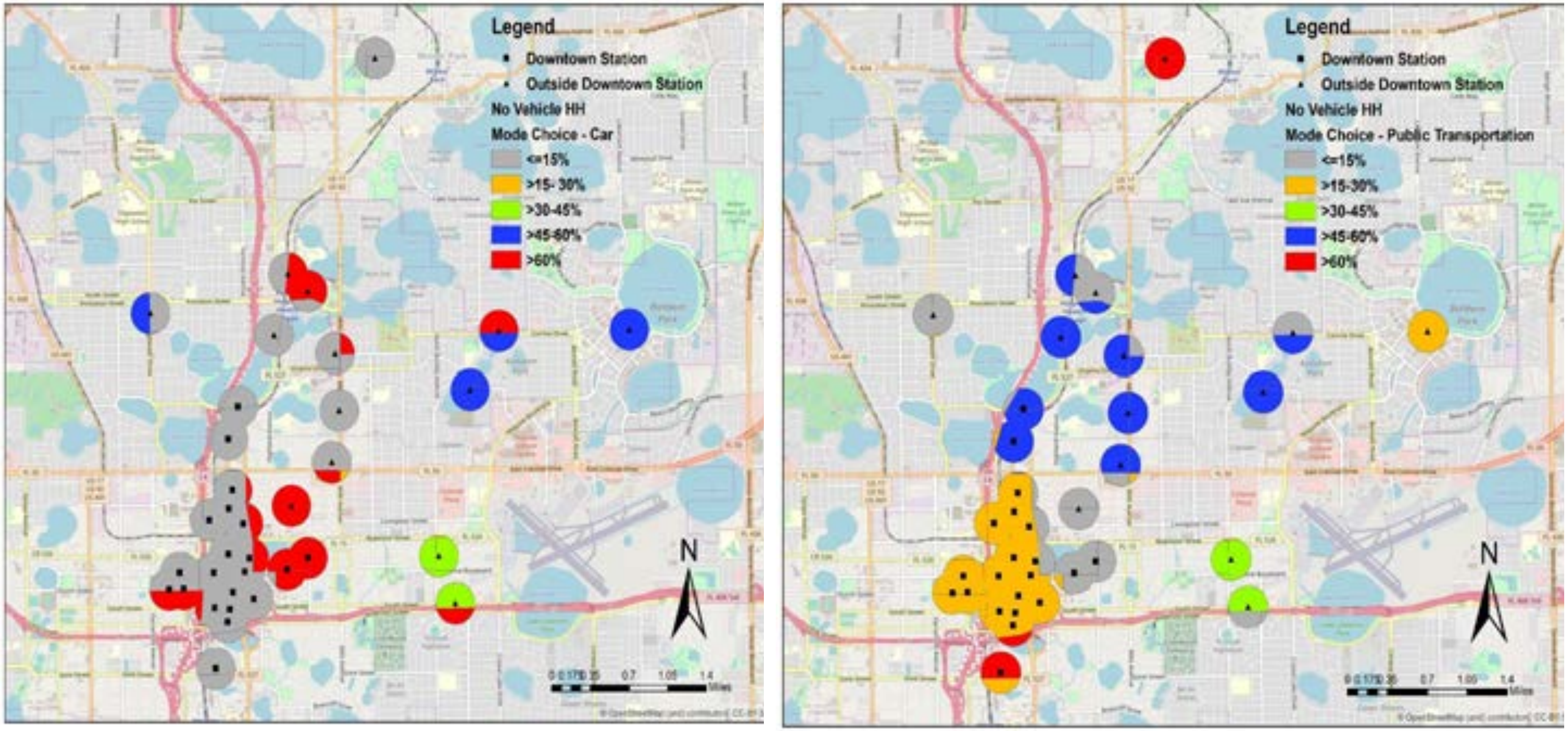
(c) Walk



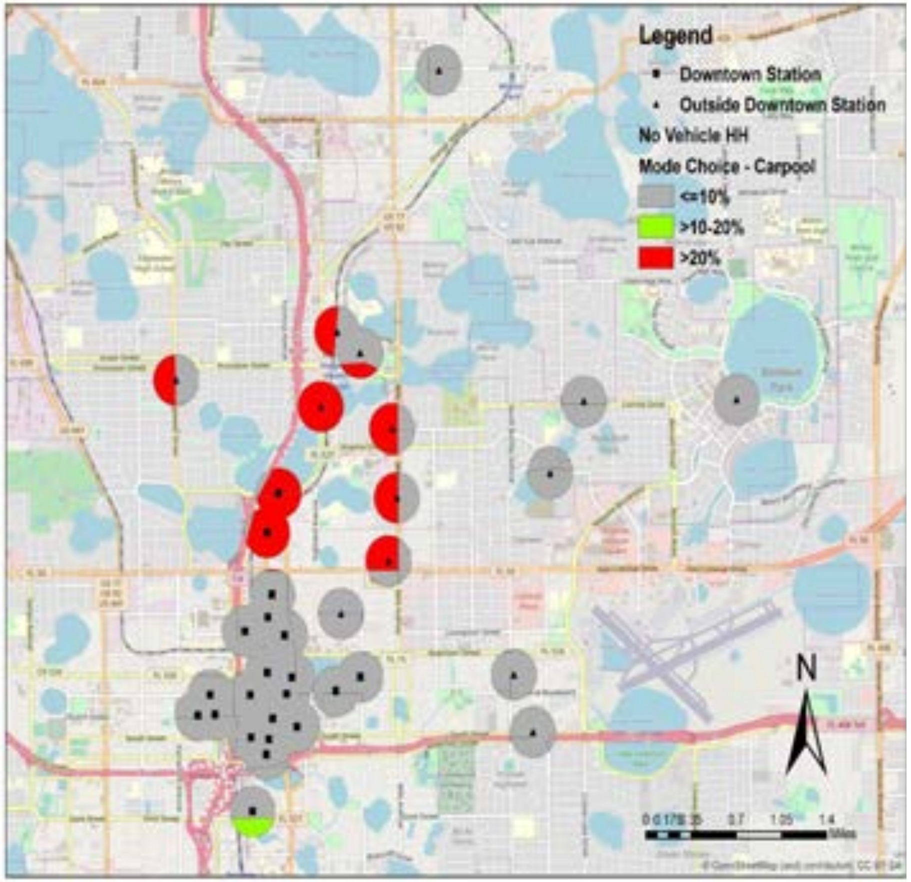


(d) Carpool **(e) Taxicab, Bike or Motorcycle**

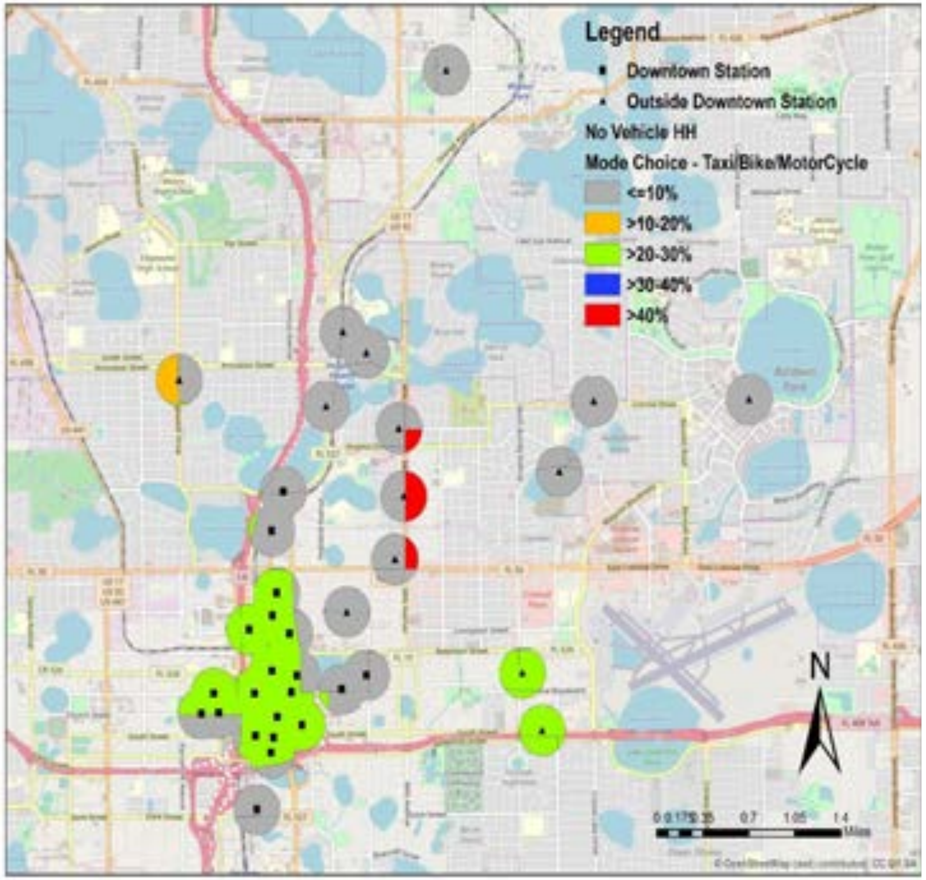
Figure 3.47: Distribution of Mode Choice for No Vehicle HH Workers around I-4 Expansion Buffers



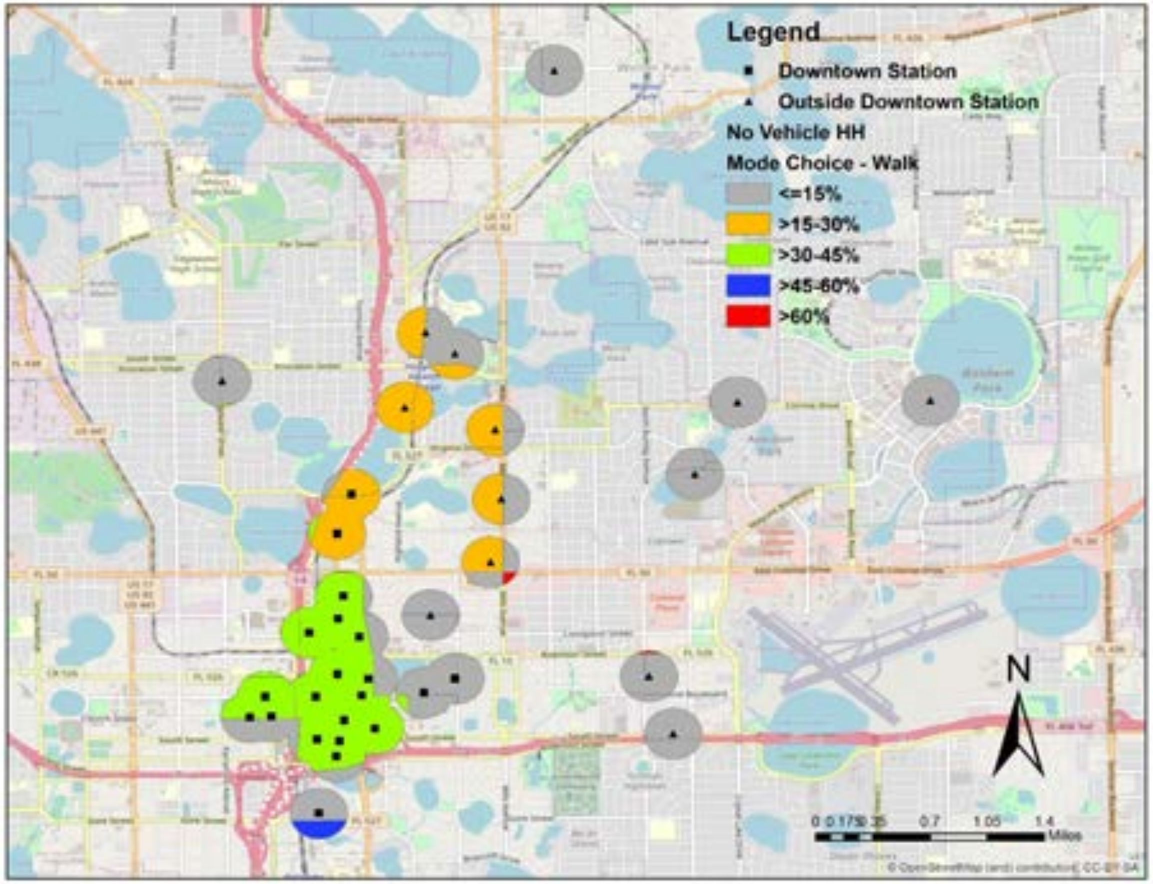
(a) Car- Drive Alone **(b) Public Transportation**



(c) Carpool



(d) Taxicab, Bike or Motorcycle



(e) Walk

Figure 3.48: Distribution of Mode Choice for No Vehicle HH Workers around JUICE Orlando Bikeshare Station Buffers

3.3 MEASURES OF EFFECTIVENESS (MOE) RESULTS

In the previous chapter, data layer preparation to compute the measure of effectiveness (MOE) for the year 2012 was presented. In the current chapter, the MOEs are generated across the study time period and the results for these measures are discussed.

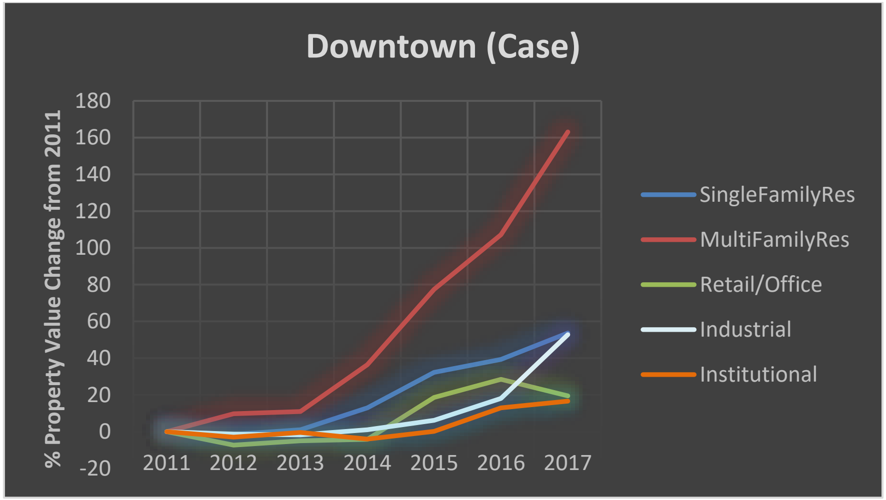
3.3.1 Property Value Variation

3.3.1.1 SunRail

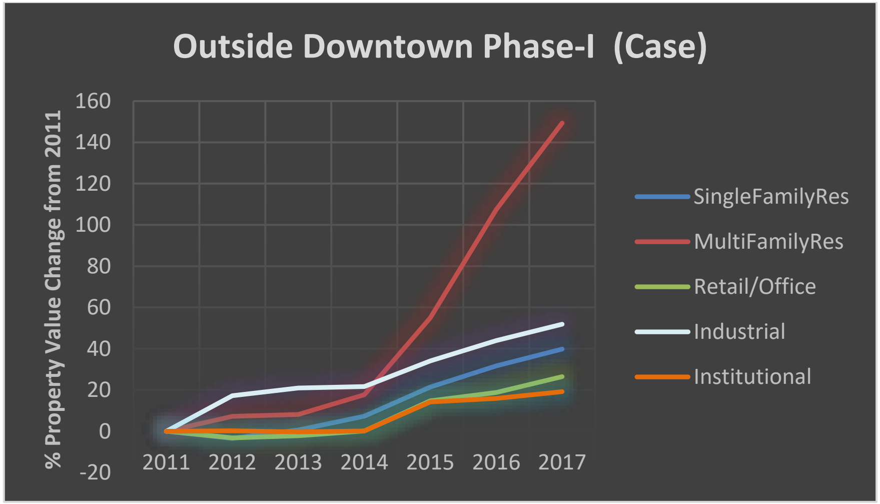
The procedure described in 3.2.1.1 for case and control areas was employed for the years 2011-2017 to capture the property value variation for all stations. The average property value per acre area for these three regions for year of 2011 to 2017 was computed. Figure 3.49 presents the percentage of average property value variation for each year from 2011 for case parcels (i.e. 2011 property value serves as base price). The results for control parcels are presented in Figure 3.50. For case parcels, as expected property price variation follows similar trends for downtown stations and outside downtown stations for all 5 land use types. Property value for all land use types increase significantly from year 2014. The improvement in the local economy coupled with the opening of SunRail stations may be responsible for the increase.

The trends highlight that the increase is almost 140% for multi-family residential land use type from 2014 for downtown and outside downtown stations. The stations operational from 2014 experience increases starting from 2014 while the Phase 2 stations show more than 300% increases for multi-family and office land use type for 2017 highlighting how the starting of construction for Phase 2 is strongly affecting property values.

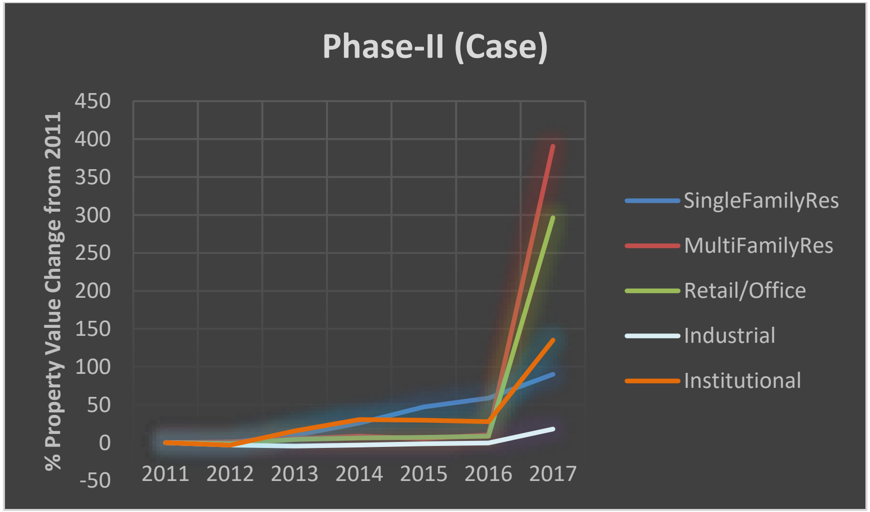
The general trend for control parcels is also found to be similar to the case parcels. However, the magnitude of change is substantially different from changes to case parcels. For downtown and outside downtown stations, multifamily residential property value increased around 100%. In some cases (as for Phase II stations), the multi-family land use type increases are much lower than single family house price increases. While the property value of single family residential land use value increased by around 55% from 2016 to 2017, multi-family residential land use only increased by around 5%. Overall, the trends clearly highlight the role of SunRail stations in leading to substantial price increase percentages across various land use types.



(a) Property Value Variation (Downtown)

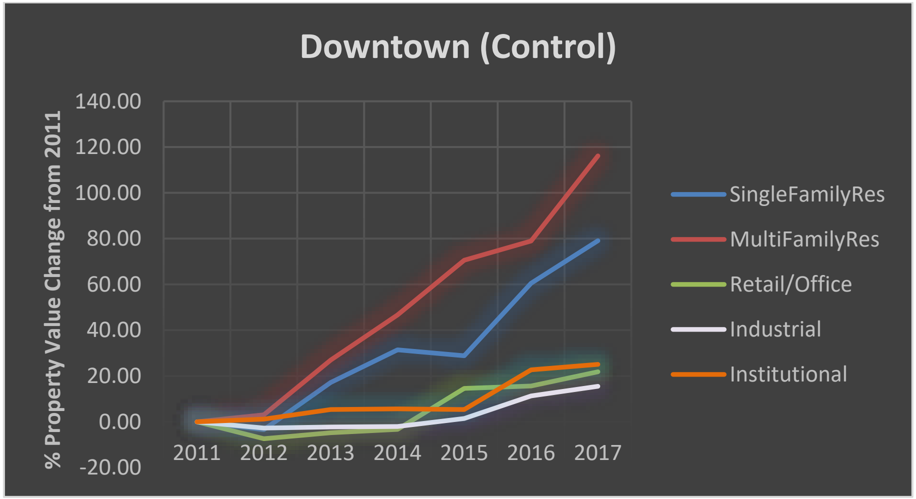


(b) Property Value Variation (Outside Downtown)

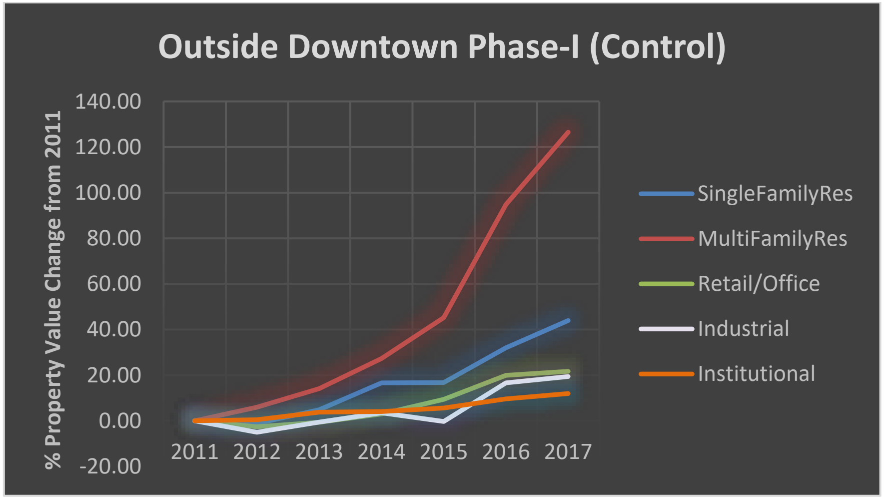


(c) Property Value Variation (Phase-II)

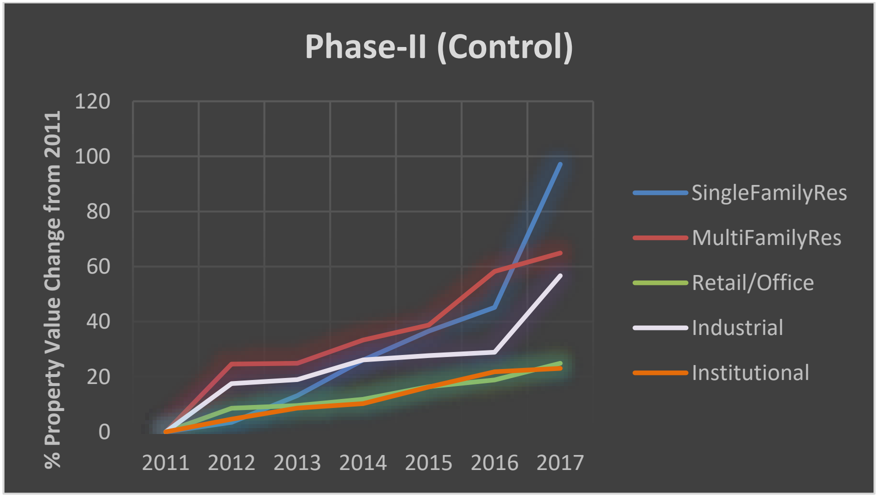
Figure 3.49: Property Value Variation for SunRail Station's Case Area



(a) Property Value Variation (Downtown)



(b) Property Value Variation (Outside Downtown)



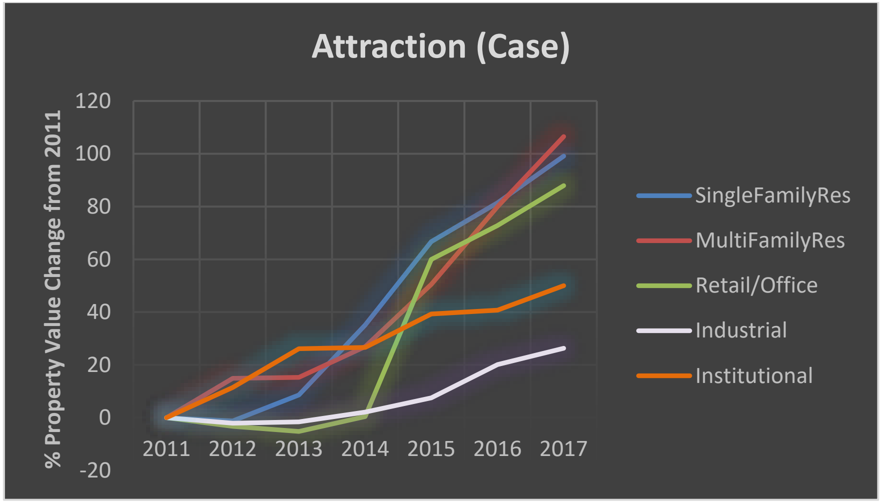
(c) Property Value Variation (Phase-II)

Figure 3.50: Property Value Variation for SunRail Station's Control Area

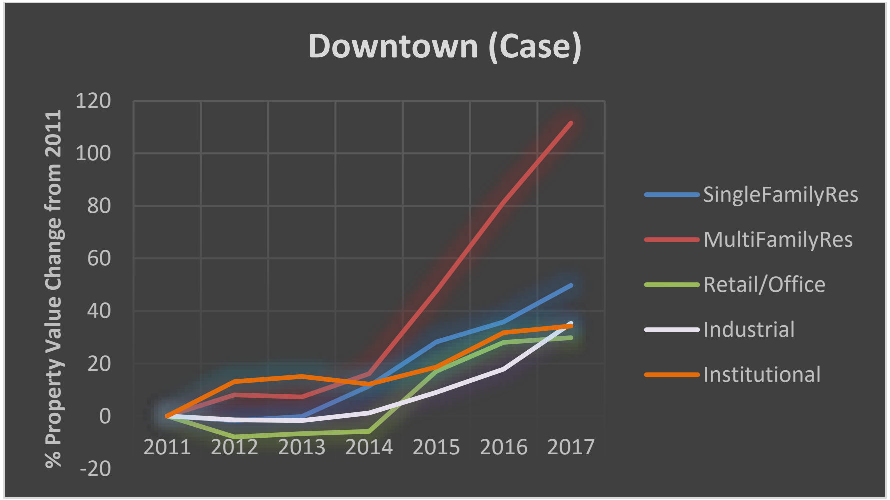
3.3.1.2 I-4 Expansion

For case parcels, property value for 1-mile buffer of I-4 ultimate (Attraction, Downtown, Ivanhoe and Altamonte) were computed for 2011 to 2017 using similar analysis techniques as described in 2.2.1.2. Figure 3.51 presents the percentage of average property value variation from 2011 for each year. Across all sections, multifamily land use type parcels have experienced significant price increases. Of the 4 sections, Attractions section experience an increase in property value across land use types (compared to other sections). For the Ivanhoe section, the increase in multifamily land use type is quite large (nearly 250%) while for other sections increases are about100%.

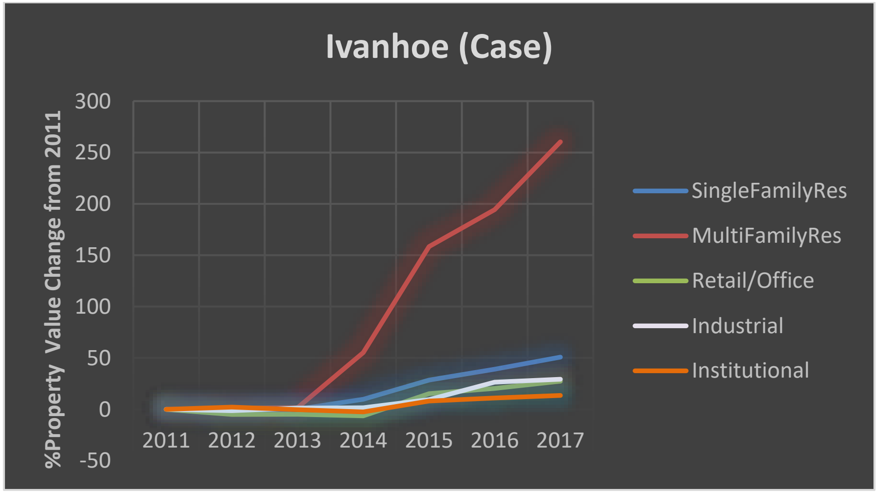
For control parcels, Figure 3.52 captures the percentage of average property value variation for each year from 2011. The change in property values offer trends very similar to the case parcels. In fact, in some cases the increase in property values are substantially higher in the control areas. For Attraction and Altamonte control buffer, multifamily residential property value increased by around 125% from 2014 to 2017 that was around 40% for case buffer. Overall, the results are in contrast to the SunRail results. The comparison of case and control trends provide an ambiguous result for the impact of I-4 on property values. It is possible that as I4 project is yet to be completed these results might undergo major changes at the time of completion.



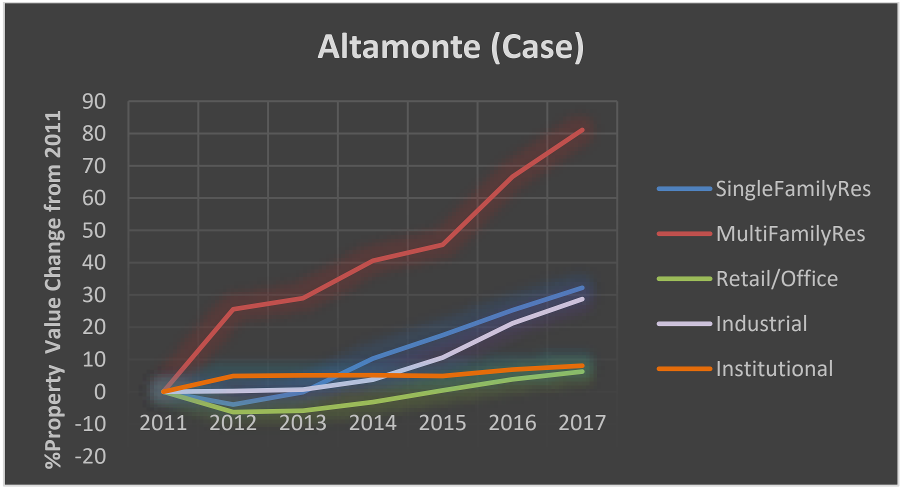
(a) Property Value Variation (Attraction)



(b) Property Value Variation (Downtown)

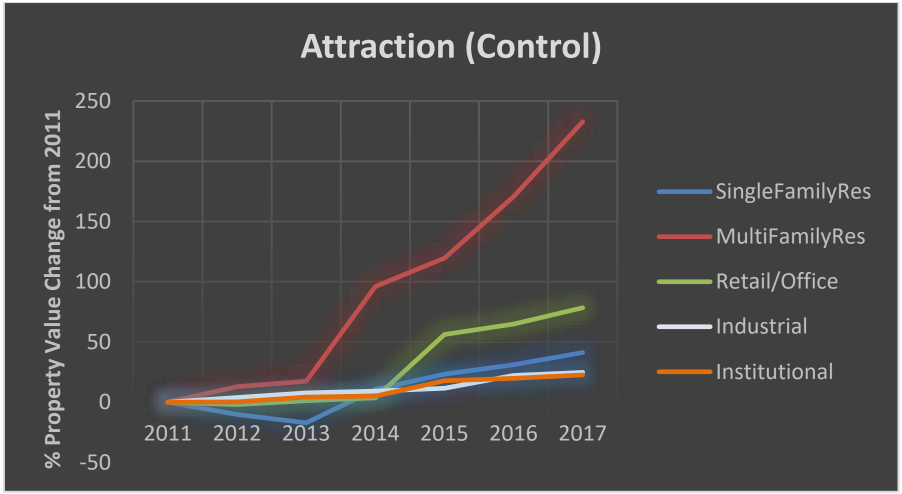


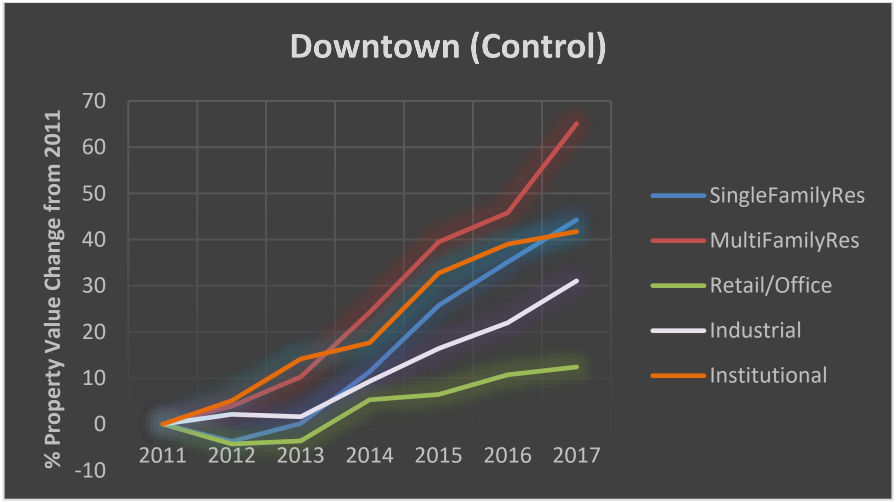
(c) Property Value Variation (Ivanhoe)



(d) Property Value Variation (Altamonte)

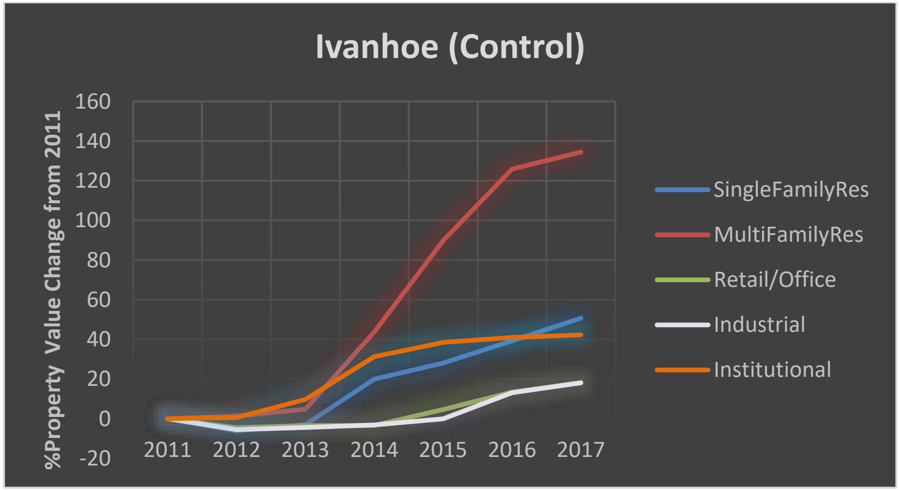
Figure 3.51: Property Value Variation for I-4 Ultimate Case Area

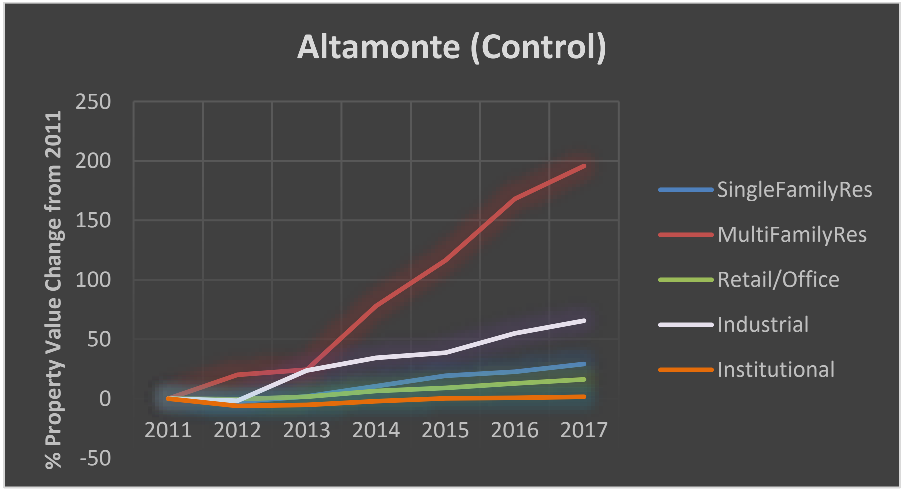




(a) Property Value Variation (Attraction)

(b) Property Value Variation (Downtown)





(c) Property Value Variation (Ivanhoe)

(d) Property Value Variation (Altamonte)

Figure 3.52: Property Value Variation for I-4 Ultimate Control Area

3.3.1.3 JUICE Orlando Bikeshare

Average property value changes from year 2011 to other consecutive years for downtown area stations are shown in Figure 3.53. The property increase trends are similar to the results from previous analysis for downtown regions. A significant increasing trend is observed for multi-family land use type across years (nearly 200% increase). The only anomaly is the substantial spike in price for industrial land-use in 2017 that sudden increase is more than 200%.

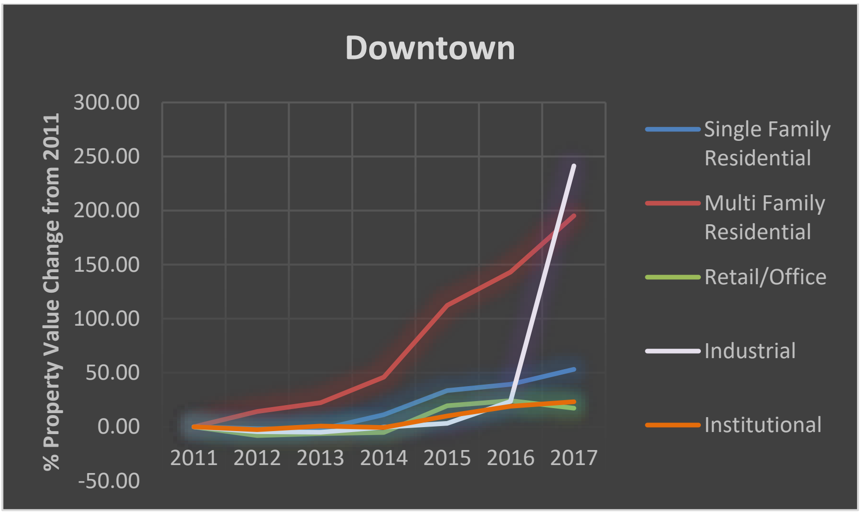


Figure 3.53: Property Value Variation for Downtown JUICE Bikeshare Stations Buffer

Figure 3.54 presents the average property value variation from 2011 to 2017 for control areas. The results offer substantial contrasts to results for downtown parcels. The increase in property values are higher for outside downtown control parcels. This is expected because downtown parcels are likely to be at a premium even prior to installation of Juice and are unlikely to experience as large increases as those possible outside downtown. The reader will note that, due the nature of Juice system, we did not have control parcels to compare the changes in property values. Hence, the results do not provide conclusive evidence that the increase is completely attributable to Juice system.

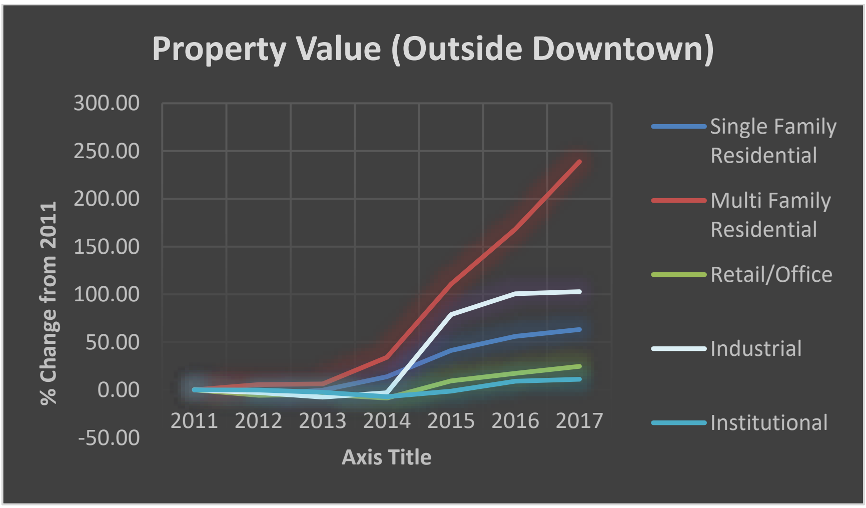


Figure 3.54: Property Value Variation for Outside Downtown JUICE Bikeshare Stations Buffer

3.3.2 Accessibility to Employment Variation

3.3.2.1 SunRail

The analysis described in 3.2.2.1 is repeated for all the years to measure the count of accessible job for three case and control regions (downtown, outside downtown and phase-II). Then average job counts per station for the three case areas was computed by dividing total job count for all stations with number of stations within the three case areas. Figure 3.55 presents the job count variation for each year from 2011. From the Figure, it is evident that the number of accessible jobs from downtown stations are substantially higher than other two regions. Specifically, the number of jobs vary as follows across the three areas between 2011 and 2016: (a) for downtown 530,000-570,000, (b) for Phase I outside downtown 143,000-382,000 and (3) for Phase II 166,000-215,000.

Total number of jobs accessible within the control area across SunRail stations is presented in Figure 3.56. The trends reveal a reversal of the trends for control parcels. Specifically, the highest job accessibility is observed for Phase II. Specifically, the number of jobs vary as follows across the three areas between 2011 and 2016: (a) for downtown 353,000-628,000, (b) for Phase I outside downtown 178,000-553,000 and (3) for Phase II 695,000-868,000. The results indicate that the counts of accessible jobs have not substantially benefitted from SunRail stations.

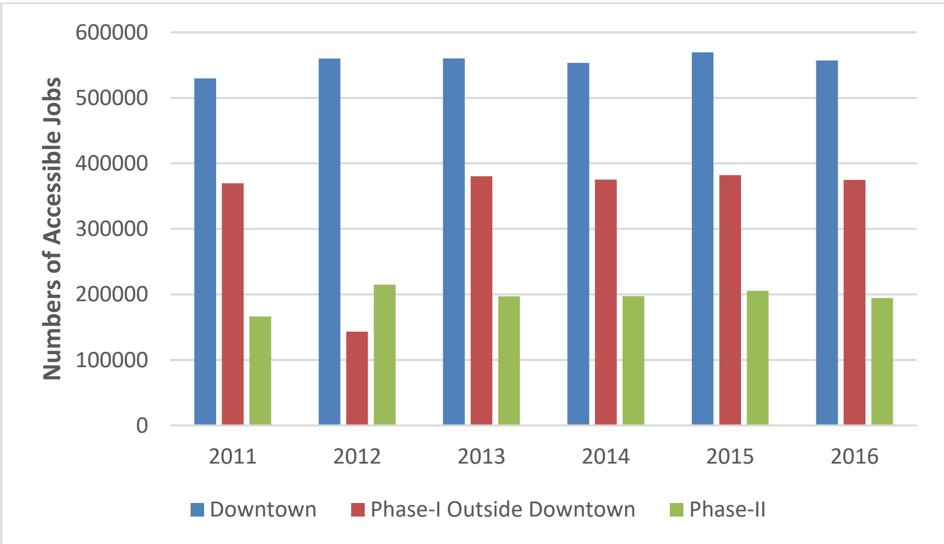


Figure 3.55: Number of Accessible Jobs Variation for SunRail Station's Case Area

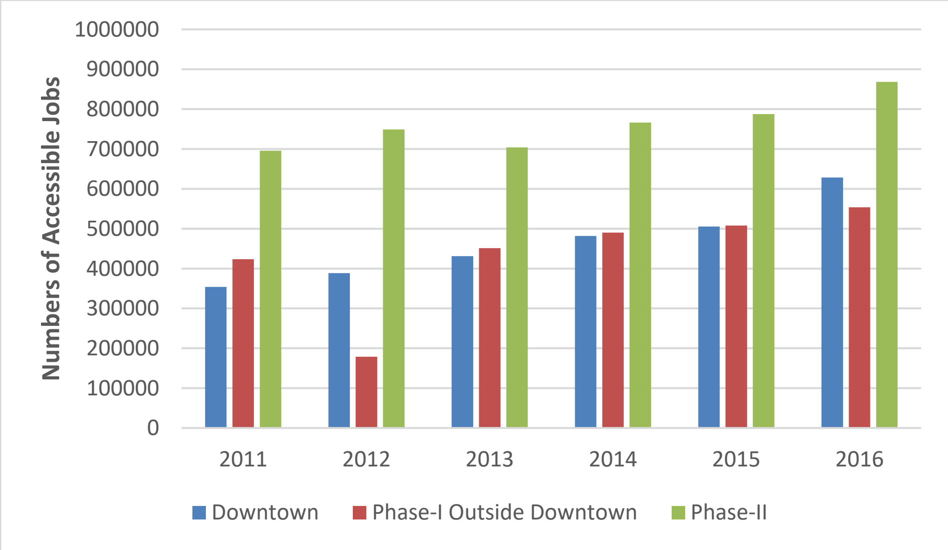


Figure 3.56: Number of Accessible Jobs Variation for SunRail Station's Control Area

3.3.2.2 I-4 Expansion

The procedure discussed in 3.2.2.2 section was used to compute average accessible job counts for all years for four segments of I-4 expansion. Then average job counts for each of those four case segments was computed. Figure 3.57 captures the job count variation for each year from 2011. From Figure 3.57 it is clear that threshold segment of downtown has higher job accessibility by a range of 10,000 to 70,000 followed by Ivanhoe segment from 2011 to 2016. Attraction region experienced substantial increase in job accessibility over the study period.

Total number of jobs accessible from each I-4 segment within the control areas were computed from 2011-2016 and presented in Figure 3.58. For control areas, Attraction segment has 200,000 more job accessibility than second highest zone of Altamonte at 2011 while the difference reduced to 100,00 in 2017. The variation in job accessibility for Downtown, Ivanhoe and Altamonte segments are quite similar. Similar to the SunRail case, there is no clear increase in job accessibility as a result of the I4 project based on how it is evaluated in our study.

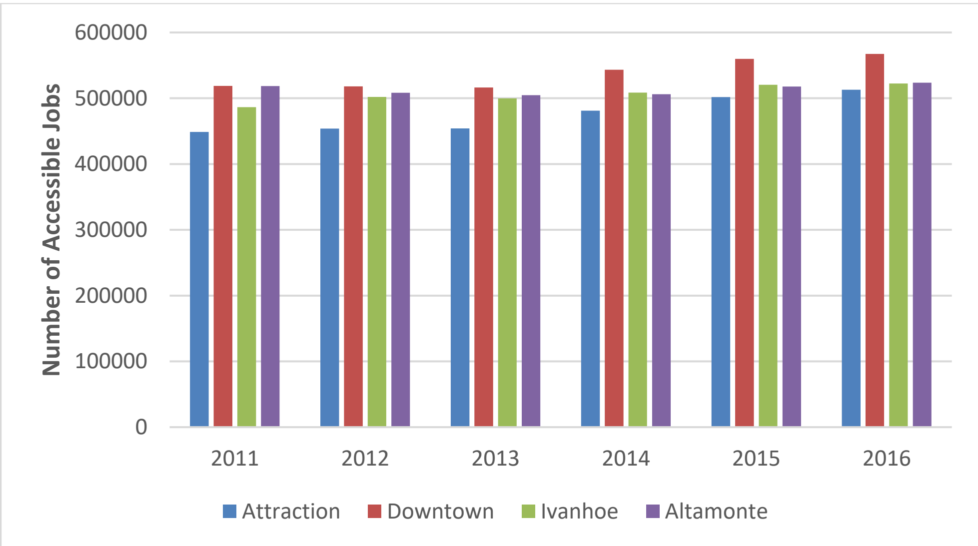


Figure 3.57: Number of Accessible Jobs Variation for I-4 Ultimate Case Area

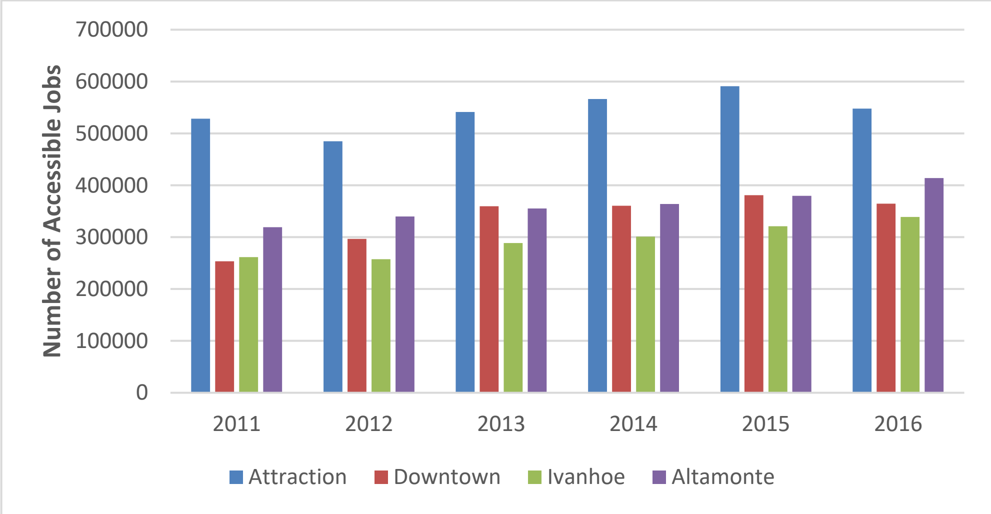


Figure 3.58: Number of Accessible Jobs Variation for I-4 Ultimate Control Area

3.3.2.3 JUICE Orlando Bikeshare

To compare accessible job count throughout years, a total number of jobs accessible per station from 2011 to 2016 was estimated by using similar techniques as discussed in 3.2.2.3. Figure 3.59 present job accessibility for each year from 2011. From the Figure, the average number of accessible jobs in downtown area has gradually increased across years from around 82,000 to 97,000.

Figure 3.60 shows average number of jobs accessible to each station from outside downtown control area. The average number of accessible jobs from outside downtown stations is increased in a gradual manner across the years from 72,000 to 82,000. However, the average number of accessible jobs to each non-downtown station for all years are lower than the corresponding values for downtown stations.

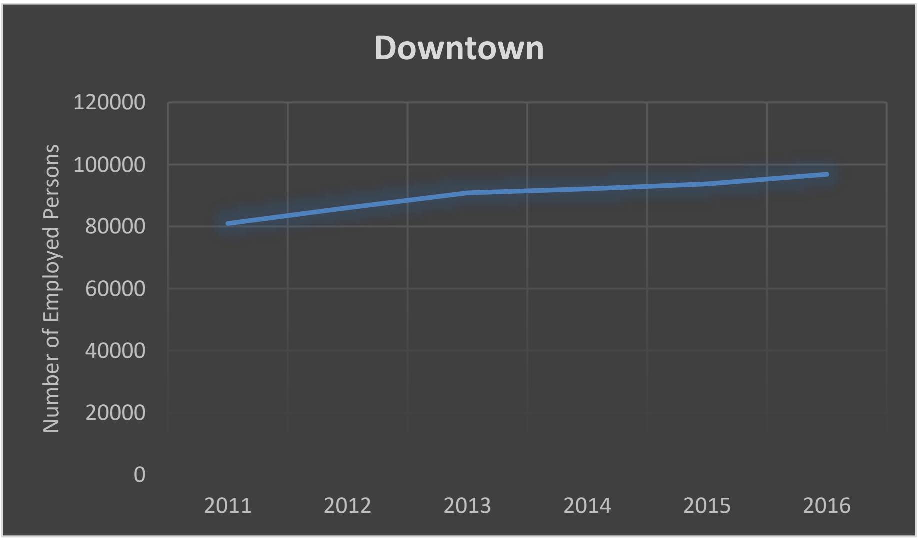


Figure 3.59: Distribution of Total Number of Accessible Jobs within Downtown Bikeshare Stations

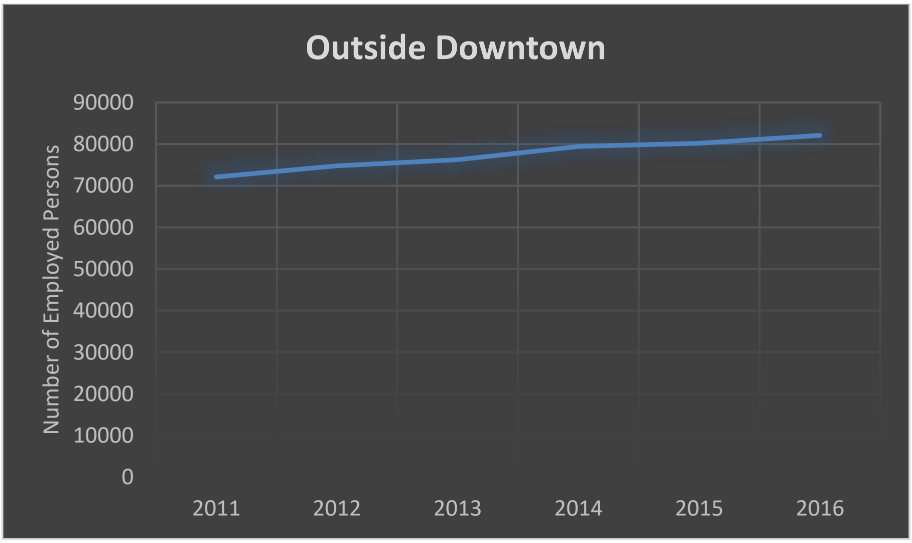


Figure 3.60: Distribution of Total Number of Accessible Jobs within Outside Downtown Bikeshare Stations

3.3.3 Commuting Time Variation

3.3.3.1 SunRail

The procedure discussed in 3.2.3.1 was repeated for creating layers for other years from 2011-2016 to compute average commuting time for each station. Then average commuting time has been estimated for three SunRail station's buffer area (Downtown, Outside Downtown and Phase-II). The average commuting time for each case area is shown in Figure 3.61. Commuting time of downtown stations is lower than the commuting time for the other two case areas. The figure clearly shows that phase-II stations have longer commute times compared to the other regions. Over the years, the travel times in general have remained reasonably stable across each region as follows: (a) for downtown between 21 and 24 minutes, (b) for Phase I outside downtown between 26 to 28 minutes and (3) for Phase II stations between 26 to 28. The corresponding values for the control parcels are as follows: (a) for downtown around 27 minutes, (b) for Phase I outside downtown between 23 to 26 minutes and (3) for Phase II stations between 28 to 29. The results indicate that commute times for individuals around SunRail stations are consistently lower than the corresponding values from control areas.

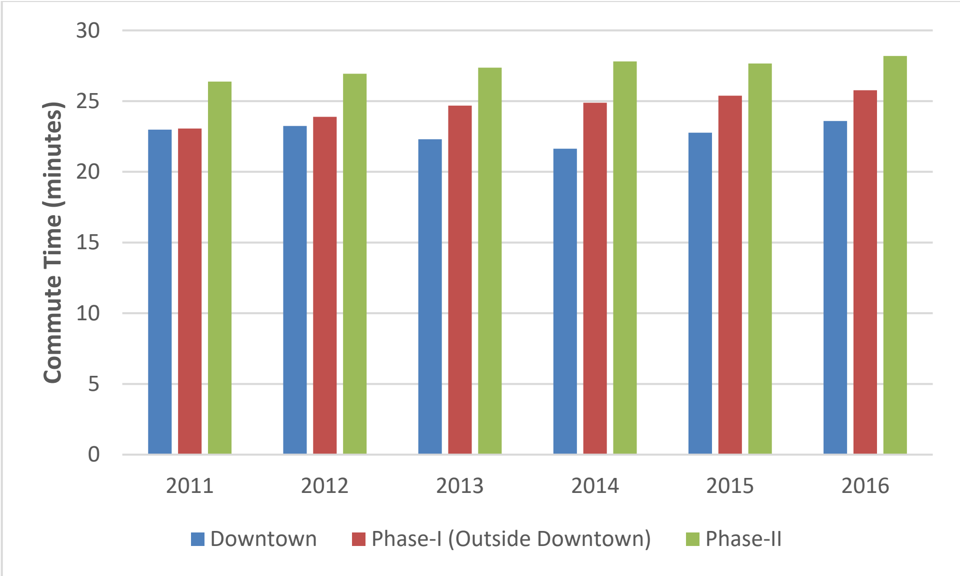


Figure 3.61: Commuting Time Variation for SunRail Station's Case Area

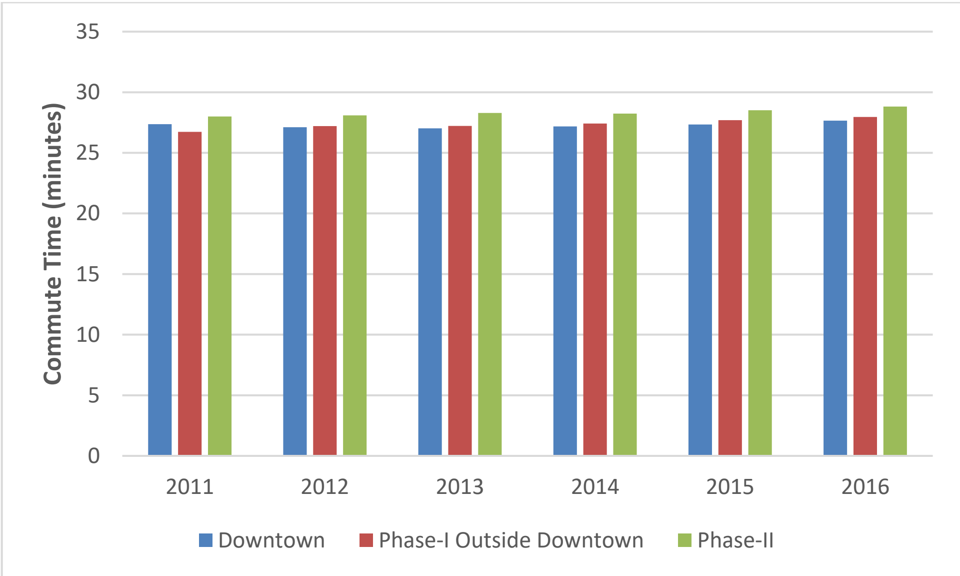


Figure 3.62: Commuting Time Variation for SunRail Station's Control Area

3.3.3.2 I-4 Expansion

The average commuting time for both case and control for four I-4 segments for 2011-2016 were computed by using same procedure as described 3.2.3.2. The results are presented in Figure 3.63 and Figure 3.64 respectively. The results clearly indicate that census tracts in case locations have lower commute times compared to the census tracts from control locations.

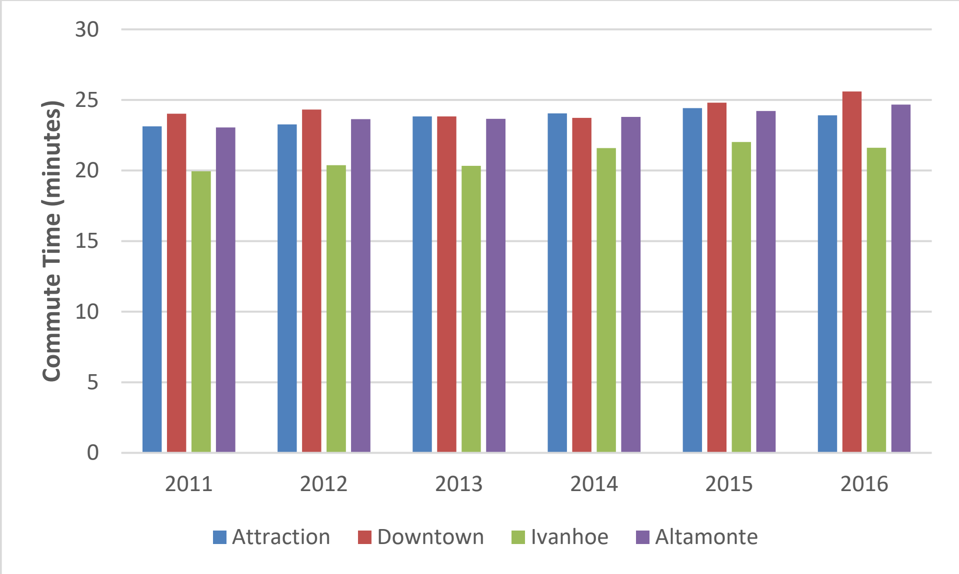


Figure 3.63: Commuting Time Variation for I-4 Ultimate Case Area

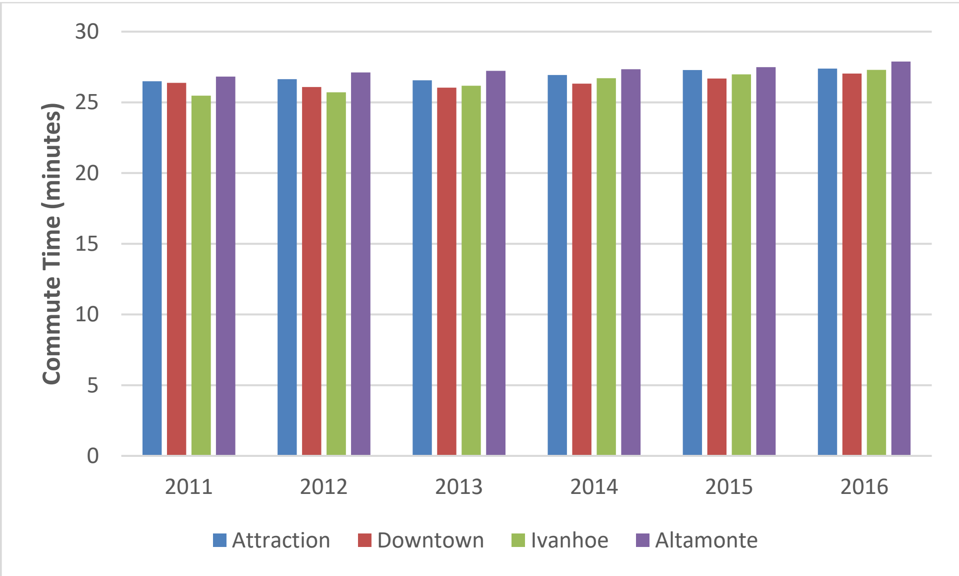


Figure 3.64: Commuting Time Variation for I-4 Ultimate Control Area

3.3.3.3 JUICE Orlando Bikeshare

Figure 3.65 presents average commuting time for downtown and outside downtown stations for 2011-2016. The results indicate that in the earlier years of the study period, commute times were longer for downtown stations. Over time, the differences have narrowed significantly.

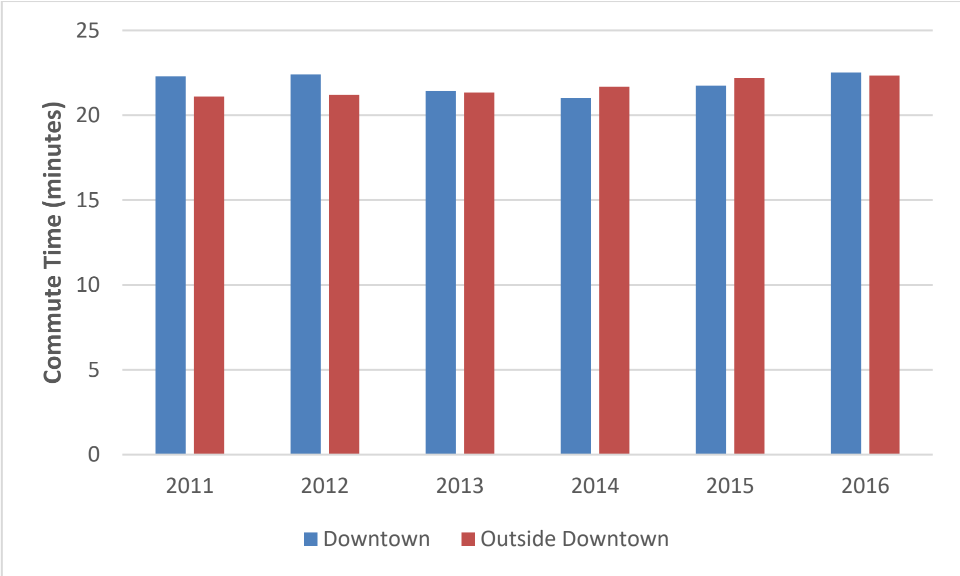


Figure 3.65: Commuting Time Variation for Bikeshare Stations

3.3.4 Land Use Variation

3.3.4.1 SunRail

The procedure described in 3.2.4.1 was repeated for creating layers for all years from 2011-2016. Then the conversion of area (acres) from vacant to other land use types for two consecutive years for each SunRail station was computed. Then total area was estimated for three SunRail station's buffer area (Downtown, Outside Downtown and Phase-II). The total conversion area (acres) for each case area is shown in Table 3.6. Single family residential and office are the major land use type that converted from vacant each year for all three case buffers. Other residential[4] and public are other major types that undergo changes from vacant land use type.

Also, area conversion (acres) for each of the three control areas was computed (shown in Table 3.7). Similar to case buffer, single family residential and office area are the major land use type conversions from vacant type. The results indicate substantially higher rates of conversion in the control areas.

[4] Other residential defined to those residential type that excludes 'Single family residential' and 'Multi-family residential' land use type. Few categories that belongs to 'Other residential' based on DOR based land use category are Mobile Homes, Condominiums, Cooperatives, Retirement Homes not eligible for exemption, Miscellaneous Residential (migrant camps, boarding homes, etc.) and Residential Common Elements / Areas.

Table 3.6: Land Use Change (Acres) from Vacant Area at SunRail Stations Throughout Years for Case

Case Area	Year	Single Family Residential	Multi-family Residential	Other Residential	Retail/Office	Industrial	Agricultural	Public	Other	Total
Downtown	**2011-12**	1.83	0.00	0.00	41.96	0.57	0.00	6.67	0.00	51.03
	2012-13	0.75	0.00	0.00	1.21	0.15	0.00	0.00	0.00	2.11
	2013-14	1.27	4.82	0.00	0.34	0.00	0.00	0.00	0.00	6.43
	2014-15	1.63	4.25	76.85	0.86	0.00	0.00	0.00	0.52	84.11
	2015-16	1.31	0.00	0.00	2.56	0.00	0.00	4.38	0.00	8.25
	2016-17	3.31	4.42	0.00	3.83	0.00	0.00	0.00	0.00	11.56
Outside Downtown	**2011-12**	7.14	0.19	0.75	36.04	14.88	0.93	13.75	11.51	85.19
	2012-13	13.87	0.00	5.76	43.32	3.58	8.87	0.17	1.91	77.48
	2013-14	12.30	9.84	0.63	12.77	0.60	0.01	0.39	8.30	44.84
	2014-15	16.21	6.24	270.97	11.20	33.55	0.00	24.42	2.04	364.63
	2015-16	25.35	14.37	1.23	8.43	0.00	0.00	1.70	13.68	64.76
	2016-17	23.37	0.32	16.14	10.03	0.00	0.00	0.00	0.00	49.86
Phase-II	**2011-12**	0.26	0.00	0.00	0.00	0.00	0.00	164.91	2.09	167.26
	2012-13	1.09	0.00	0.00	13.34	3.86	0.00	30.86	0.00	49.15
	2013-14	3.65	0.00	0.00	7.08	2.16	0.00	1.06	52.41	66.36
	2014-15	5.41	0.00	596.50	1.59	0.00	20.26	0.00	0.00	623.76
	2015-16	1.34	0.58	0.17	2.92	9.96	0.00	0.00	20.45	35.42
	2016-17	3.61	26.01	0.18	0.74	0.00	13.27	2.92	0.00	46.73

Table 3.7: Land Use Change (Acres) from Vacant Area at SunRail Stations Throughout Years for Control

Control Area	Year	Single Family Residential	Multi-family Residential	Other Residential	Retail/ Office	Industrial	Agricultural	Public	Other	Total
Downtown	**2011-12**	23.81	0.86	12.81	75.95	0.00	0.00	1.82	64.34	179.59
	2012-13	23.81	0.86	12.81	75.95	0.00	0.00	1.82	64.34	179.59
	2013-14	16.95	0.00	159.19	44.08	0.00	0.00	0.00	15.13	235.35
	2014-15	16.00	0.00	434.94	5.20	5.21	0.00	35.03	20.15	516.53
	2015-16	10.41	0.00	0.00	12.92	0.00	0.00	0.00	0.00	23.33
	2016-17	13.44	0.48	0.00	7.92	0.00	0.00	0.00	1.39	23.23
Outside Downtown	**2011-12**	195.81	20.54	361.56	390.01	36.89	121.43	231.52	67.23	1424.99
	2012-13	195.81	20.54	361.56	390.01	36.89	121.43	231.52	67.23	1424.99
	2013-14	201.12	32.14	153.28	96.95	14.67	216.65	62.67	89.08	866.56
	2014-15	134.87	22.52	497.93	91.91	33.12	79.22	43.67	325.61	1228.85
	2015-16	128.46	11.96	25.52	94.97	65.25	97.40	173.46	62.97	659.99
	2016-17	97.16	57.57	65.99	55.26	53.85	10.72	44.31	0.91	385.77
Phase-II	**2011-12**	56.50	0.00	63.23	54.43	1.68	38.25	0.77	181.36	396.22
	2012-13	56.50	0.00	63.23	54.43	1.68	38.25	0.77	181.36	396.22
	2013-14	290.89	22.18	23.02	19.98	0.00	138.93	23.21	22.04	540.25
	2014-15	270.96	35.39	573.59	33.08	32.10	56.78	44.82	6.10	1052.82
	2015-16	158.78	18.74	25.54	60.71	0.00	28.45	202.66	424.99	919.87
	2016-17	268.33	12.16	8.73	28.87	2.00	20.57	18.17	53.38	412.21

3.3.4.2 I-4 Expansion

The technique described in 3.2.4.2 was applied to compute area conversion from vacant for each year from 2011 to 2017 (see Table 3.8). Single family residential and office area are the major land use type conversions from vacant area for each year. Also, I-4 control buffer were used to estimate area (acre) that converted from vacant to non-vacant area for each consecutive year in a similar manner as case (see Table 3.9). The results are quite similar to results from comparison as single family residential and office area are the major land use type converted from vacant control parcels.

3.3.4.3 JUICE Orlando Bikeshare

Table 3.10 represents area (acre) changes from 2011-2017 around JUICE bikeshare stations. Very small percentage of area for each land use type has changed for both downtown and outside downtown parcels. Within these small changes, office area is the major land use type changing from vacant type.

Table 3.8: Land Use Change (Acres) from Vacant Area at I-4 Expansion Throughout Years for Case

Case Area	Year	Single Family Residential	Multi-family Residential	Other Residential	Retail/ Office	Industrial	Agricultural	Public	Other	Total
Attraction	**2011-12**	1.13	0.00	0.33	47.49	0.56	0.00	6.67	0.00	56.18
	2012-13	0.56	0.00	17.25	2.80	0.15	0.00	0.00	0.00	20.76
	2013-14	1.03	0.00	0.00	4.58	0.00	0.00	0.00	0.00	5.61
	2014-15	1.27	1.74	204.14	4.36	0.00	0.00	0.00	0.24	211.75
	2015-16	1.03	0.00	0.00	4.06	0.00	0.00	4.37	0.00	9.46
	2016-17	5.02	1.83	0.00	5.90	0.00	0.00	0.00	0.00	12.75
Downtown	**2011-12**	2.48	0.00	0.00	31.14	0.00	0.00	8.52	0.00	42.14
	2012-13	6.10	0.00	0.00	2.76	0.00	0.00	0.00	0.00	8.86
	2013-14	1.66	4.82	0.00	9.89	0.00	0.00	0.00	0.04	16.41
	2014-15	8.10	6.92	116.39	9.22	0.00	0.00	23.68	0.84	165.15
	2015-16	9.89	0.48	0.00	5.53	0.65	0.00	0.00	0.00	16.55
	2016-17	9.71	2.91	0.00	4.20	0.00	0.00	0.00	0.00	16.82
Ivanhoe	**2011-12**	0.94	0.42	0.00	4.99	0.00	0.00	0.24	1.61	8.20
	2012-13	6.84	0.00	0.00	0.50	0.00	0.00	0.00	0.00	7.34
	2013-14	1.74	0.00	1.10	6.79	0.00	0.00	0.00	0.40	10.03
	2014-15	0.98	0.00	128.48	0.14	0.00	0.00	0.00	6.18	135.78
	2015-16	3.84	11.60	0.00	1.46	0.00	0.00	31.08	0.00	47.98
	2016-17	1.85	0.00	0.00	1.44	0.00	0.00	0.00	0.00	3.29
Altamonte	**2011-12**	1.22	0.00	1.80	72.88	0.00	0.00	0.10	33.98	109.98
	2012-13	6.60	0.00	55.32	80.02	0.00	0.00	0.00	46.16	188.10
	2013-14	14.23	0.00	7.97	3.25	0.00	0.00	0.00	0.00	25.45
	2014-15	22.35	0.00	678.78	42.81	0.00	0.00	0.10	46.73	790.77
	2015-16	9.23	31.15	0.00	1.43	0.00	0.00	15.93	0.00	57.74
	2016-17	0.34	0.00	0.00	31.07	0.00	0.00	0.00	0.00	31.41

Table 3.9: Land Use Change (Acres) from Vacant Area at I-4 Expansion Throughout Years for Control

Case Area	Year	Single Family Residential	Multi-family Residential	Other Residential	Retail/ Office	Industrial	Agricultural	Public	Other	Total
Attraction	2011-12	114.50	0.86	17.55	298.79	20.36	4.40	195.33	53.46	705.25
	2012-13	153.63	22.49	136.98	115.76	6.44	0.00	3.74	72.25	511.29
	2013-14	125.02	43.90	264.50	70.99	12.43	0.00	0.00	22.27	539.11
	2014-15	159.31	18.48	995.04	74.04	19.03	22.89	0.00	395.40	1684.19
	2015-16	107.43	14.11	3.60	28.73	18.69	17.53	89.81	2.93	282.83
	2016-17	90.07	9.53	16.48	101.86	14.52	0.00	41.35	52.37	326.18
Downtown	2011-12	10.37	0.00	12.17	127.74	19.08	0.00	0.00	12.89	182.25
	2012-13	5.12	0.00	94.97	50.22	7.33	0.00	0.00	4.81	162.45
	2013-14	6.68	0.00	6.26	33.05	0.90	0.00	0.00	8.59	55.48
	2014-15	9.36	0.00	501.17	2.20	10.54	10.10	1.51	16.04	550.92
	2015-16	10.92	0.00	2.38	22.59	1.45	0.00	0.00	0.00	37.34
	2016-17	12.52	0.79	13.76	18.24	16.06	0.00	2.33	0.00	63.70
Ivanhoe	2011-12	19.68	0.26	0.09	71.06	3.90	0.00	37.30	2.38	134.67
	2012-13	42.18	0.00	7.41	30.22	0.00	0.00	3.36	0.00	83.17
	2013-14	45.06	10.25	9.40	29.83	1.53	0.00	0.00	19.14	115.21
	2014-15	21.47	4.04	930.36	7.77	0.75	0.00	39.49	7.96	1011.84
	2015-16	20.99	0.00	0.00	8.95	12.33	5.12	0.00	1.67	49.06
	2016-17	19.62	10.00	5.18	5.01	4.15	0.00	0.00	0.82	44.78
Altamonte	2011-12	84.26	0.19	13.03	49.18	7.66	2.51	3.03	17.66	177.52
	2012-13	96.96	29.28	16.27	39.14	3.05	30.91	0.17	0.91	216.69
	2013-14	104.13	12.15	9.69	26.76	2.91	3.03	9.49	14.83	182.99
	2014-15	62.29	2.02	627.68	11.56	23.15	11.45	4.53	190.55	933.23
	2015-16	66.02	9.78	10.08	21.39	8.21	0.00	0.00	79.23	194.71
	2016-17	34.97	4.71	45.79	12.92	11.99	0.00	0.00	0.08	110.46

Table 3.10: Land Use Change (Acres) from Vacant Area Around JUICE Bikeshare Stations

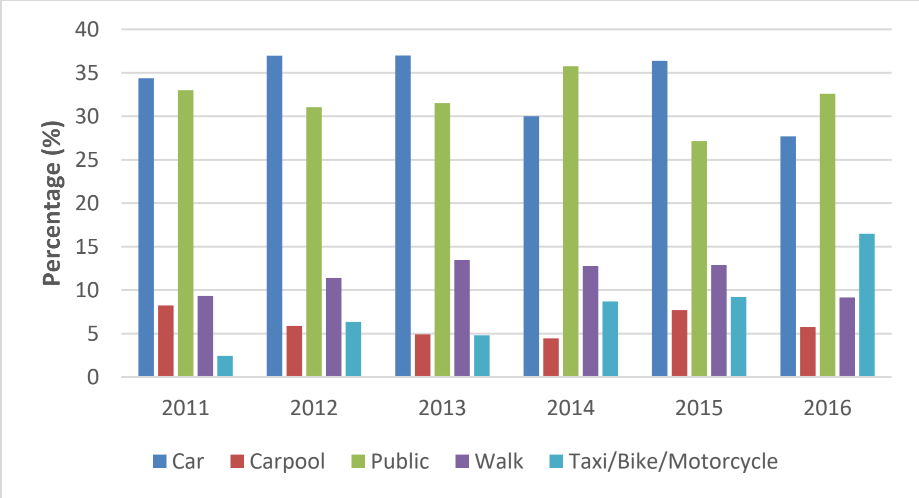
Year	Single Family Residential		Multi-family Residential		Other Residential		Retail/Office		Public		Total	
	Downtown	Outside Downtown	Downtown	Outside Downtown	Downtown	Outside Downtown	Downtown	Outside Downtown	Downtown	Outside Downtown	Downtown	Outside Downtown
2011-12	0.00	0.25	0.00	0.00	0.00	0.00	12.78	15.40	0.00	4.52	12.78	20.17
2012-13	0.00	0.39	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.00	0.48	0.39
2013-14	0.14	0.14	4.82	0.00	0.00	9.02	0.00	5.00	0.00	0.00	4.96	14.16
2014-15	0.00	1.07	4.25	4.57	20.82	24.60	0.12	0.58	0.00	0.00	25.19	30.82
2015-16	0.00	1.75	0.00	4.62	0.00	0.00	0.53	0.62	2.99	0.00	3.52	6.99
2016-17	0.00	2.90	4.42	29.41	0.00	0.00	0.00	0.40	0.00	0.00	4.42	32.71

3.3.5 Travel Pattern Variation for Zero Car HH

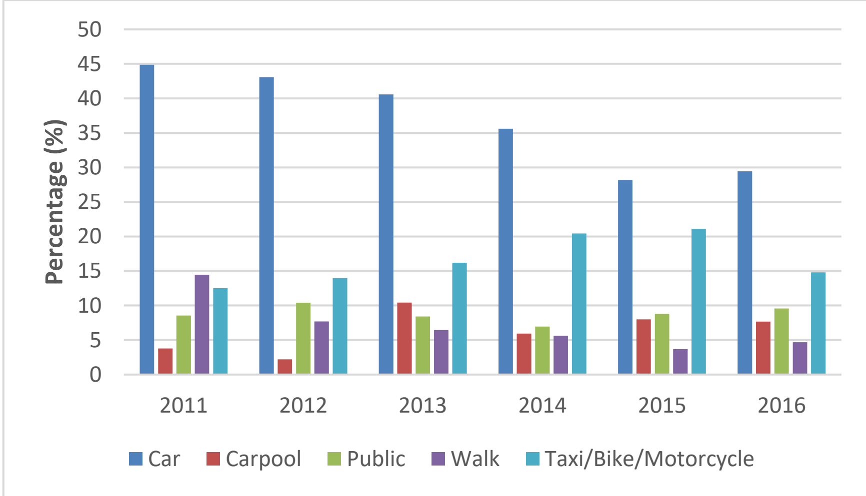
3.3.5.1 SunRail

The procedure described in 3.2.5.1 was used for creating layers for all years from 2011-2016 to capture the variation in zero car household work mode distribution for each station. The average mode distribution for three SunRail station's buffer area (Downtown, Outside Downtown and Phase-II) were computed. The average value for each case area is shown in Figure 3.66. It is interesting to see that use of public transport increased by 10% and 5% around downtown and Phase-II stations respectively from 2015. Taxi or bike or motorcycle have increased by almost 14% around downtown stations from 2011 to 2016 while these mode shares have not changed for other station areas.

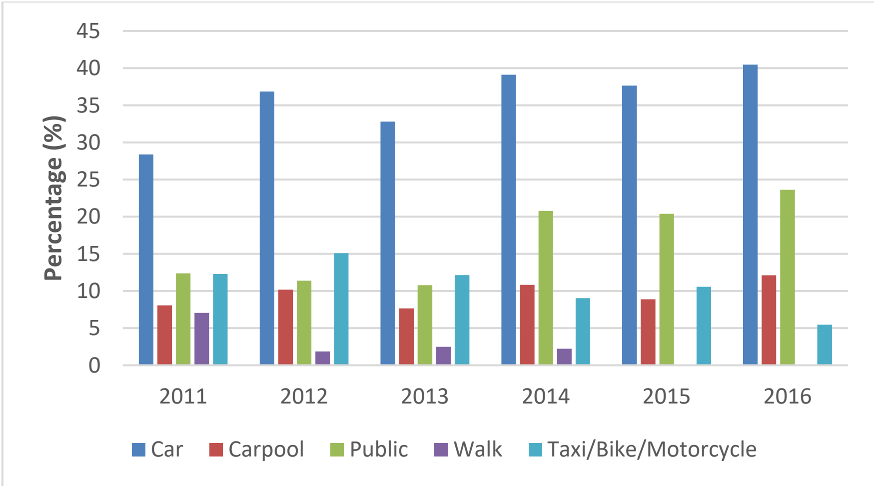
Average mode share for control areas for 2011-2016 was also estimated (see Figure 3.67). From the figure, public transportation use has reduced by 5% around downtown control buffer area. For downtown control taxi or bike or motorcycle mode have increased by 5% while reduced by 2-5% for control buffer area.



(a) Travel Pattern Variation (Downtown)

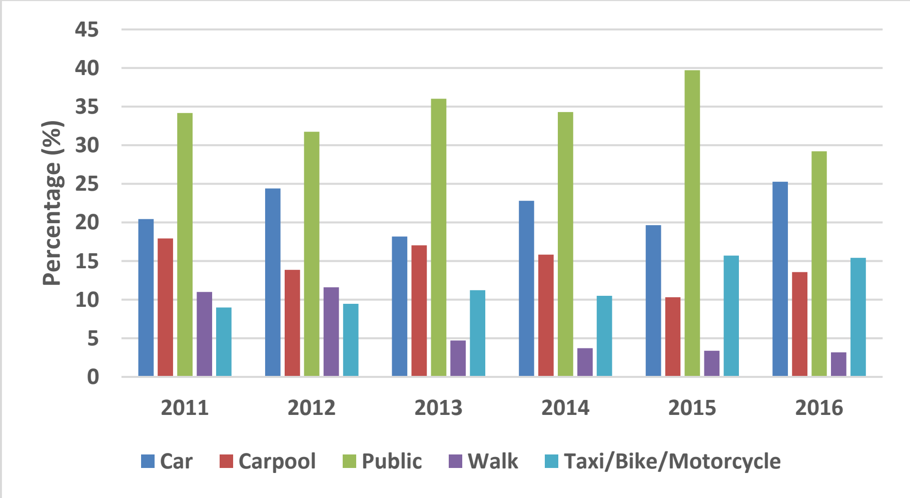


(b) Travel Pattern Variation (Outside Downtown)

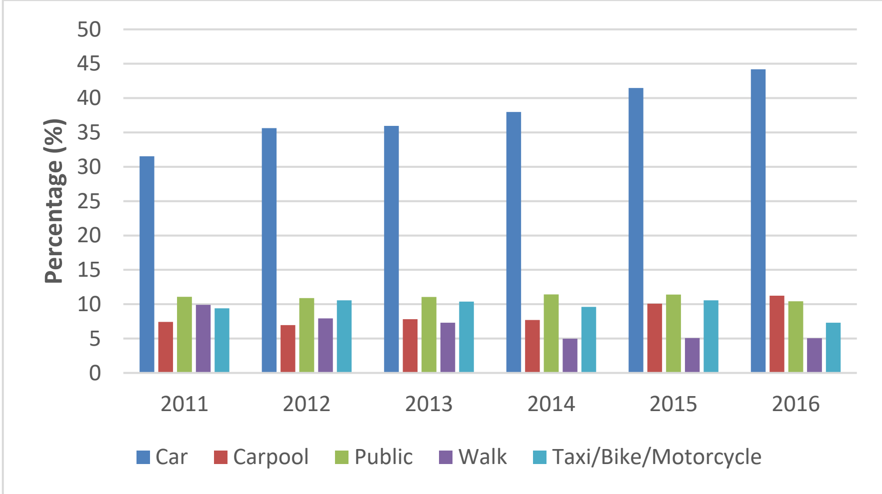


(c) Travel Pattern Variation (Phase-II)

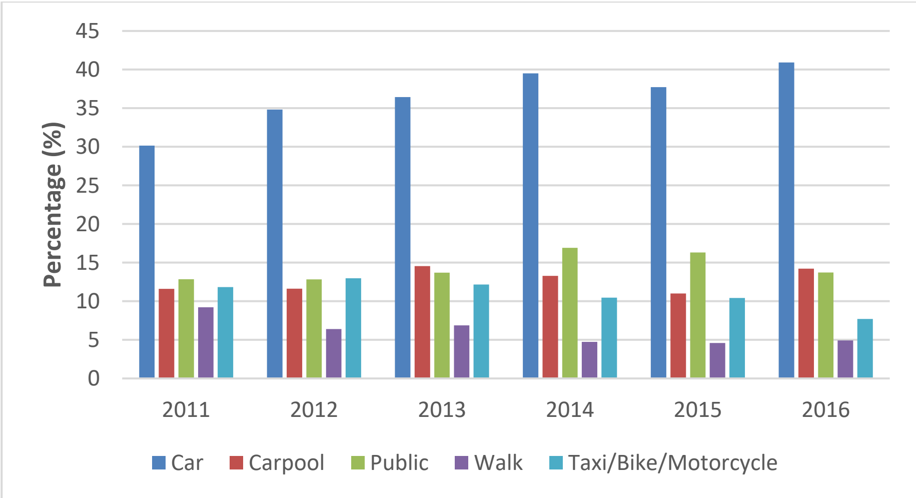
Figure 3.66: Travel Pattern Variation for Case Buffer Area of SunRail Stations



(a) Travel Pattern Variation (Downtown)



(b) Travel Pattern Variation (Outside Downtown)



(c) Travel Pattern Variation (Phase-II)

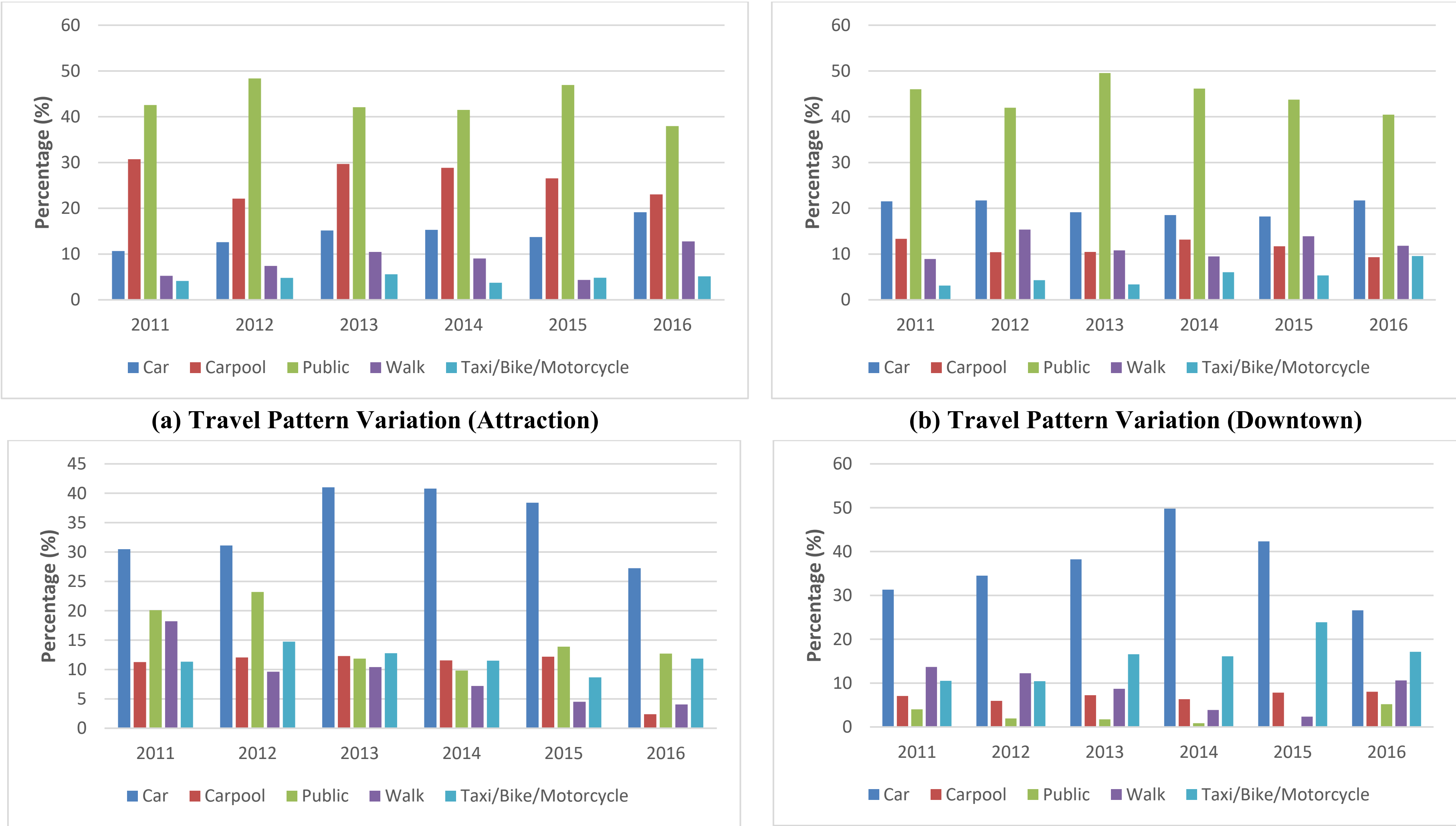
Figure 3.67: Travel Pattern Variation for Control Buffer Area of SunRail Stations

3.3.5.2 I-4 Expansion

The average mode distribution around four I-4 segments were computed for 2011-2016 by using the procedure described in 3.2.5.2. Figure 3.68 presents the variation for different years. For households with zero vehicles, public transportation is the main mode of transportation in attraction and downtown regions. The results for control segments (see Figure 3.69) indicate that for downtown region, the share of public transportation is lower. Given the small sample size of the zero car households, the results needed to be considered with caution.

3.3.5.3 JUICE Orlando Bikeshare

The average mode share were computed for downtown (see Figure 3.70) and non-downtown stations (see Figure 3.71) for 2011-2016. Share of public transportation presents an increasing trend for downtown while showing a decreasing trend for non-downtown buffer areas. The installation of bikeshare stations appears to have resulted in a significant jump in taxi/bike/motorcycle and walk mode share. Specifically, taxi/bike/motorcycle mode share increased by around 10% and 20% respectively for downtown and outside downtown stations' buffer while walk mode has increased by 5% for downtown and reduced by 15% for outside downtown stations buffer



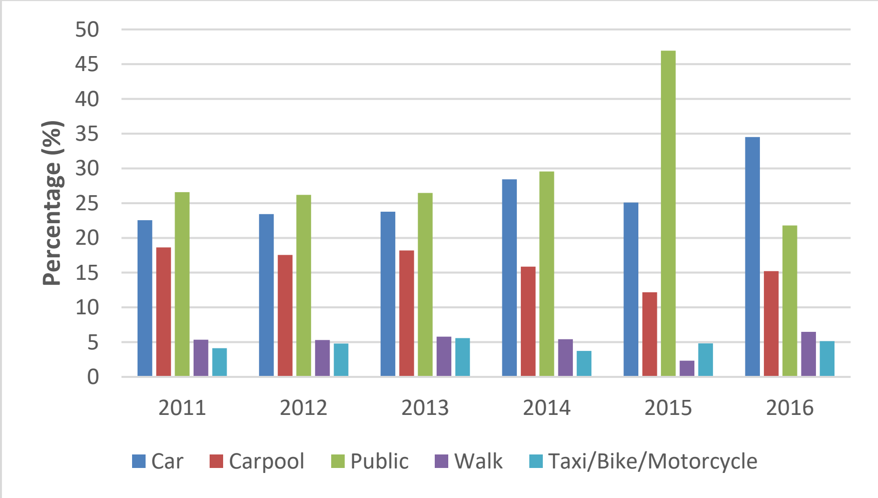
(a) Travel Pattern Variation (Attraction)

(b) Travel Pattern Variation (Downtown)

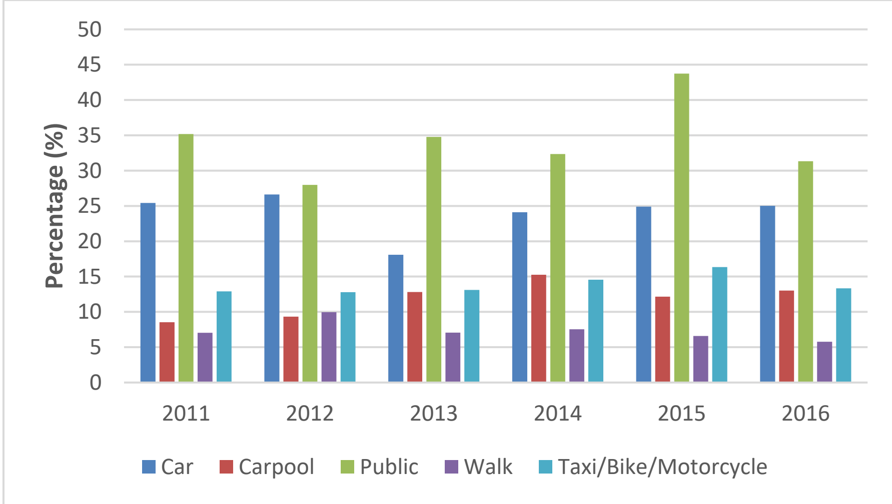
(c) Travel Pattern Variation (Ivanhoe)

(d) Travel Pattern Variation (Altamonte)

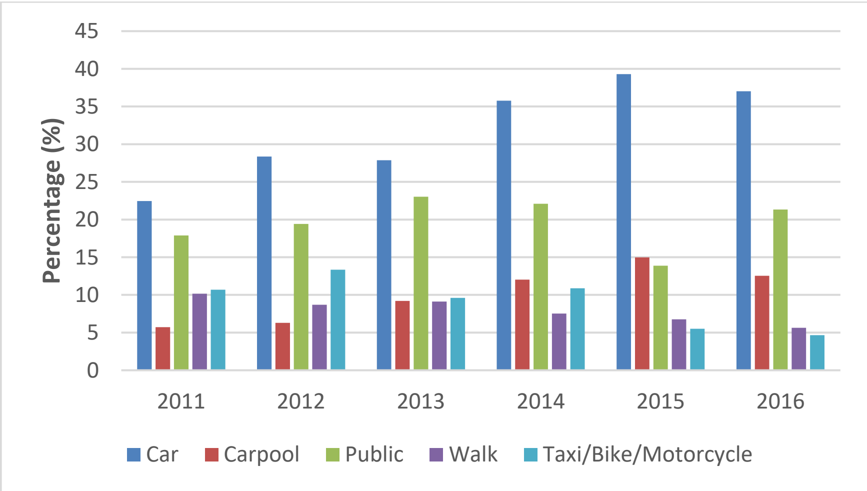
Figure 3.68: Travel Pattern Variation for Case Buffer Are of I-4 Expansion



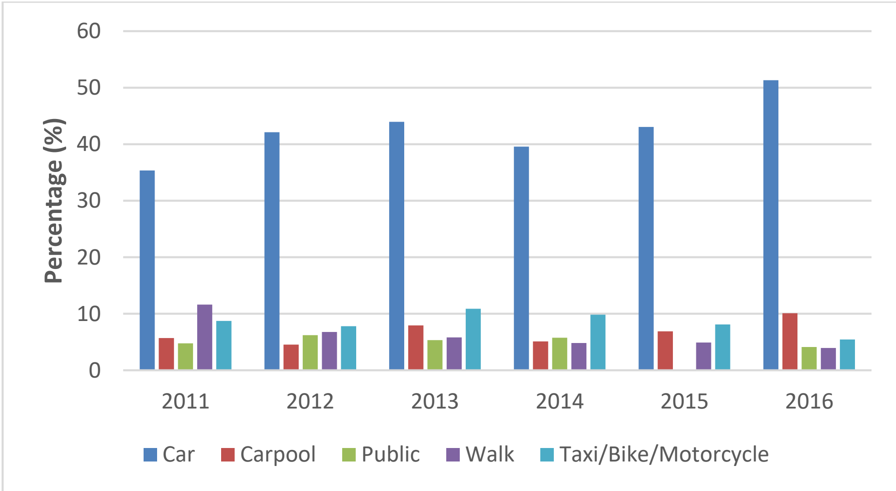
(a) Travel Pattern Variation (Attraction)



(b) Travel Pattern Variation (Downtown)



(c) Travel Pattern Variation (Ivanhoe)



(d) Travel Pattern Variation (Altamonte)

Figure 3.69: Travel Pattern Variation for Control Buffer Area of I-4 Expansion

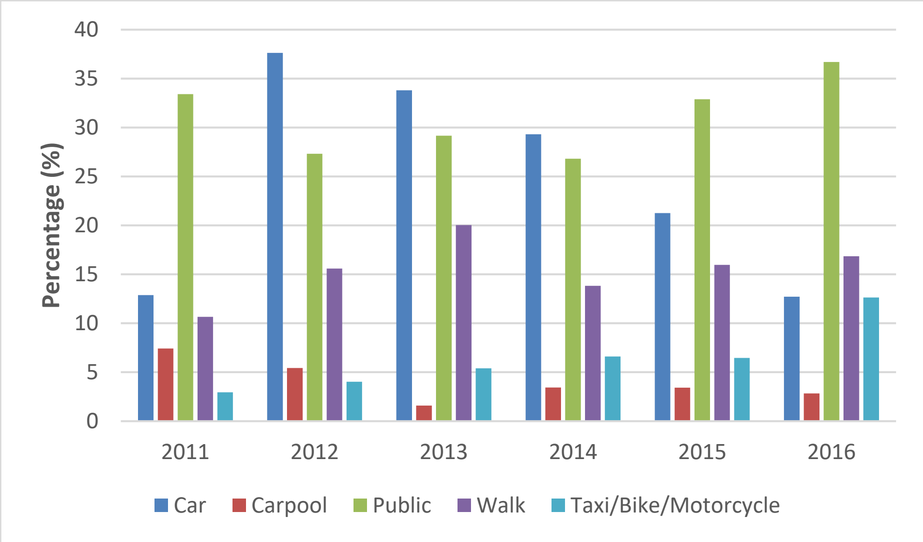


Figure 3.70: Travel Pattern Variation for Case Buffer Area of JUICE Bikeshare Stations

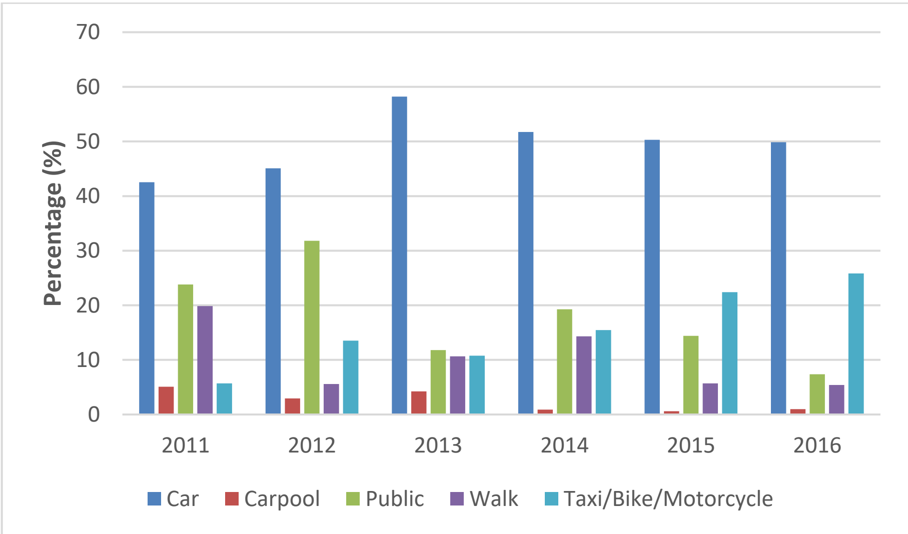


Figure 3.71: Travel Pattern Variation for Control Buffer Area of JUICE Bikeshare Stations

CHAPTER 4: SOCIAL MEDIA DATA ANALYTICS

4.1 STUDY APPROACH

Toward understanding public feedback on several established and ongoing transportation projects in the Central Florida region, we have extensively collected social media data in phase 1. For the project, we have selected Twitter as a reliable data source as it is the most widely used social media platform in the USA with 67 million active users (Omnicore, 2017). Twitter is a micro blogging service used to share views, activities, and thoughts through a 280 characters long message called 'tweet'. Apart from the text portion of a tweet, there are a number of features which carry important clues to latent attributes of social media users. With twitter, one can extract spatial (geo-tagged) and temporal (time-stamped) information for a longer period of time and for large samples without accessing personal details or the content of the tweets (Frias-Martinez et al., 2012; Hasan and Ukkusuri, 2015).

In addition, data from Twitter can be collected without any cost. Twitter is a micro blogging service used to share activities and opinions through a 280 characters long message called 'tweet'. In Phase 2, we have continued the data collection effort and extended the datasets with recently collected data. In this phase, we have several tasks:

- Perform sentiment analysis to measure public opinion about several ongoing projects in Central Florida
    - Perform *subjectivity* analysis to determine the level of community opinion of transportation projects
    - Perform *polarity* analysis to determine the degree of community likeability of transportation projects
- Perform topic analysis to understand specific public perspectives of different transportation projects

In this report, we describe our extended dataset and the findings from the sentiment and topic analysis of the datasets.

4.2 DATA COLLECTION PROCESS FROM TWITTER

Among various social media platforms, Twitter is a potential source as data from it can be easily collected through simple web scraping and has a wide range of information within each post (tweets). The data collection effort of this part was described in detail in our Phase 1 Final Report. To maintain continuity, we repeat the description here. However, we have updated all the tables with new statistics of the extended datasets.

To collect data from Twitter, it requires a set of authentication keys providing an OAuth (Open Authorization) which is a standard for token-based authentication for accessing web data. Through a set of unique OAuth keys, we have used Twitter's REST Application Program Interface (API) and Stream API to web scrap from twitter web pages. The REST API provides programmatic access to read and write Twitter data, i.e. create a new Tweet, read user profile and follower data etc. and Streaming API continuously delivers new responses to API queries over a long-lived HTTP connection receiving updates on the latest Tweets matching a search query, stay in sync with user profile updates etc. (Twitter Developer Documentation (a), 2017). These developer keys are freely available within a certain query limits for specific types of search requests (Twitter Developer Documentation (b), 2017). In brief, with valid OAuth keys one can search for tweets containing certain keywords and/or a group of keywords, tweets from certain user accounts, specific tweets within a selected geographical boundary box etc. For this project, a set of keyword and some specific Twitter accounts have been selected to collect data. The Appendix sections (Appendix C-Appendix E) contain the python scripts used to analyze the data.

4.2.1 Tweet Search using Specific Keywords

The research team has selected some specific keywords, with consultation of the FDOT officials, which represents the key components of the transportation infrastructure in the Central Florida region. We mainly focused on several ongoing major transportation projects in the Central Florida region including second phase of SunRail commuter rail extension, I-4 expansion, pedestrian and bicycling facility installation, and bicycle sharing system (Juice) introduction. Within the limitations of twitter search API, data from the last 8 to 9 days can be collected for any specific keyword or a group of keywords. Keeping this condition in mind, data are being collected once in every 7 to 8 days starting from 24 February 2017. Table 4.1 shows the collected number of tweets using different keyword and different group of keywords up to November 15, 2018.

Table 4.1: Tweets Collected using Specific Keyword Search

Sl. No.	Keywords	Total Unique Tweets	Geo-tagged Tweets
1	florida bus	10059	82
2	florida crime	40338	19
3	florida sidewalk	601	19
4	florida walking	29712	160
5	I-4 Construction	1190	0
6	I-4 Crash	7659	1
7	I-4 Ultimate	215	0
8	Juice Bike	1963	21
9	juicebike	4	0
10	lakexpress	33	0
11	lynx bus	1399	23
12	Lynx Vanpool	0	0
13	Space Coast Area Transit	84	4
14	sunrail	4378	82
15	Sunshine Skyway	5472	260
16	suntrail	133	1
17	suntran ocala	32	2
Total		**103,272**	**674**

4.2.2 Tweet Search from Specific User Accounts

After careful observation and discussions, we have identified some Twitter accounts which disseminate important information about the existing and on-going transportation projects in the Central Florida region. In addition, we have collected data from 14 FDOT 511 service Twitter accounts that share incidents and real-time traffic information throughout the state. Each account provides traffic information for specific regions and/or facilities maintained by FDOT. Among these accounts, tweets have been collected from 13 accounts which use English language (Table 4.2) except the account named 'FL511_Estatal' which uses the Spanish language. For a particular user, Twitter search API restricts the maximum retrievable tweets up to the latest 3,240 tweets at a time. Table 4.2 shows the tweets collected from the 26 user accounts until November 15, 2018. Several accounts such as juicebikes, lakexpress, lynxbusorlando, RideSunRail, and SunRailRider have posted a significant number of tweets. For instance, Lynx posts about 7 tweets per day and SunRail posts about 8 tweets per day.

Table 4.2: Tweets Collected from Specific User Accounts

User Name	Total Tweets	Created at	Earliest Tweet	Latest Tweet	Duration in Days	Daily Tweets
321Transit	6,218	1/12/2012 14:48	2/1/2017 21:00	11/15/2018 5:49	652	9.54
965traffic	19,315	1/24/2017 19:51	2/24/2017 21:02	11/15/2018 3:38	629	30.71
BikeWalkCFL	17,769	10/6/2010 16:54	2/12/2017 0:25	11/15/2018 3:48	641	27.72
fl_511_i4	61,040	10/6/2010 17:30	1/30/2017 12:52	11/15/2018 23:56	654	93.33
FL511_95Express	58,032	10/6/2010 17:33	2/17/2017 17:31	11/15/2018 23:53	636	91.25
fl511_central	61,296	10/6/2010 17:37	2/24/2017 13:14	11/15/2018 23:50	629	97.45
fl511_i10	61,249	10/7/2010 12:38	3/11/2017 7:24	11/15/2018 22:44	614	99.75
fl511_i75	61,323	1/12/2012 14:20	1/28/2017 11:56	11/15/2018 23:57	656	93.48
fl511_i95	61,370	5/10/2017 1:42	4/13/2017 12:58	11/15/2018 23:53	581	105.63
fl511_northeast	61,315	10/6/2010 17:15	1/20/2017 10:41	11/15/2018 22:25	664	92.34
fl511_panhandl	61,289	10/7/2010 12:57	4/29/2017 19:18	11/15/2018 22:44	565	108.48
FL511_SOUTHEAST	61,276	10/6/2010 17:01	2/11/2017 17:56	11/15/2018 23:57	642	95.45
fl511_southwest	61,244	10/6/2010 17:23	2/4/2017 19:34	11/15/2018 21:12	649	94.37
fl511_state	61,192	3/7/2017 20:31	7/21/2017 9:31	11/15/2018 23:57	482	126.95
fl511_tampabay	61,334	8/25/2010 15:58	8/25/2010 16:04	11/15/2018 23:56	3004	20.42
fl511_turnpike	61,325	4/7/2011 13:54	9/29/2016 13:38	11/15/2018 23:48	777	78.93

I4Ultimate	57,893	8/29/2013 19:02	8/30/2013 17:58	2/24/2017 1:59	1274	45.44
juicebikes	1,360	11/25/2014 17:19	1/17/2017 14:20	11/14/2018 12:30	666	2.04
lakexpress	378	3/23/2009 22:59	3/19/2011 21:53	10/26/2017 17:45	2413	0.16
lynxbusorlando	19,321	8/13/2009 20:37	9/29/2010 18:45	11/15/2018 15:00	2969	6.51
RideSunRail	16,171	6/4/2009 19:39	4/10/2013 13:46	11/15/2018 21:19	2045	7.91
SunRailRider	2,580	5/7/2012 20:50	5/10/2014 15:59	8/29/2014 11:12	111	23.24
SunTranTDP2017	145	3/24/2011 13:54	4/4/2011 22:41	6/13/2017 15:08	2262	0.06
WazeTrafficOrl	58,392	11/9/2016 15:20	11/9/2016 17:44	2/24/2017 1:59	107	545.72
Total Tweets	**992,827**			**Average**	**1013.42**	**79.04**

4.3 TWITTER DATA ANALYSIS

4.3.1 Sentiment Analysis

Public sentiment towards a specific transportation infrastructure project is essential for understanding community building impacts of that project. Using Twitter data, indicators can be constructed to reflect such public sentiment. We have applied a natural language processing (NLP) tool for analyzing the text data available in tweets. To analyze the sentiment of tweet contents, we have run TextBlob (Vijayarani and Janani, 2016), an open-source Python NLP tool, over Twitter data. Based on the tweet text, the software returns the polarity and subjectivity of a tweet.

The subjectivity index is a number within the range [0.0, 1.0] where 0.0 is very objective indicating a lack of opinion and 1.0 is very subjective indicating the presence of a strong opinion in a tweet. The subjectivity index of a tweet may potentially indicate the quality of being based on or influenced by personal feelings, which can provide more sentiment information of individuals. The polarity index is a number within the range [-1.0, 1.0] where -1.0 indicates a very negative and +1.0 indicates a very positive sentiment. The polarity index of a tweet may potentially indicate the likeability of an individual towards a specific transportation project.

To determine the sentiment trends over time, we chose three time periods to show the sentiment analysis results. Sentiment trends over different time periods can reveal the development of individual attitude of the individuals towards transportation projects. These three time periods are as follows:

- *Period 1*: February 2017 – July 2017
- *Period 2*: August 2017 – December 2017
- *Period 3*: January 2018 – August 2018

Figure 4.1-4.3 shows the distributions of subjectivity and polarity of the tweets collected for specific keywords during the data collection period. Figure 4.1-4.3 shows the results for three keywords only (SunRail, Juice Bike, and I-4 Ultimate) and the results of the remaining keywords are presented in Appendix F. We observe that, in general, the polarities of most of the tweets are equal to or more than 0, which indicates that majority of the tweets have a neutral or positive sentiment. It shows that most people tend to have a neutral to positive opinion of the infrastructure topics. The distribution of subjectivity shows different patterns across the three keywords. For SunRail and Juice Bike, the subjectivity of most tweets is equal to 0, which means that they do not contain much opinions. But for the keyword “I-4 Ultimate”, it shows that the subjectivity of most tweets is more than 0, which reveals that the tweets containing “I-4 Ultimate” are more subjective. The value of subjectivity can be used as a filter to select more relevant data for other tasks, such as a topic analysis. Although it has been expected to observe any shift of subjectivity or polarity across the three time periods, such phenomena have not been observed. The time horizon for this analysis is too short to observe such shifts of opinion.

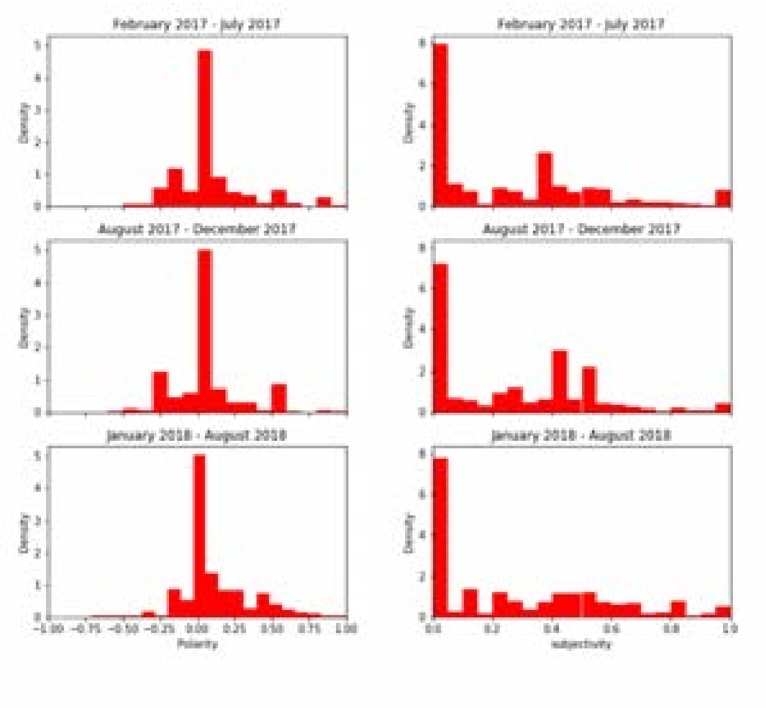


Figure 4.1: Sentiment Analysis Results of SunRail

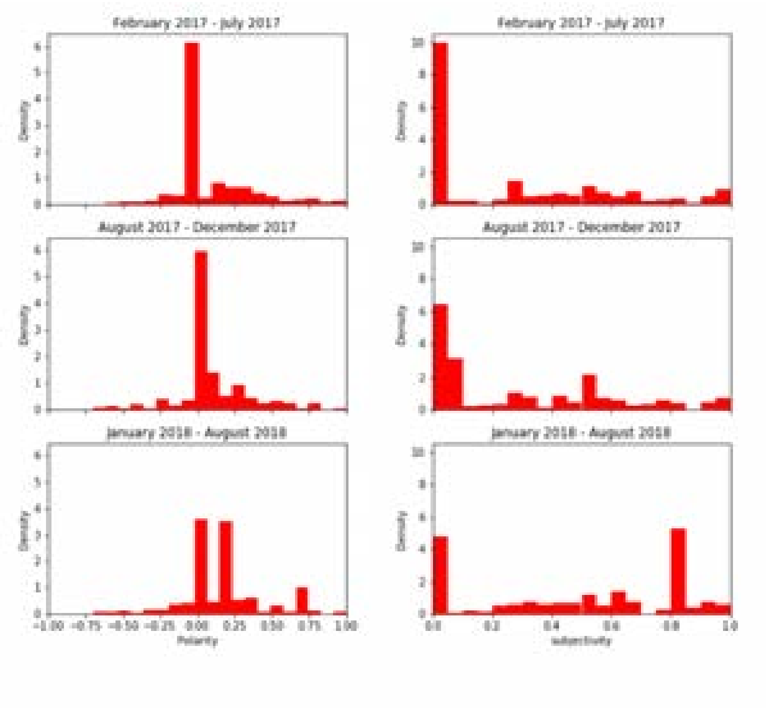


Figure 4.2: Sentiment Analysis Results of Juice Bike

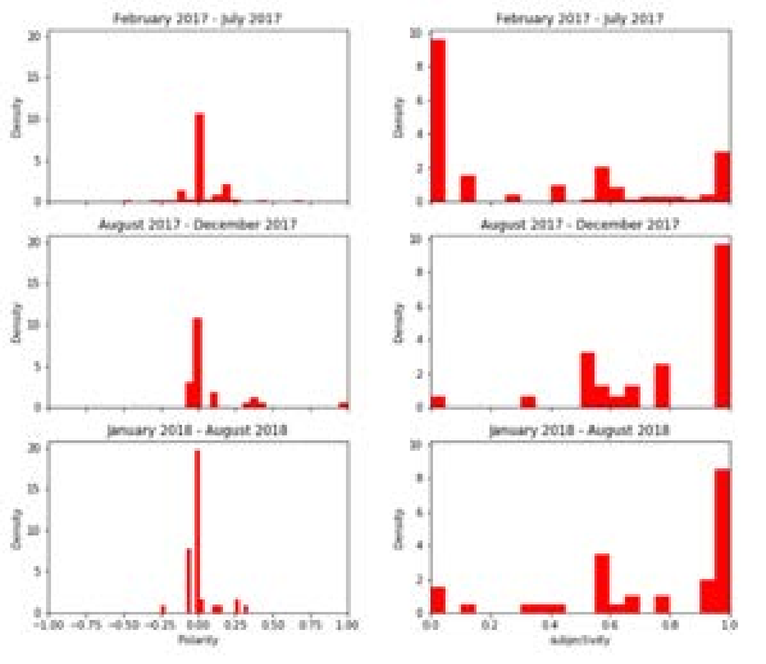
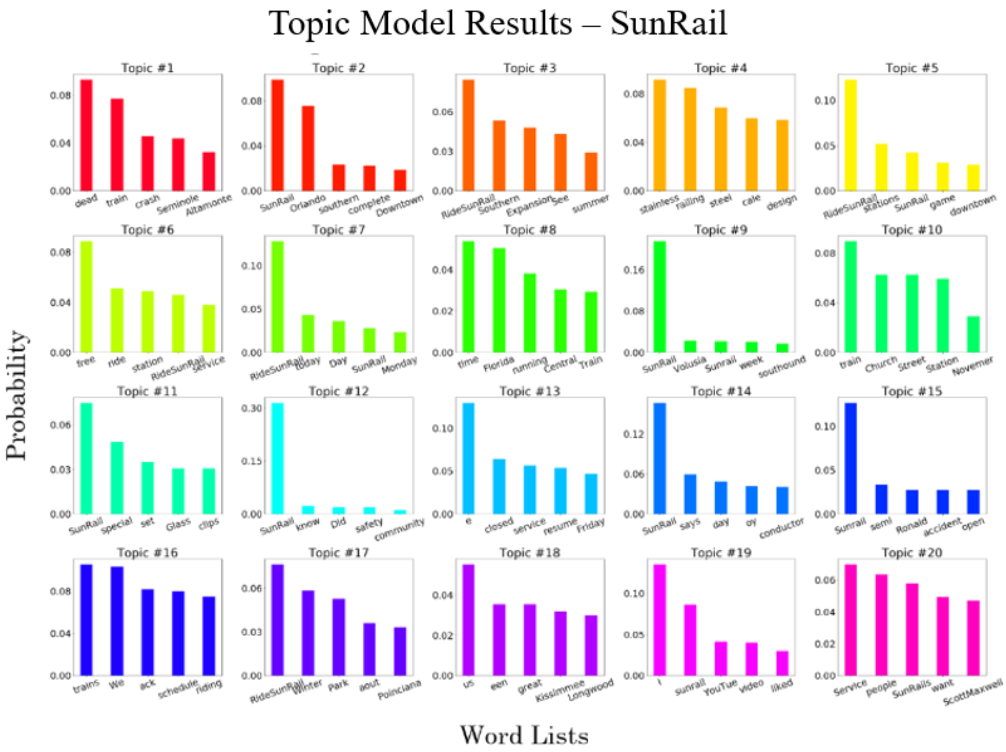


Figure 4.3: Sentiment Analysis Results of I-4 Ultimate

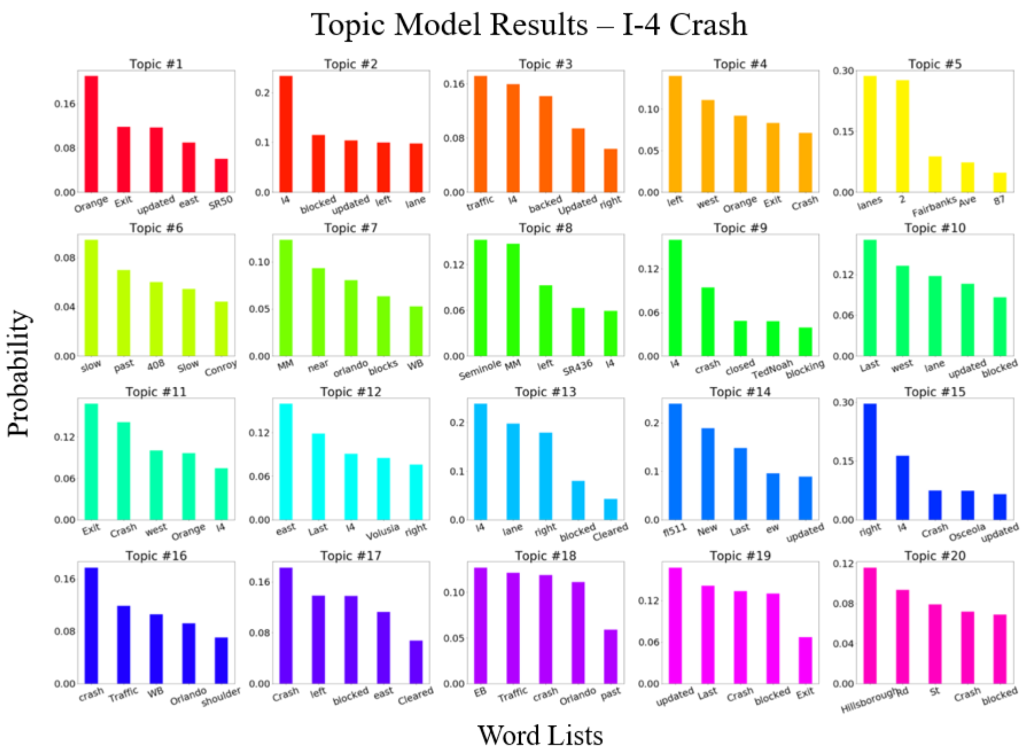
4.3.2 Topic Analysis

To understand public perspectives on different issues, we have used topic models (Hasan & Ukkusuri, 2014) to analyze the tweets. A topic model uses an algorithm that finds out the latent semantic structures of an extensive text body. It is generally used for finding the topics in a large corpus of documents where each document is modeled as a mixture of topics; each topic is modeled as a distribution of words. A topic model assumes each document as a 'bag of word' considering the number of times each word appears in a document. From a given document (e.g., tweet texts), a topic model provides the probability of finding particular words in a given tweet.

In this project, topic model has been applied to find out the probability distribution of certain words in a tweet. From the sentiment analysis, we observe zero subjectivity values of some tweets indicating that these tweets lack enough opinions. Thus, in topic analysis, we only used the tweets whose subjectivity values are greater than 0. Figure 4.4 shows the results of the topic analysis for two keywords only; the rest are presented in Appendix G. These topics have been identified by running an algorithm over the Twitter data. For the topic analysis of Sunrail, we can find topics #1, #12, and #15 are about safety related issues. Topic #4 indicates conversations about Sunrail design. Topics #6, #13, and #20 indicate various aspects of SunRail services (e.g., free ride and closed service). For the topic analysis of I-4 related tweets, a topic model has been run over I-4 crash related data. These topics indicate the local areas affected by crashes in I-4 and related traffic advisory services. Such information services are critical for travelers. The main outcome of this analysis is that unstructured text data available from social media can now be processed by an algorithm. Outputs from topic models can inform authorities which aspects of a transportation project are attracting public attention.



(a)



(b)

Figure 4.4: Topic Model Results: (a) SunRail and (b) I-4 Crash

However, it appears that some keywords do not have enough relevant data to apply the topic model. Table 3.1 lists the keywords which do not have enough data to run a topic model. Larger sample size with relevant information will be needed to run topic analysis for these keywords.

Table 4.3: Keywords Without Sufficient Relevant Data for a Topic Analysis

Keywords	Number of Tweets
juicebike	4
lakexpress	33
lynx bus	1399
Lynx Vanpool	0
Space Coast Area Transit	84
suntrail	133
suntran ocala	32

4.4 RECOMMENDATIONS

In this task, an analysis of social media data has been conducted. The dataset has been extended from Phase 1 though recent data collection efforts. Several recommendations are suggested based on this analysis:

- Useful indicators based on social media data can be constructed to understand community perception on transportation investments. These indicators will show the community building impacts of transportation projects.
- Data collected over some of the keywords lack sufficient relevant information for running a topic analysis.
- Additional data can be obtained by purchasing data from Twitter and modifying the keywords.
- The findings from this phase suggest that an analytics tool can be created to harvest and analyze social media data over a longer period to monitor community impacts of transportation investments.

CHAPTER 5: CONCLUSION

The purpose of this project was to assess the community building impact of the major transportation investment projects ongoing in the Central Florida region. In this task, we have proposed the following Measures of Effectiveness (MOE): (1) property price, (2) accessibility to employment, (3) commuting time, (4) land use change and (5) travel patterns for zero car households for measuring community impacts. In addition, we have described in detail the procedure of how the various layers are prepared and how the MOEs were estimated.

The MOEs property value and land use changes were computed for the study period 2011-2017; the other MOEs were computed for the study period 2011-2016. Control areas were used to compare the impact of case areas for various years. Most highlighted outcomes are as follows:

- As expected, an increasing trend was found in average property value. Multi-family residential land use has major increases in property value for all transportation investments projects. As expected, employment concentration is higher around the downtown area for all the three investment projects (SunRail, I-4 expansion and JUICE Orlando Bikeshare).
- In case of commuting time, downtown area residents have lower travel times.
- For land use changes, the change in vacant parcels to other land use type in the next year was computed. The results indicate a high share of vacant land use type converted to single family residential and retail/office land use types.
- Workers of zero car household share higher percentage of car and public transportation mode for all investment projects.

In summary, the results offer a glimpse of the complex interaction of transportation projects and the various MOEs.

An analysis of social media data has also been conducted. The analysis illustrated how useful indicators based on social media data can be constructed to understand community perception on transportation investments. The findings suggest that an analytics tool can be created to harvest and analyze social media data over a longer period to monitor community impacts of transportation investments. However, data collected based on keywords lack sufficient relevant information for running topic analysis. Additional data can be obtained by purchasing data from Twitter and modifying the keywords.

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APPENDIX A: DOR BASED LAND USE CODE

001 = Single Family Residential
002 = Mobile Homes
003 = Multi-family - 10 units or more
004 = Condominiums
005 = Cooperatives
006 = Retirement Homes not eligible for exemption.
007 = Miscellaneous Residential (migrant camps, boarding homes, etc.)
008 = Multi-family - less than 10 units
009 = Residential Common Elements / Areas
010 = Vacant Commercial
011 = Stores One-Story
012 = Mixed use - store and office or store and residential or residential combination
013 = Department Stores
014 = Supermarkets
015 = Regional Shopping Centers
016 = Community Shopping Centers
017 = Office buildings, non-professional service buildings, one story
018 = Office buildings, non-professional service buildings, multi-story
019 = Professional Service Buildings
020 = Airports (private or commercial), bus terminals, marine terminals, piers, marinas.
021 = Restaurants, Cafeterias
022 = Drive-in Restaurants
023 = Financial institutions (banks, saving and loan companies, mortgage companies, credit services)
024 = Insurance Company Offices
025 = Repair service shops (excluding automotive), radio and T.V. repair, refrigeration service, electric repair, laundries, laundromats.
026 = Service Stations
027 = Auto sales, auto repair and storage, auto service shops, body and fender shops, commercial garages, farm and machinery sales and services, auto rental, marine equipment, trailers and related equipment, mobile home sales, motorcycles, construction vehicle sales.
028 = Parking lots (commercial or patron) mobile home parks.
029 = Wholesale outlets, produce houses, manufacturing outlets.
030 = Florist, greenhouses
031 = Drive-in theaters, open stadiums
032 = Enclosed theaters, enclosed auditoriums
033 = Nightclubs, cocktail lounges, bars
034 = Bowling alleys, skating rinks, pool halls, enclosed arenas
035 = Tourist attractions, permanent exhibits, other entertainment facilities, fairgrounds (privately owned).

036 = Camps
037 = Race tracks; horse, auto or dog
038 = Golf courses, driving ranges
039 = Hotels, motels
040 = Vacant Industrial
041 = Light manufacturing, small equipment manufacturing plants, small machine shops, instrument manufacturing printing plants.
042 = Heavy industrial, heavy equipment manufacturing, large machine shops, foundries, steel fabricating plants, auto or aircraft plants
043 = Lumber yards, sawmills, planing mills
044 = Packing plants, fruit and vegetable packing plants, meat packing plants
045 = Canneries, fruit and vegetable, bottlers and brewers distilleries, wineries
046 = Other food processing, candy factories, bakeries, potato chip factories
047 = Mineral processing, phosphate processing, cement plants, refineries, clay plants, rock and gravel plants
048 = Warehousing, distribution terminals, trucking terminals, van and storage warehousing
049 = Open storage, new and used building supplies, junk yards, auto wrecking, fuel storage, equipment and material storage
050 = Improved agricultural
051 = Cropland soil capability Class I
052 = Cropland soil capability Class II
053 = Cropland soil capability Class III
054 = Timberland - site index 90 and above
055 = Timberland - site index 80 to 89
056 = Timberland - site index 70 to 79
057 = Timberland - site index 60 to 69
058 = Timberland - site index 50 to 59
059 = Timberland not classified by site index to Pines
060 = Grazing land soil capability Class I
061 = Grazing land soil capability Class II
062 = Grazing land soil capability Class III
063 = Grazing land soil capability Class IV
064 = Grazing land soil capability Class V
065 = Grazing land soil capability Class VI
066 = Orchard Groves, Citrus, etc.
067 = Poultry, bees, tropical fish, rabbits, etc.
068 = Dairies, feed lots
069 = Ornamentals, miscellaneous agricultural
070 = Vacant, with or without extra features
071 = Churches
072 = Private schools and colleges
073 = Privately owned hospitals

074 = Homes for the aged
075 = Orphanages, other non-profit or charitable services
076 = Mortuaries, cemeteries, crematoriums
077 = Clubs, lodges, union halls
078 = Sanitariums, convalescent and rest homes
079 = Cultural organizations, facilities
080 = Vacant Governmental
081 = Military
082 = Forest, parks, recreational areas
083 = Public county schools - include all property of Board of Public Instruction
084 = Colleges
085 = Hospitals
086 = Counties (other than public schools, colleges, hospitals) including non-municipal government.
087 = State, other than military, forests, parks, recreational areas, colleges, hospitals
088 = Federal, other than military, forests, parks, recreational areas, hospitals, colleges
089 = Municipal, other than parks, recreational areas, colleges, hospitals
090 = Leasehold interests (government owned property leased by a non-governmental lessee)
091 = Utility, gas and electricity, telephone and telegraph, locally assessed railroads, water and sewer service, pipelines, canals, radio/television communication
092 = Mining lands, petroleum lands, or gas lands
093 = Subsurface rights
094 = Right-of-way, streets, roads, irrigation channel, ditch, etc.
095 = Rivers and lakes, submerged lands
096 = Sewage disposal, solid waste, borrow pits, drainage reservoirs, waste land, marsh, sand dunes, swamps
097 = Outdoor recreational or parkland, or high-water recharge subject to classified use assessment.
098 = Centrally assessed
099 = Acreage not zoned agricultural with or without extra features
100 = Parcels with no values.
995 = No Data Available (Water)
999 = No Data Available

APPENDIX B: LAND USE PROFILE OF SUNRAIL STATIONS

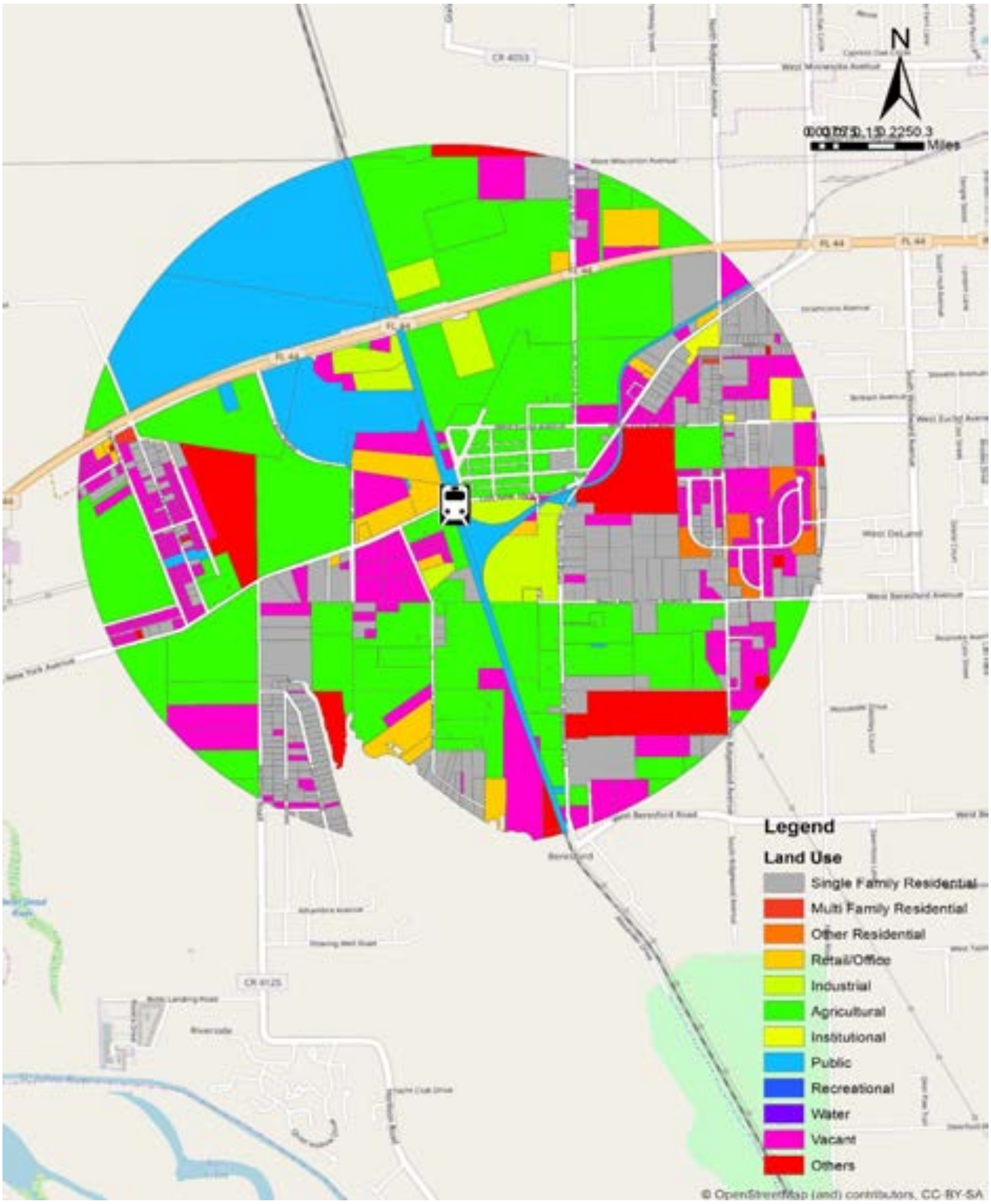


Figure B.1: Land Use Profile of DeLand Station

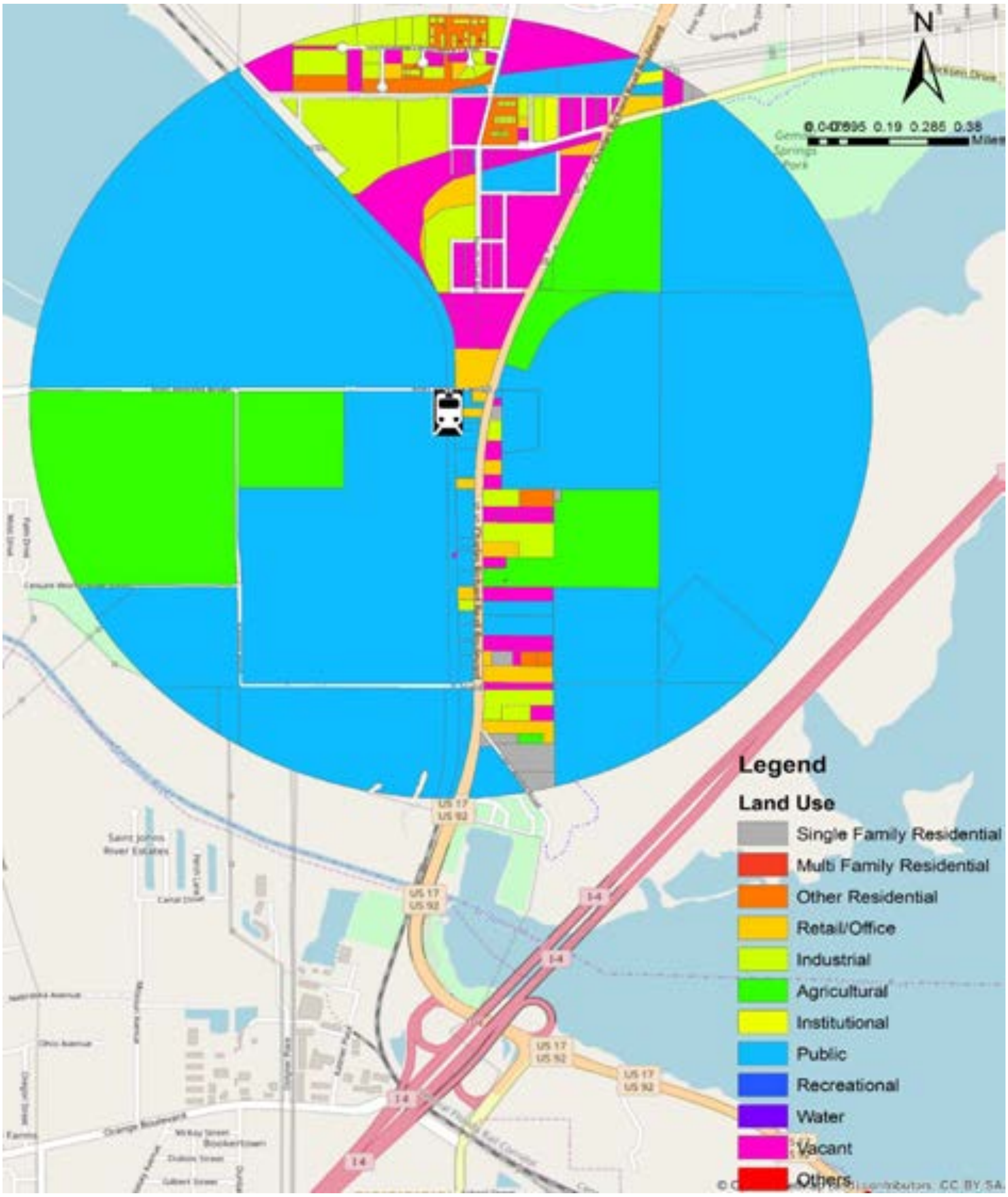


Figure B.2: Land Use Profile of DeBary Station

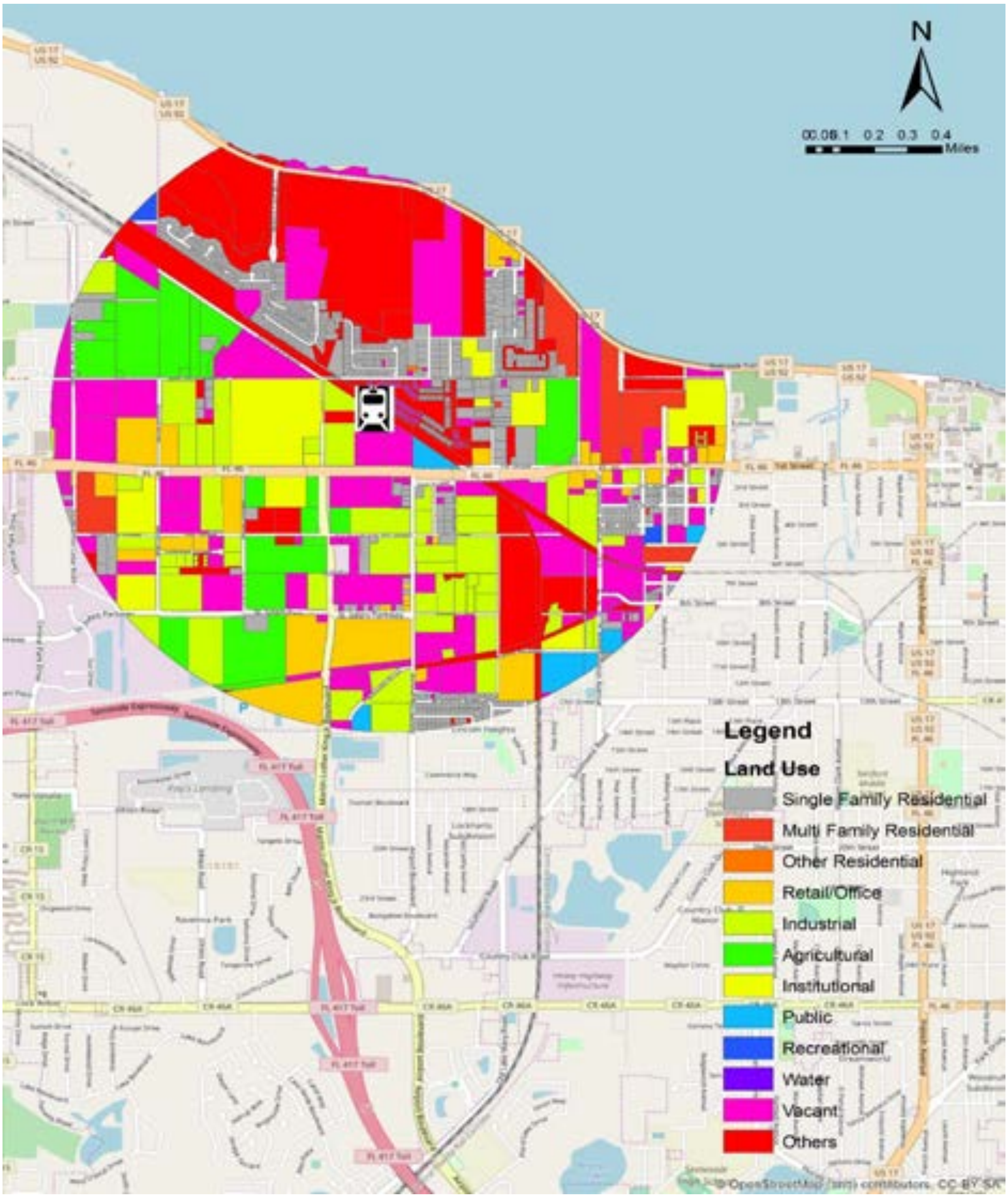


Figure B.3: Land Use Profile of Sanford Station

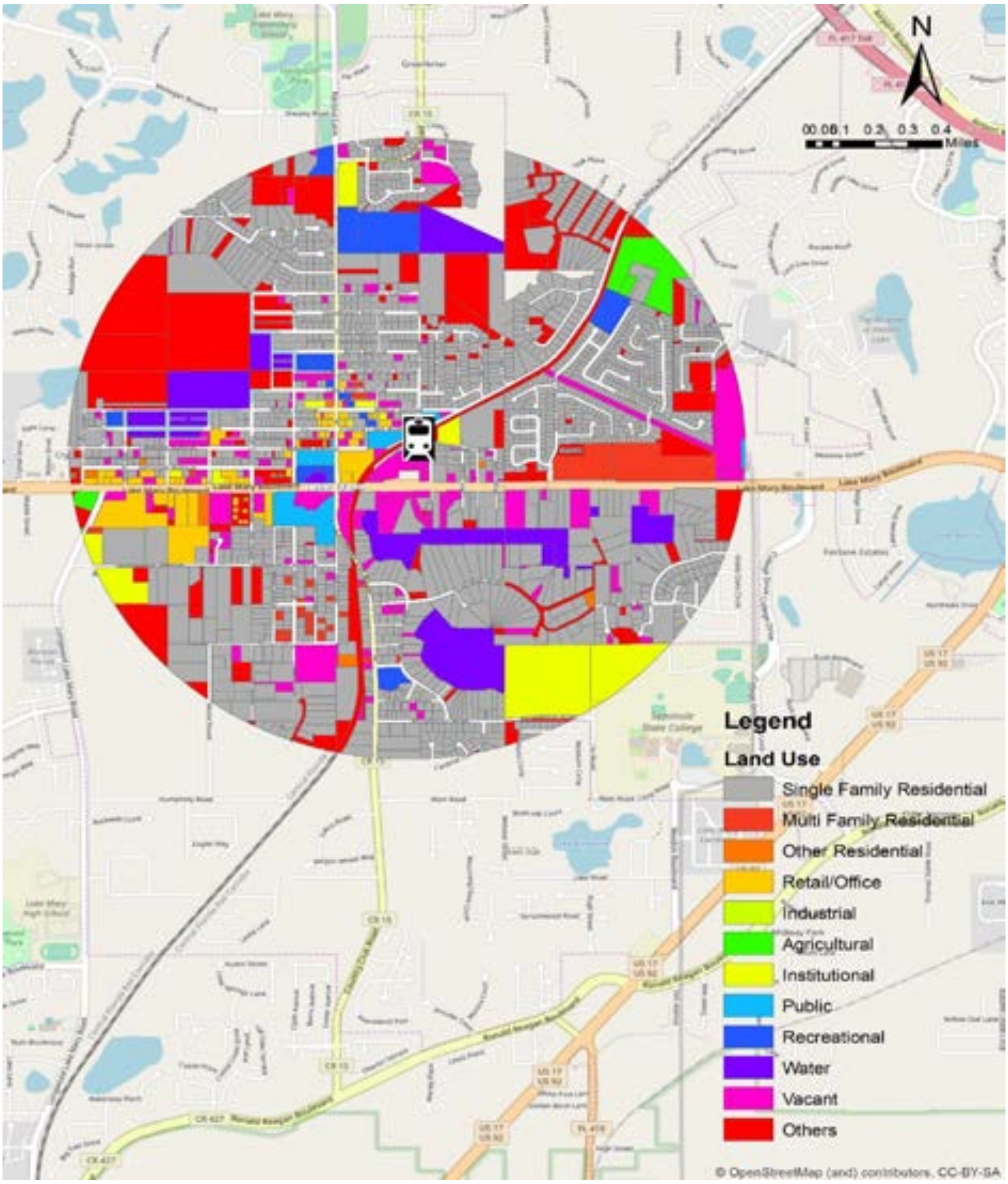


Figure B.4: Land Use Profile of Lake Mary Station

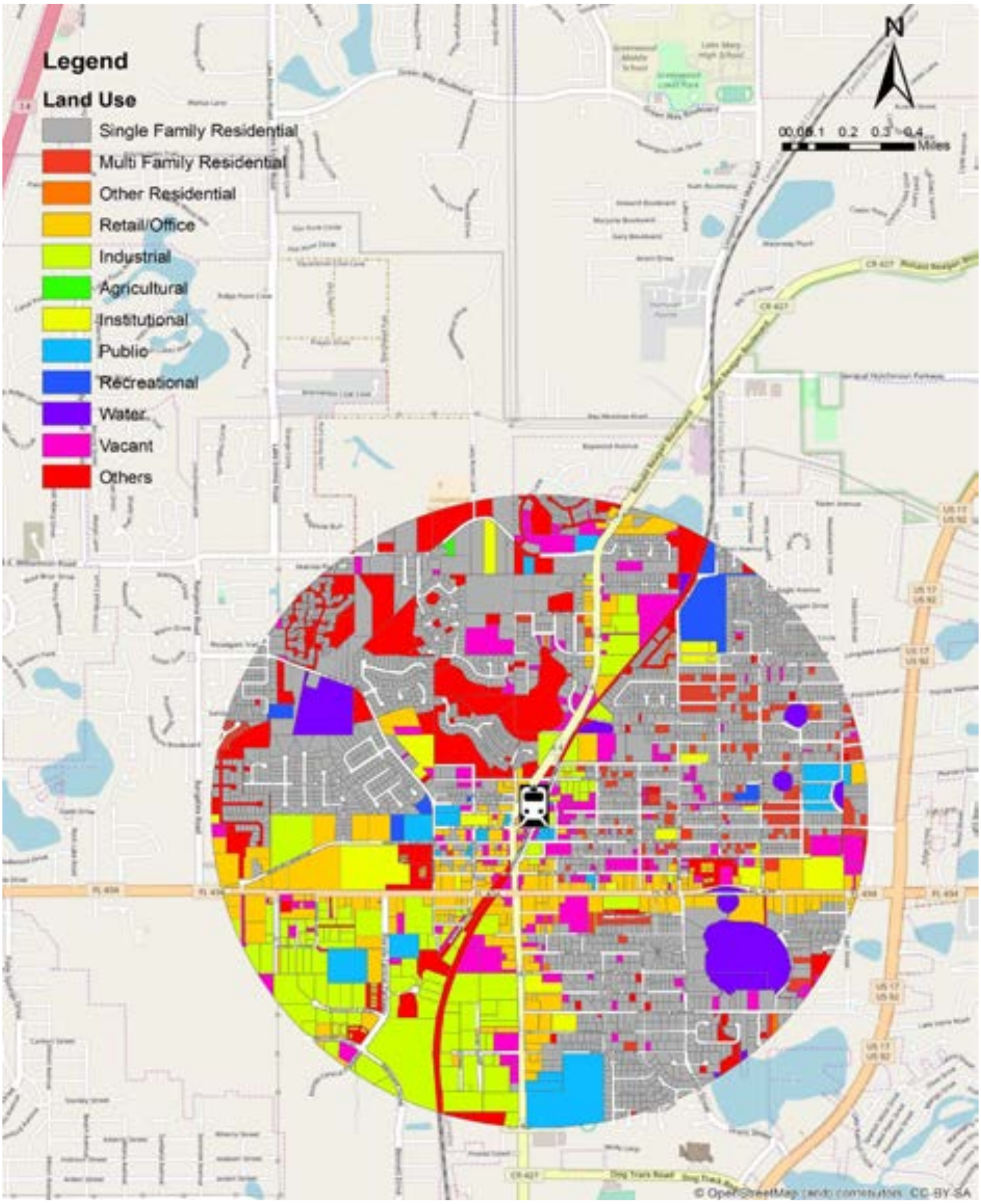


Figure B.5: Land Use Profile of Longwood Station

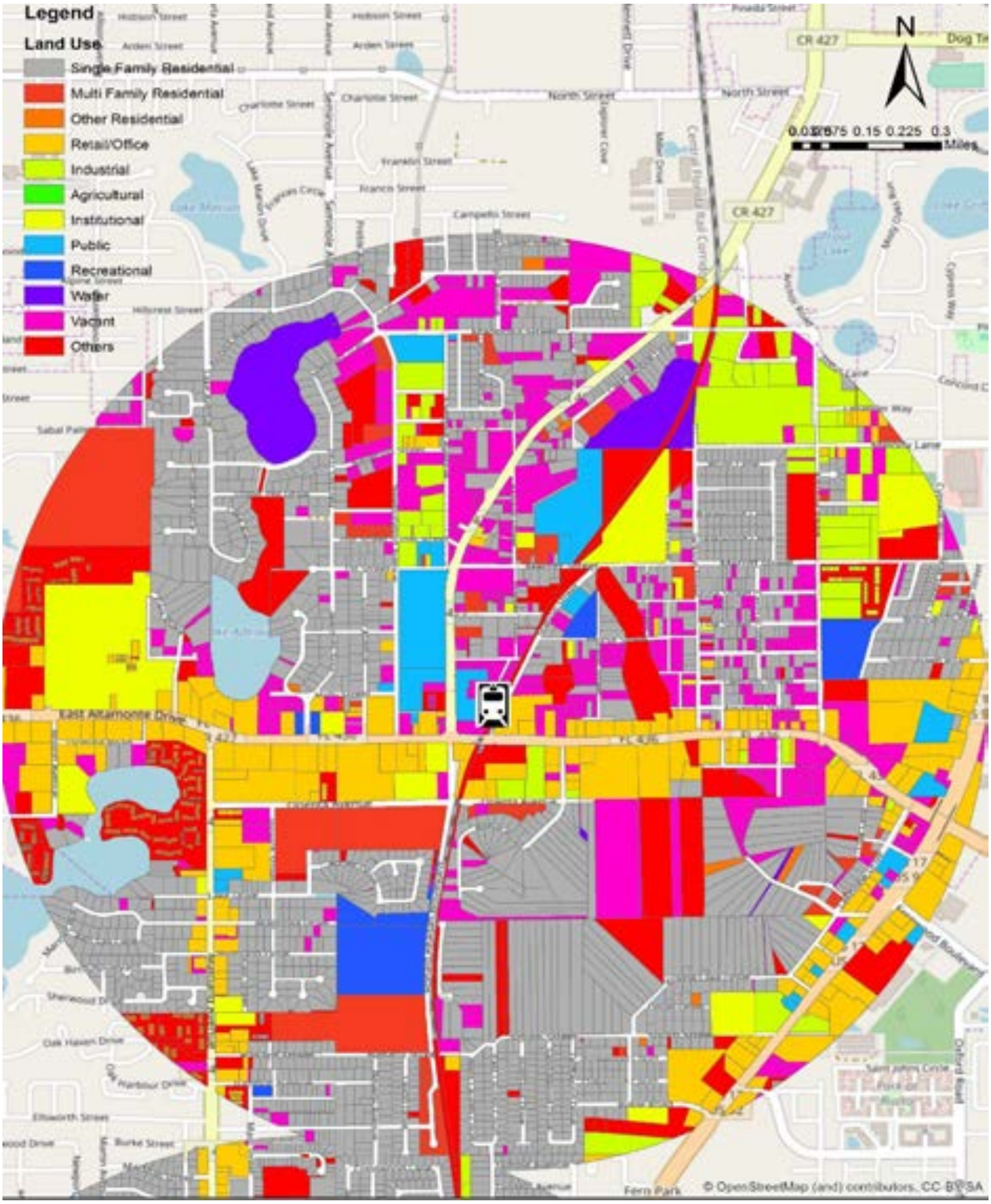


Figure B.6: Land Use Profile of Altamonte Springs Station

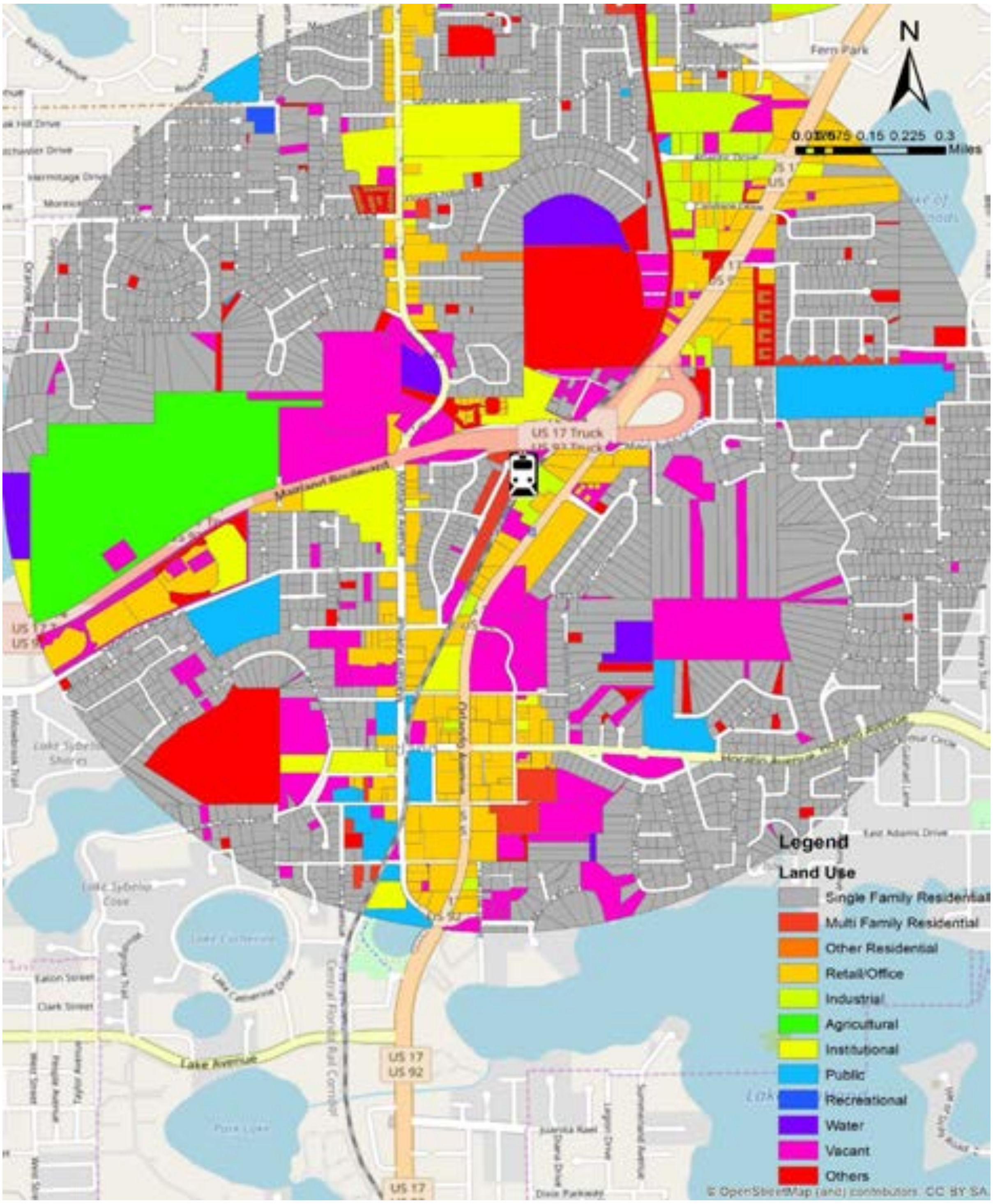


Figure B.7: Land Use Profile of Maitland Station

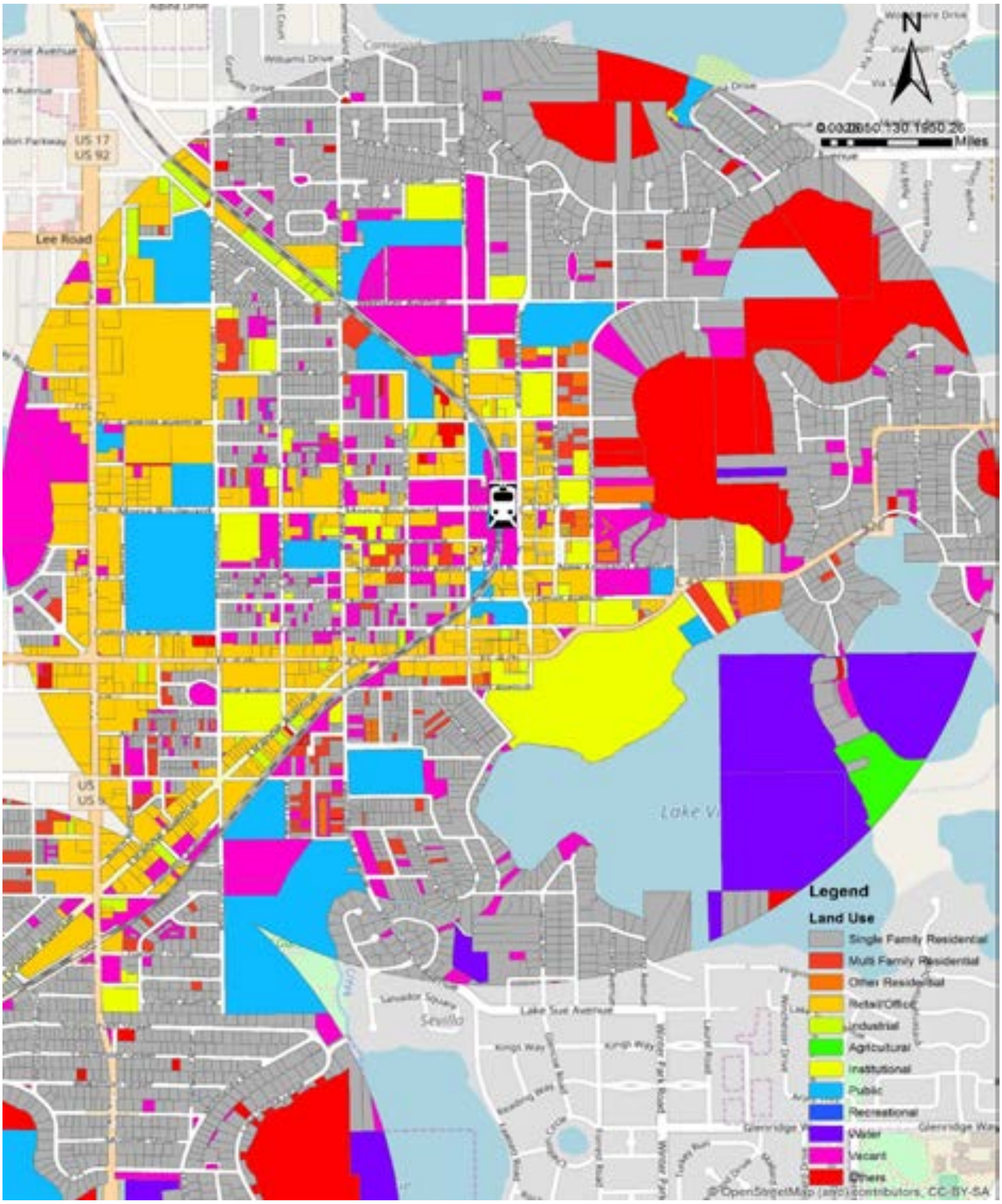


Figure B.8: Land Use Profile of Winter Park Station

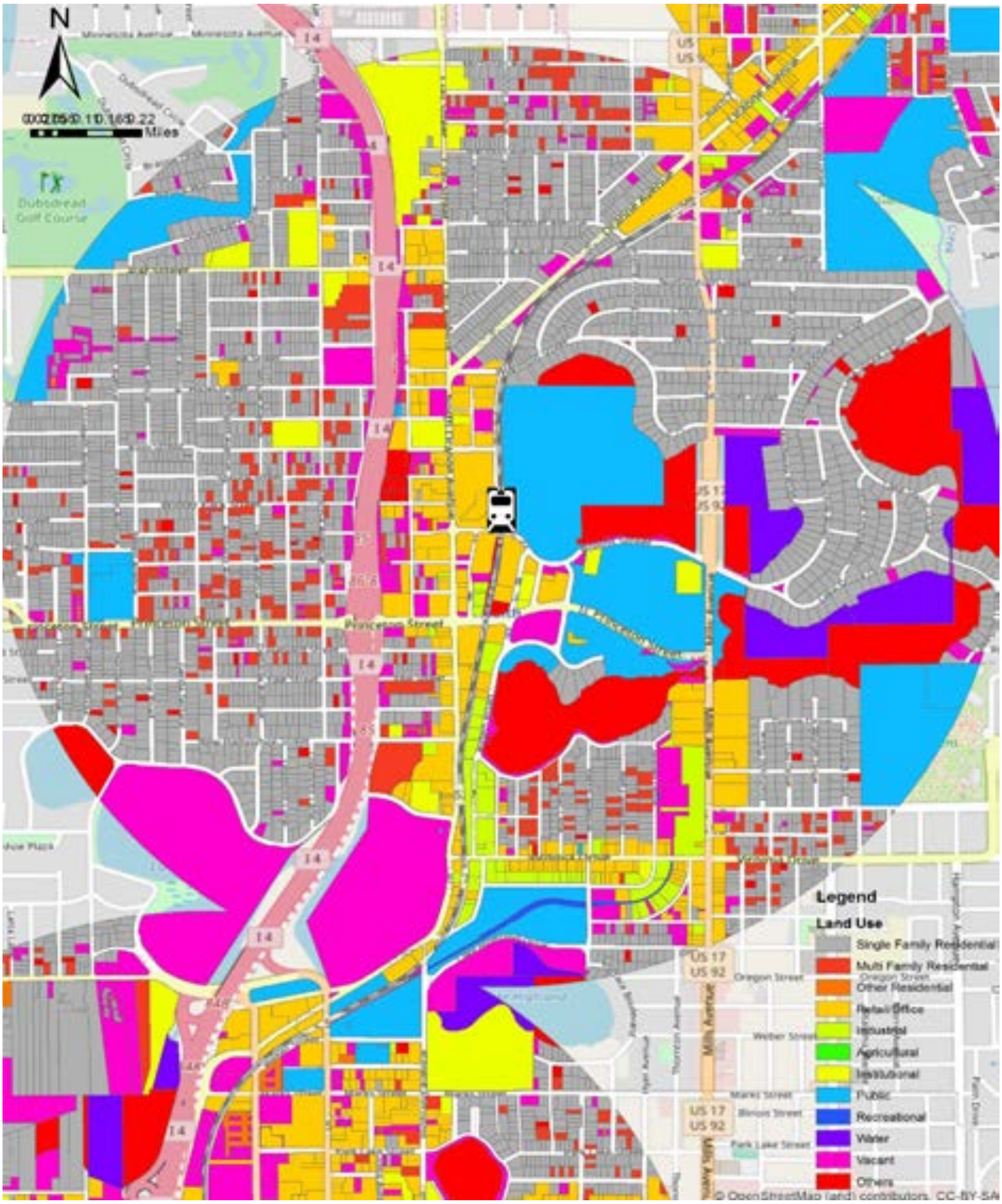


Figure B.9: Land Use Profile of Florida Hospital Station

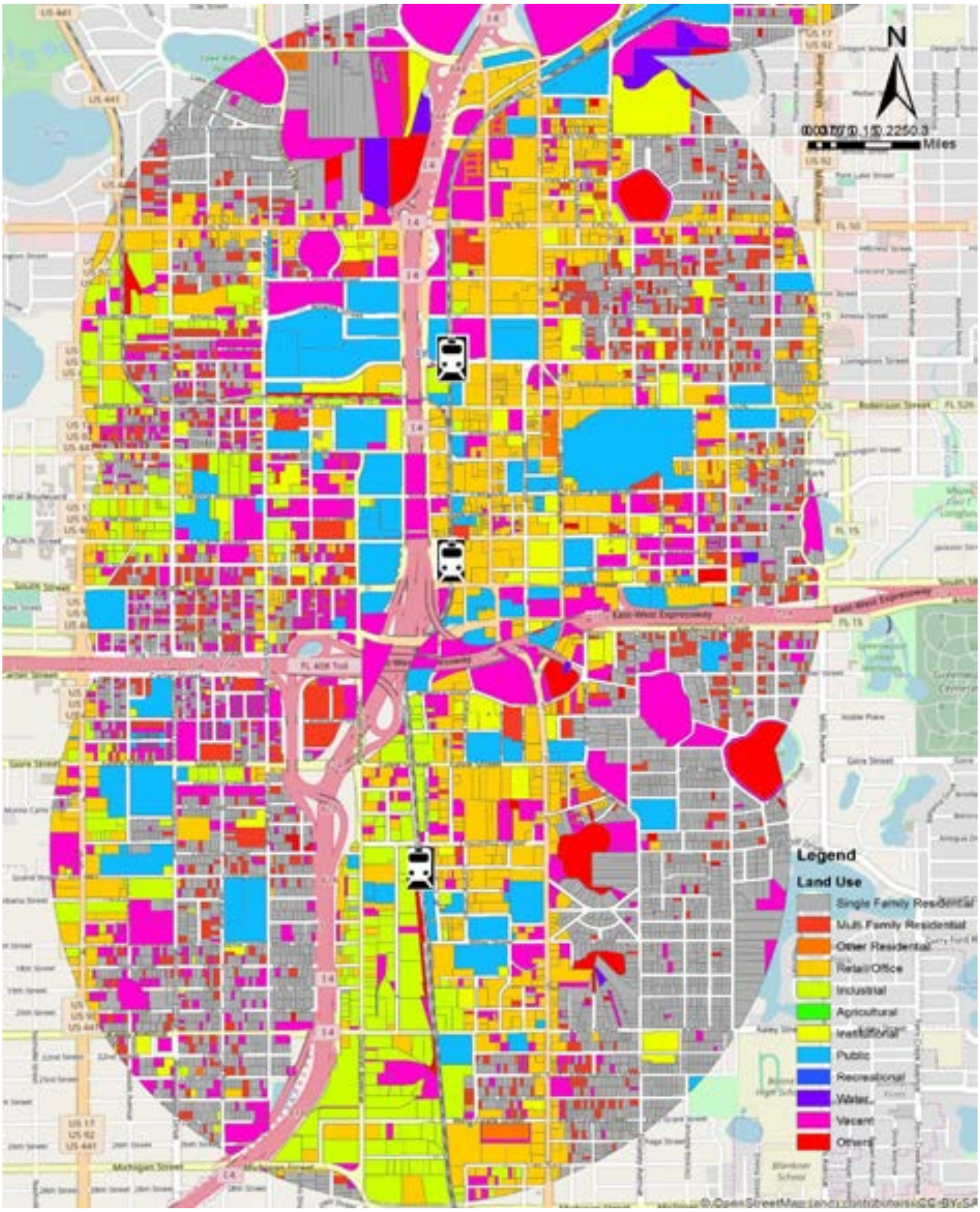


Figure B.10: Land Use Profile of LYNX Central, Church Street and Orlando Amtrak Station

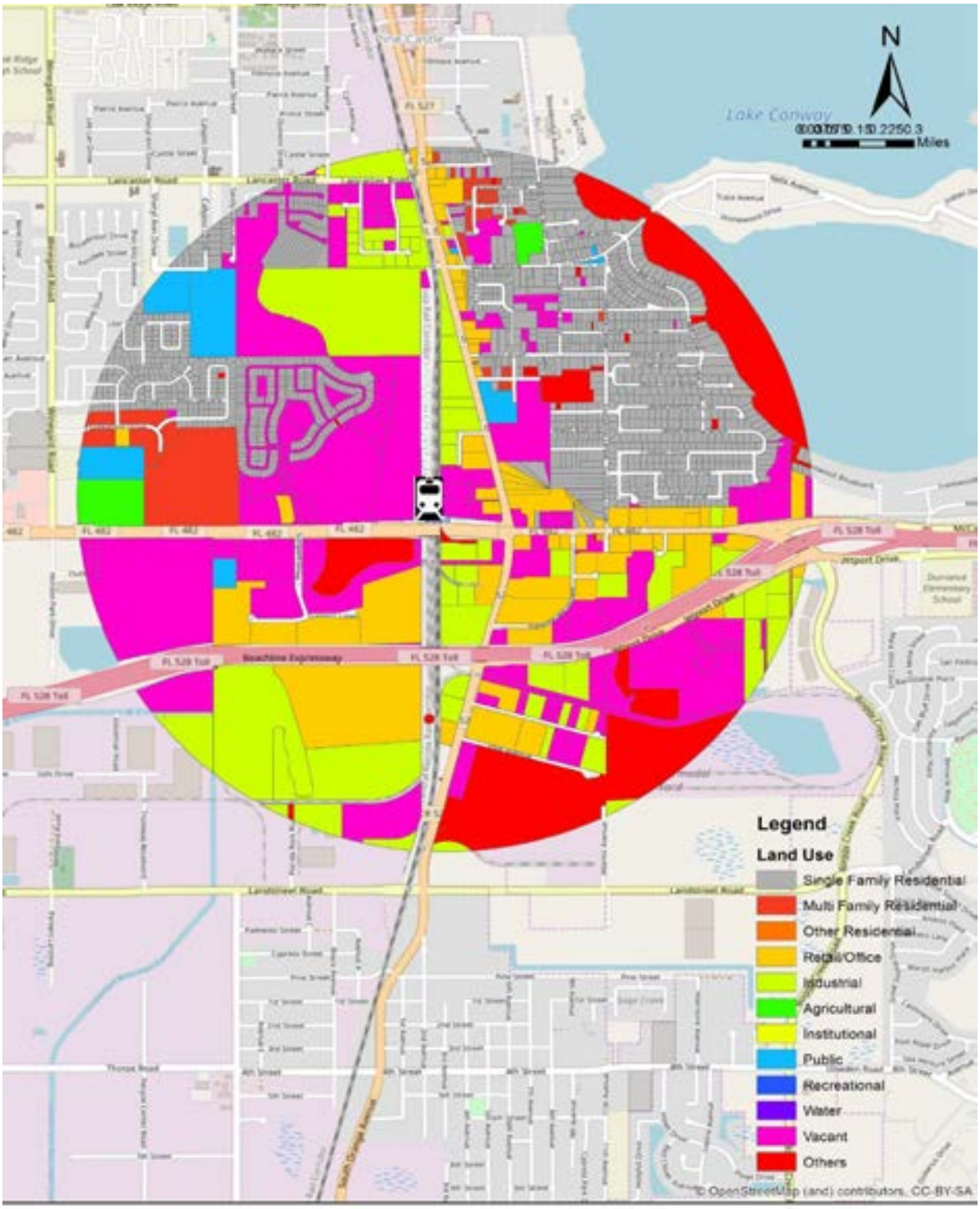


Figure B.11: Land Use Profile of Sand Lake road Station

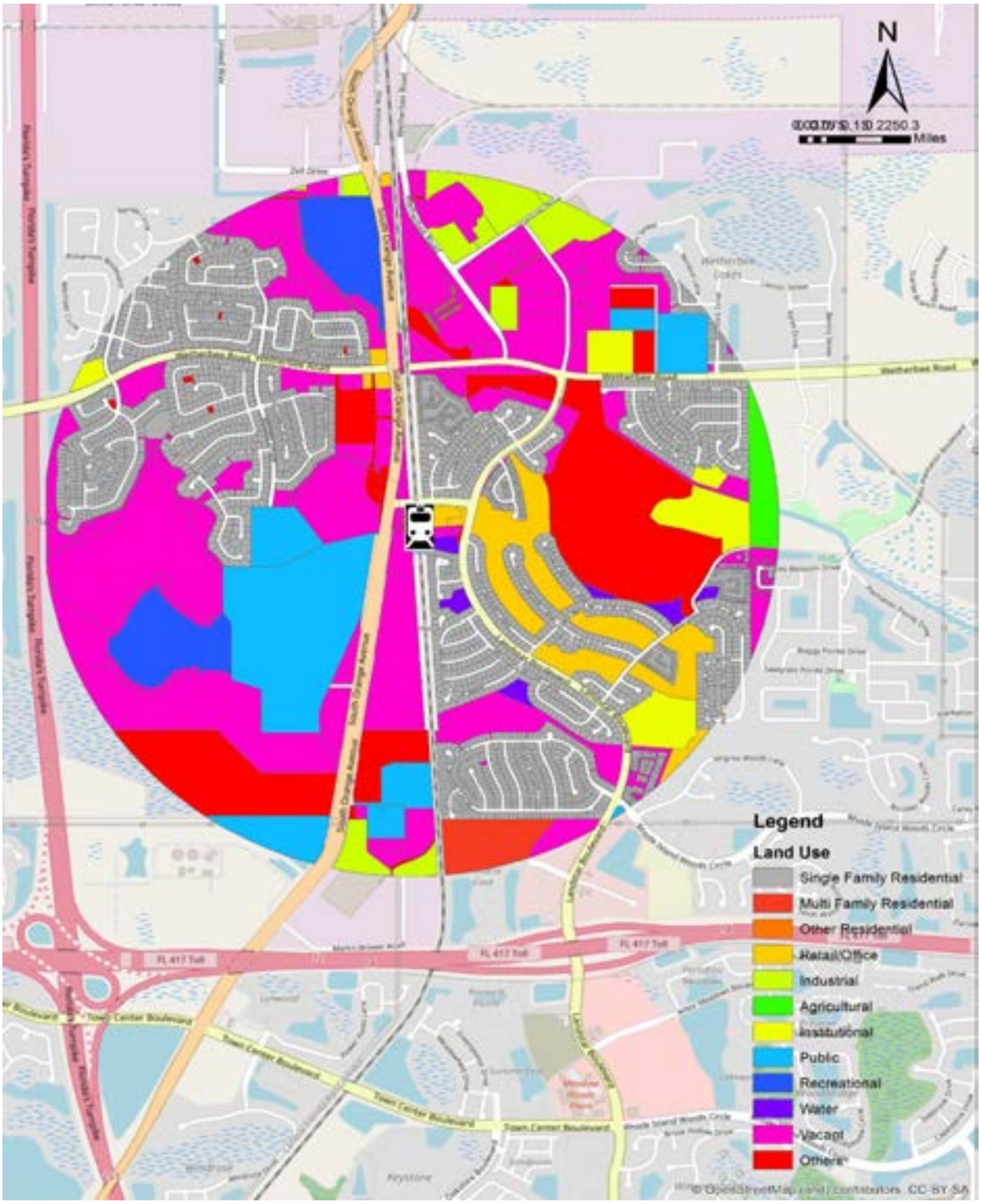


Figure B.12: Land Use Profile of Meadow Woods Station

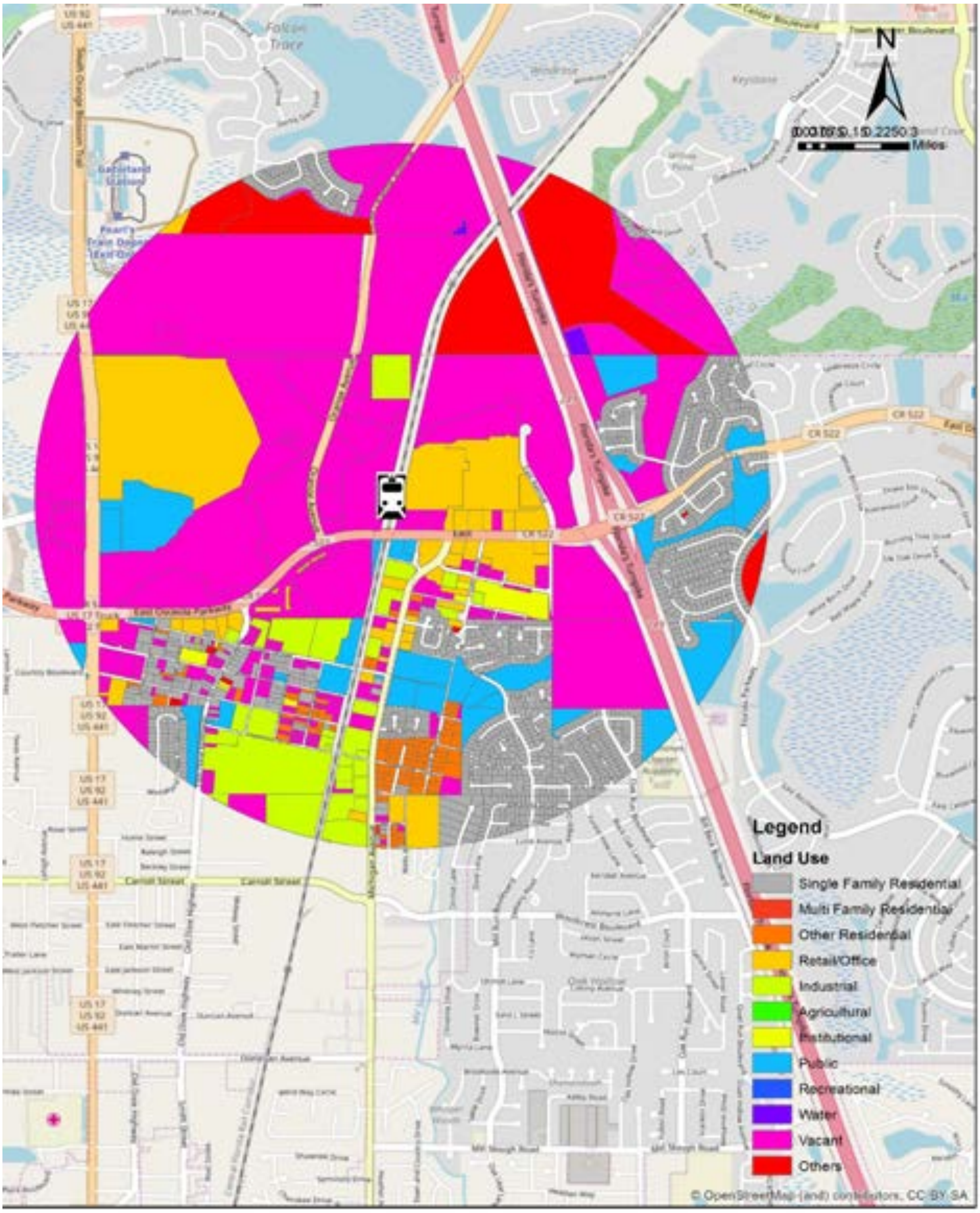


Figure B.13: Land Use Profile of Osceola Parkway Station

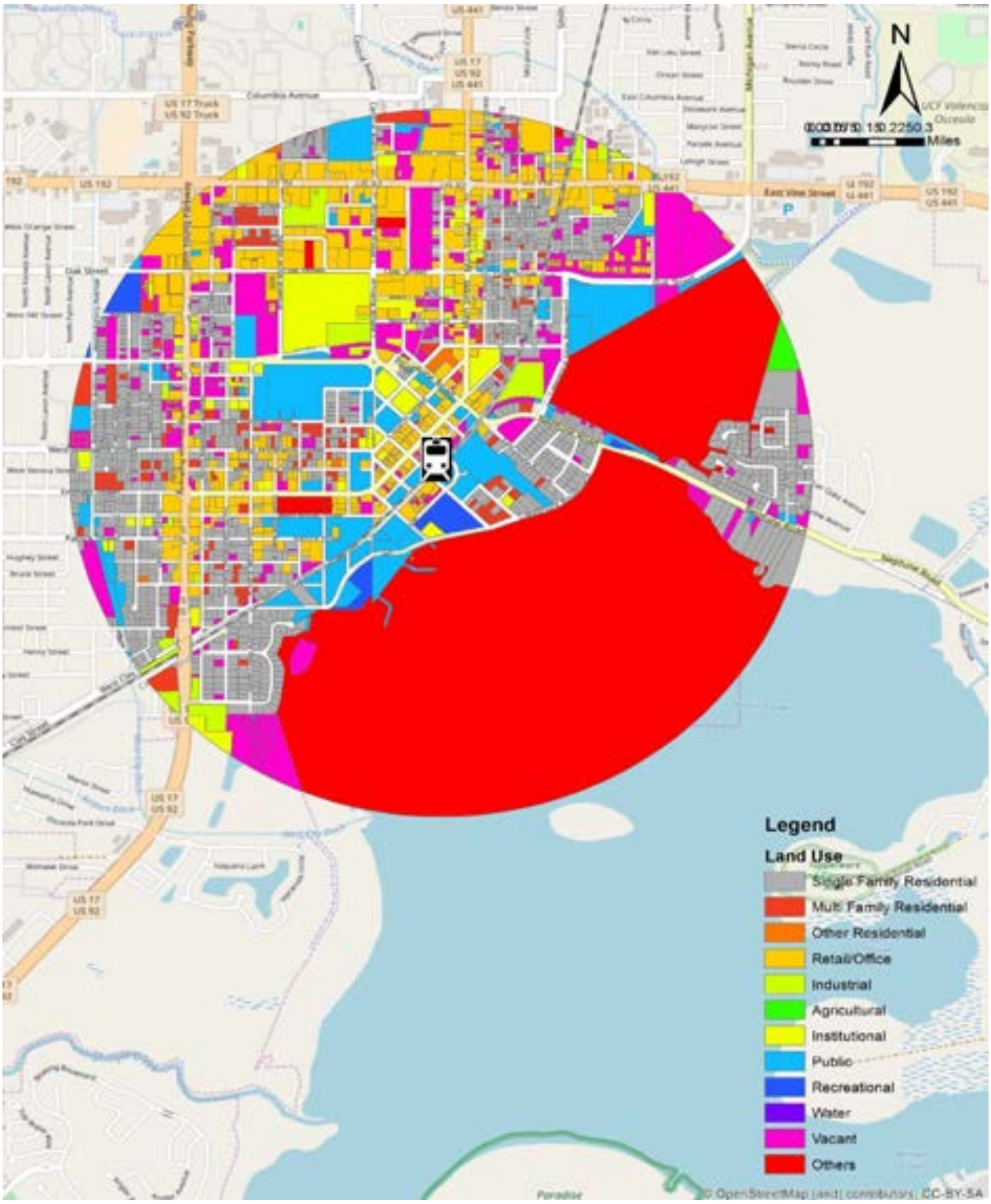


Figure B.14: Land Use Profile of Kissimmee Amtrak Station

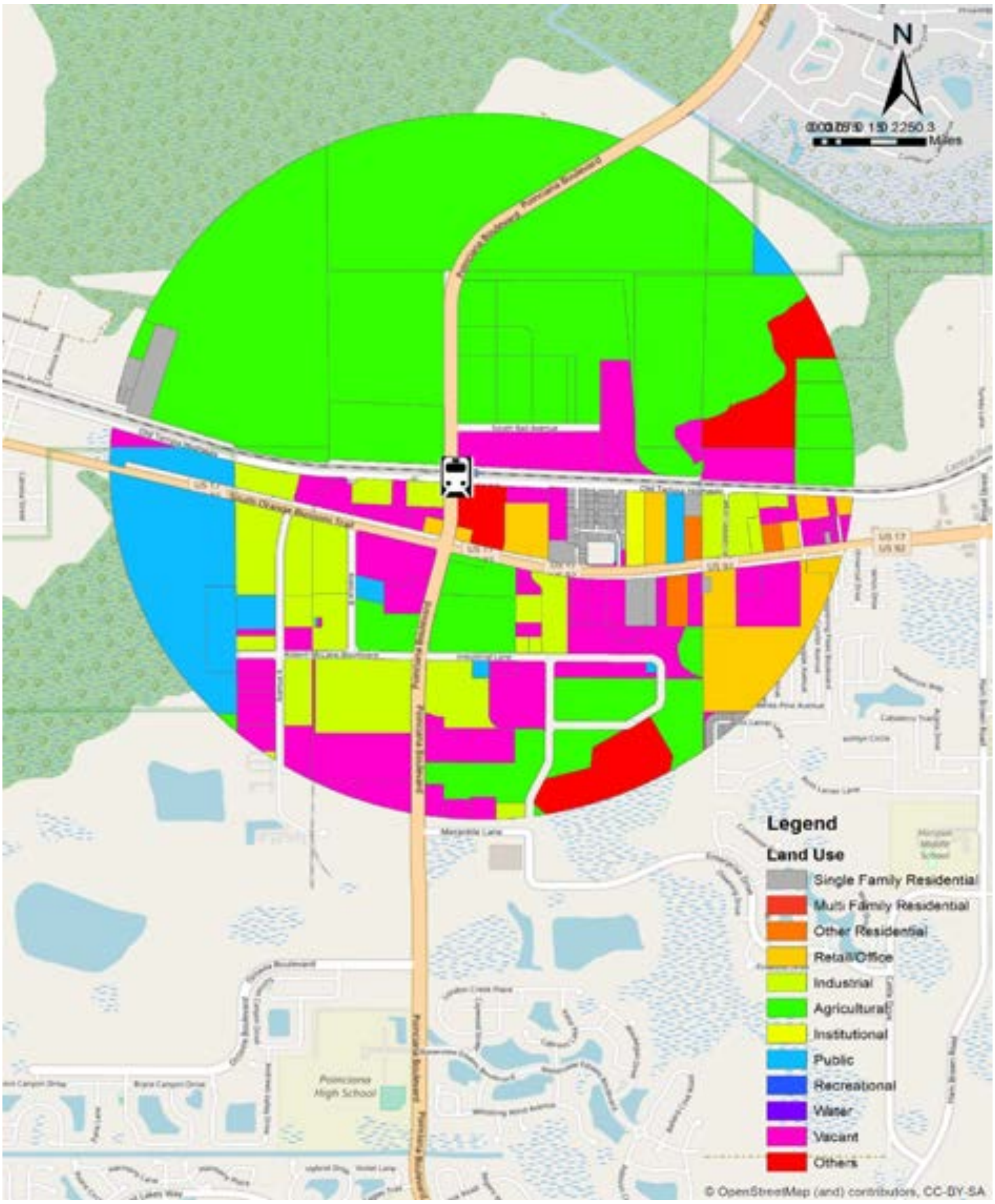


Figure B.15: Land Use Profile of Poinciana Station

APPENDIX C: PYTHON SCRIPT FOR SENTIMENT ANALYSIS

```
import os
import pandas as pd
from textblob import TextBlob
path = 'D:\\sentiment result\\final_data\\I4 Construction_Unique_Upto_August_1' #define the path
files = os.listdir(path) #define the files in the path

def modifystr(s):
    #s = s.str.replace('[^\w\s]',")
    s = s.replace('/',")
    s = s.replace(',',")
    s = s.replace('@',")
    s = s.replace('//',")
    s = s.replace('#',")
    s = s.replace('%',")
    s = s.replace(",")
    s = s.replace('\\',")
    s = s.replace('|',")
    s = s.replace(':',")
    s = s.replace('_',")
    s = s.replace('!',")
    s = s.replace('(',")
    s = s.replace(')',")
    s = s.replace("",")
    s = s.replace(""",")
    s = s.replace(s[0],")
    s = s.replace('.',")
    return s

def sentiment(s):
    blob = TextBlob(s)
    blob_sentiment = blob.sentiment
    return blob_sentiment

df_final = pd.DataFrame (columns = ['1','2','3','4','5','6','7','8','9','10',
                          '11','12','13','14','15','16','17','18','19','20','21','22','23','24'])

for i in range(0,len(files)):
    df = files[i]
    df_name = path + "\\" + df
    df_name_final = 'D:\\sentiment result\\final_data\\key word type\\I4 Ultimate' +"\\" +df
    df1 = pd.read_csv(df_name,
                  names = ['1','2','3','4','5','6','7','8','9','10','11','12','13',
                       '14','15','16','17','18','19','20','21','22','23','24'] )
    df1.dropna(axis = 0, how = 'all', inplace = True)
    df_final = pd.concat([df_final,df1])

df_final['2']=list(map(modifystr,df_final['2']))
```

```
df_final['sentiment']=list(map(sentiment,df_final['2']))
df_final.index = range(0,len(df_final))
df_final_sentiment = pd.DataFrame(df_final[['1','2','6','7','sentiment']])

a = []
b = []

for i in range(0,len(df_final_sentiment.sentiment)):
   a.append(df_final_sentiment.sentiment[i][0])
   b.append(df_final_sentiment.sentiment[i][1])
df_final_sentiment['polarity'] = a
df_final_sentiment['subjectively'] = b
```

APPENDIX D: PYTHON SCRIPT FOR SENTIMENT ANALYSIS RESULTS VISUALIZATION

```
import pandas as pd
import matplotlib.pyplot as plt
df = pd.read_csv('D:\\sentiment result\\final_data\\whole result\\Sunshine Skyway.csv', header = 0, names = ['id','time','text','account','geotagged','sentiment','polarity','subjectivity'])
df.time = pd.to_datetime(df.time)
#select data based on the time(half year)
df_1 = df[(df.time.dt.year == 2017)&(df.time.dt.month>1)&(df.time.dt.month<8)]
df_2 = df[(df.time.dt.year == 2017)&(df.time.dt.month>7)&(df.time.dt.month<13)]
df_3 = df[(df.time.dt.year == 2018)&(df.time.dt.month>0)&(df.time.dt.month<9)]


import numpy as np
fig, axes = plt.subplots(3, 1, sharex=True, sharey=True)

fig.set_size_inches(5,10)

axes[0].hist(df_1.polarity, density = 1, bins=20, color='r',)
axes[0].set_title('February 2017 - July 2017')
axes[0].set_ylabel('Density')

axes[1].hist(df_2.polarity,density = 1, bins=20, color='r')
axes[1].set_title('August 2017 - December 2017')
axes[1].set_ylabel('Density')

axes[2].hist(df_3.polarity,density = 1, bins=20, color='r')
axes[2].set_title('January 2018 - August 2018')
axes[2].set_ylabel('Density')

plt.xlabel('Polarity')
plt.subplots_adjust(wspace =0, hspace =0.2)
```

APPENDIX E: PYTHON SCRIPT FOR TOPIC ANALYSIS RESULTS VISUALIZATION

```
import csv,pdb
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import pickle
from datetime import datetime
from matplotlib import style
import matplotlib.ticker as mticker
import matplotlib.dates as mdates
import matplotlib.cm as cm
import math

SMALL_SIZE = 12
MEDIUM_SIZE = 32
BIGGER_SIZE = 40

plt.rc('font', size=SMALL_SIZE)
plt.rc('axes', titlesize=BIGGER_SIZE)
plt.rc('axes', labelsize=MEDIUM_SIZE)
plt.rc('xtick', labelsize=MEDIUM_SIZE)
plt.rc('ytick', labelsize=MEDIUM_SIZE)
plt.rc('legend', fontsize=SMALL_SIZE)
plt.rc('figure', titlesize=BIGGER_SIZE)

path_input = "E:\\topic model\\raw-data\\I-4\\subjectivity\\I-4_subjectivity_results.csv"
path_output = "C:\\FDOT_Paper\\Topic_non_RT_user_heatmap_1.png"


df=pd.read_csv(path_input)
'''
dictUsers={}
topics=[]
for index, row in df.iterrows():
    uID=str(row['User']).lower()

    try:

        if uID not in dictUsers:
            dictUsers[uID] = {row['Topic']:float(row['Probability'])}

        else:
            dictUsers[uID][row['Topic']] = float(row['Probability'])
        if row['Topic'] not in topics:
            topics.append(row['Topic'])
    except:
```

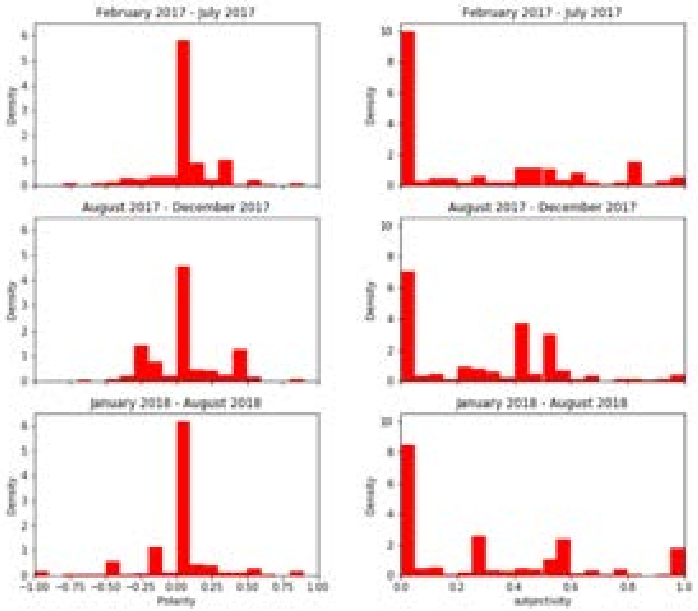
```
        print('escape')


def key_sorter(id):
    count=0
    x=len(dictUsers[id].keys())
    for date in dictUsers[id].keys():
        count+=dictUsers[id][date]
    return x,count

)
WORDS=sorted(dictUsers.keys())


data_word=[]
'''
import re

def atoi(text):
    return int(text) if text.isdigit() else text

def natural_keys(text):
    return [ atoi(c) for c in re.split('(\d+)', text) ]


'''


for word in WORDS:
    a=[]
    for topic in topics:
        try:
            a.append(dictUsers[word][topic])
        except:
            a.append(0)
    data_word.append(a)


x=topics
y=WORDS
start=1
end=len(data_word)

import matplotlib.ticker as ticker

fig=plt.figure(figsize= (15,5))
ax1 = plt.subplot2grid((3,1), (0,0), rowspan=3, colspan=1)
heatmap = plt.pcolor(np.asarray(data_word[start - 1:end]), cmap=plt.cm.CMRmap_r)
plt.xticks(np.arange(len(x)) + 0.5, x)
plt.yticks(np.arange(len(y[start - 1:end])+0.5), y[start - 1:end])
```

```
plt.title('Probability')

labels=[]
for i in range(len(ax1.xaxis.get_ticklabels())):
    if i%2==0:
        labels.append(topics[i])
    else:
        labels.append(' ')

ax1.set_xticklabels(labels)

for label in ax1.xaxis.get_ticklabels():
    label.set_rotation(90)
ax1.yaxis.set_ticks(np.arange(0.5, len(y)+0.5, 1))
ax1.set_yticklabels(y)

plt.tight_layout()
plt.colorbar(heatmap)
plt.savefig( path_output,dpi=500)

plt.show()
'''

topic_word_dict={}
topics=[]

for index, row in df.iterrows():
    topic=row['Topic']


    if topic not in topic_word_dict:
        topic_word_dict[topic] = {row['Words']:float(row['Probability'])}

    else:
        topic_word_dict[topic][row['Words']] = float(row['Probability'])
    if row['Topic'] not in topics:
        topics.append(row['Topic'])

topics.sort(key=natural_keys)


import matplotlib.pyplot as plt
from pylab import *
import numpy as np

fig=plt.figure(figsize= (45,150))
def prob_value(key,x):
    prob=[]
    for word in x:
        #print(word)
```

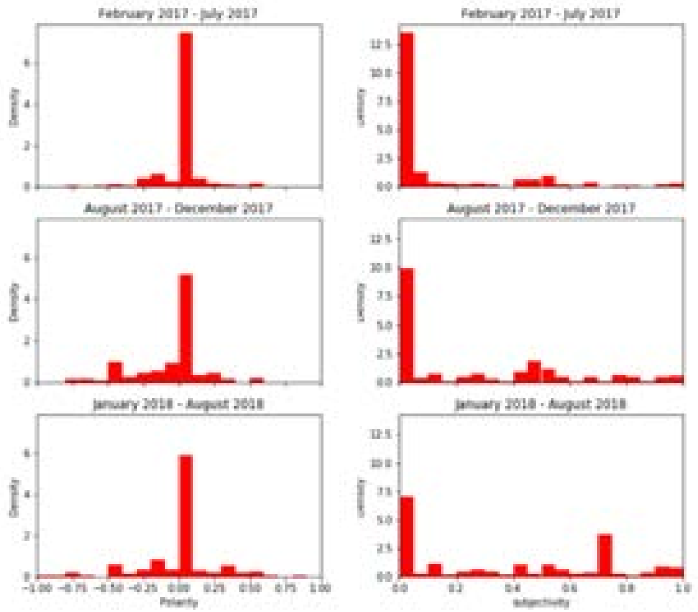
```
        prob.append(float(topic_word_dict[key][word]))
    return prob

def key_sorter(topic,word):

    val=topic_word_dict[topic][word]
    return val


number_of_subplots=20
colors = cm.gist_rainbow(np.linspace(0, 1, 20))

for i,v in enumerate(range(number_of_subplots)):

    x=sorted(topic_word_dict[topics[i]].keys(),                    key=lambda
lt:key_sorter(topics[i],lt),reverse=True)[:5]
    y=prob_value(topics[i],x)


    v = v+1
    ax1 = subplot(number_of_subplots,5,v)
    plt.title(topics[i])
    ax1.bar(range(len(x)),y,0.4,color=colors[i],)
    plt.xticks(range(len(x)),x,rotation= 20)
    ax1.yaxis.set_major_locator(mticker.MaxNLocator(3))


ax1.yaxis.set_major_locator(mticker.MaxNLocator(4))

plt.tight_layout()
plt.show()
```

APPENDIX F: SENTIMENT ANALYSIS RESULTS

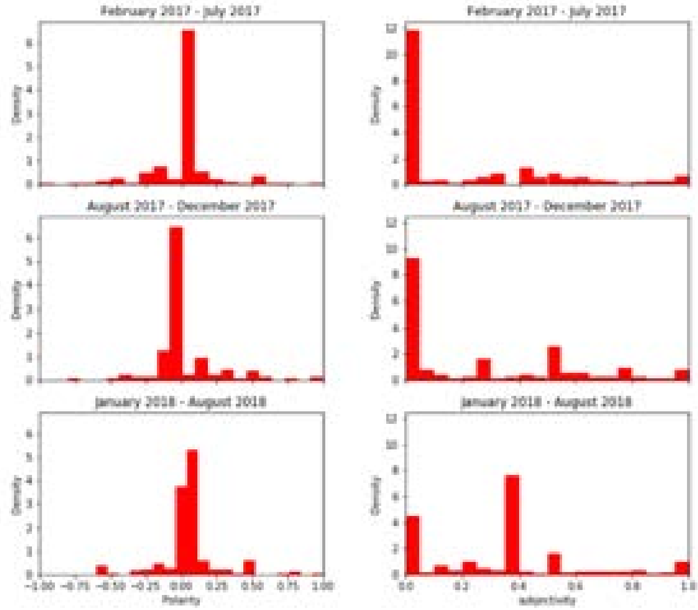
Sentiment Analysis Result – Florida Bus



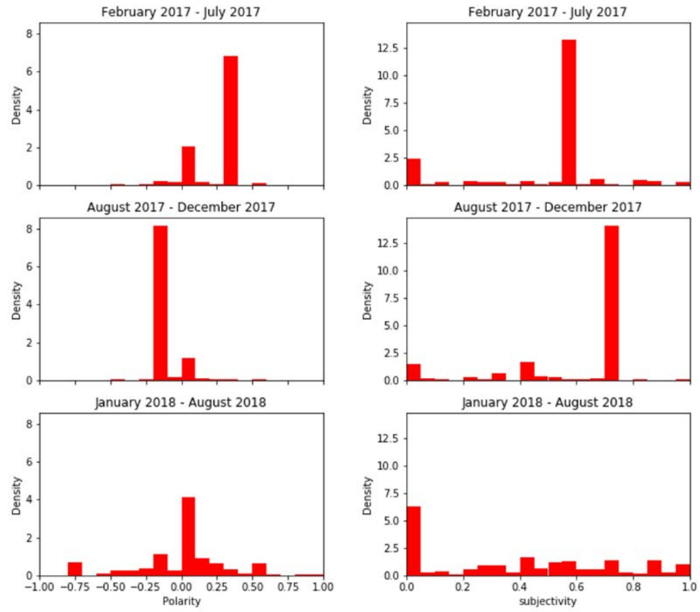
Sentiment Analysis Result – Florida Crime



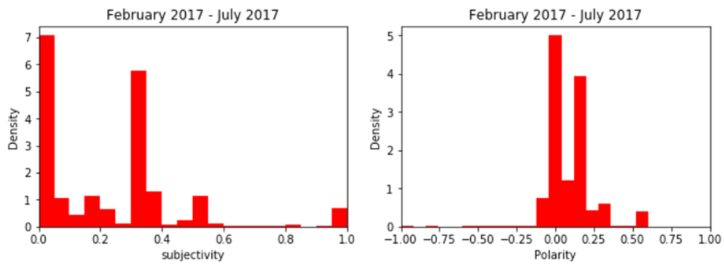
Sentiment Analysis Result – Florida Sidewalk



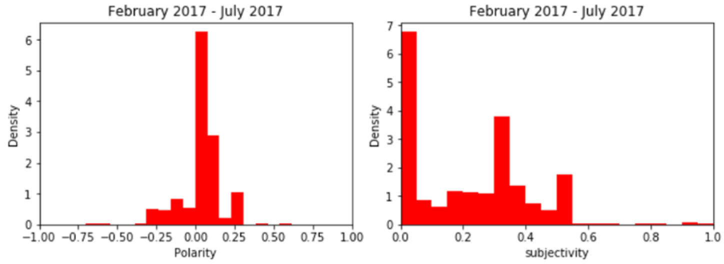
Sentiment Analysis Result – Florida Walking



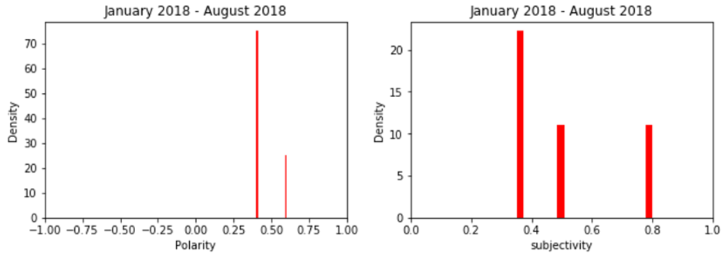
Sentiment Analysis Result – I-4 Construction



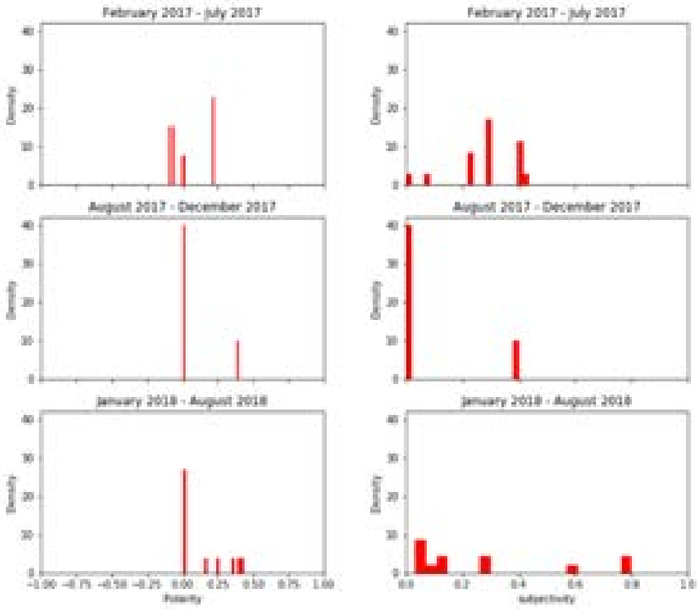
Sentiment Analysis Result – I-4 Crash



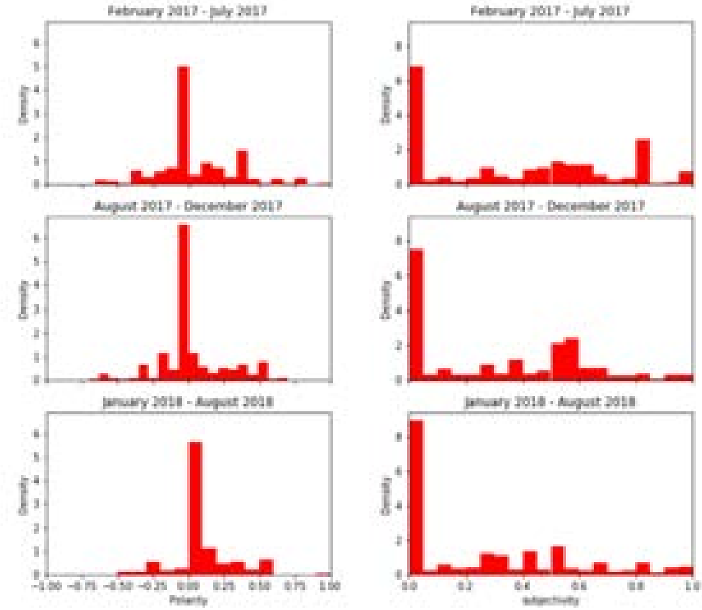
Sentiment Analysis Result – Juicebike



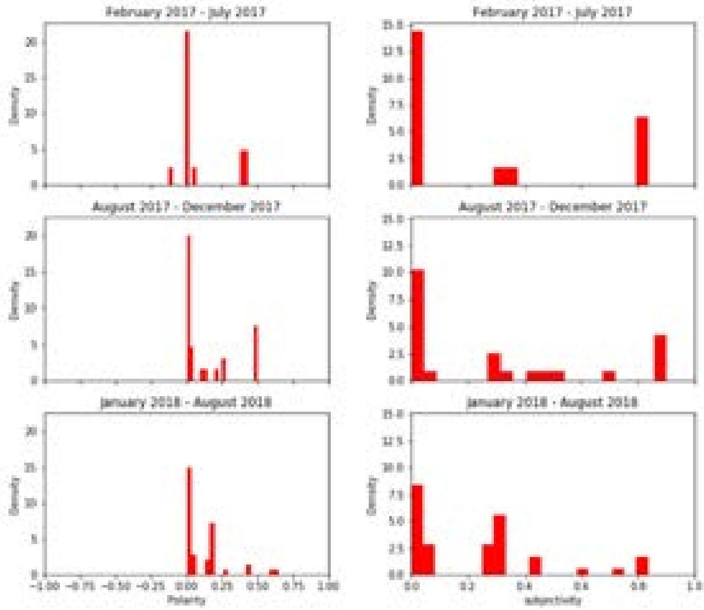
Sentiment Analysis Result – Lakexpress



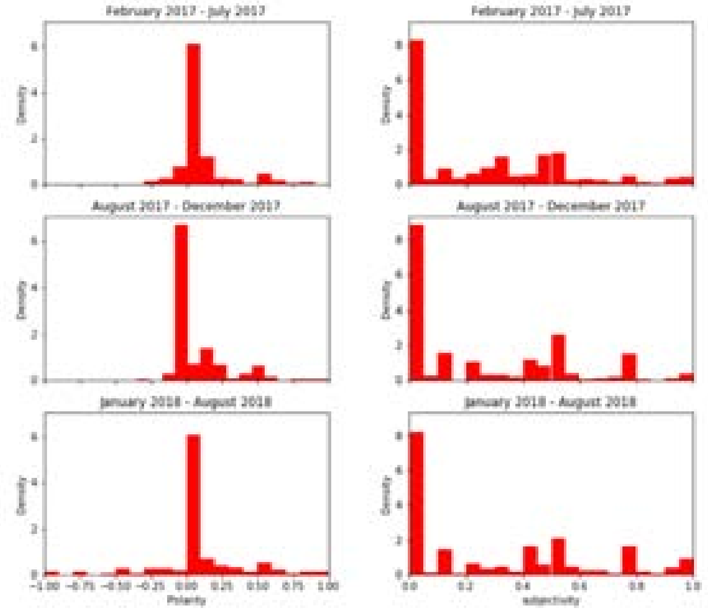
Sentiment Analysis Result – Lynx Bus



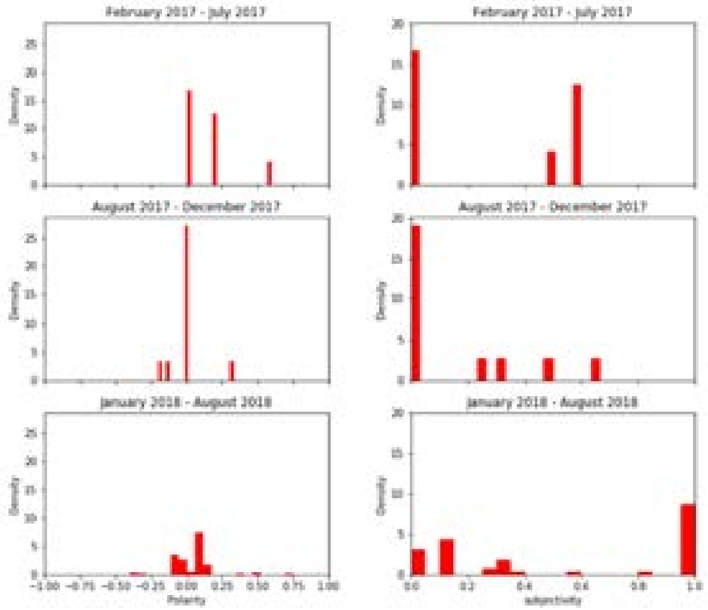
Sentiment Analysis Result – Space Coast Area Transit



Sentiment Analysis Result – Sunshine Skyway

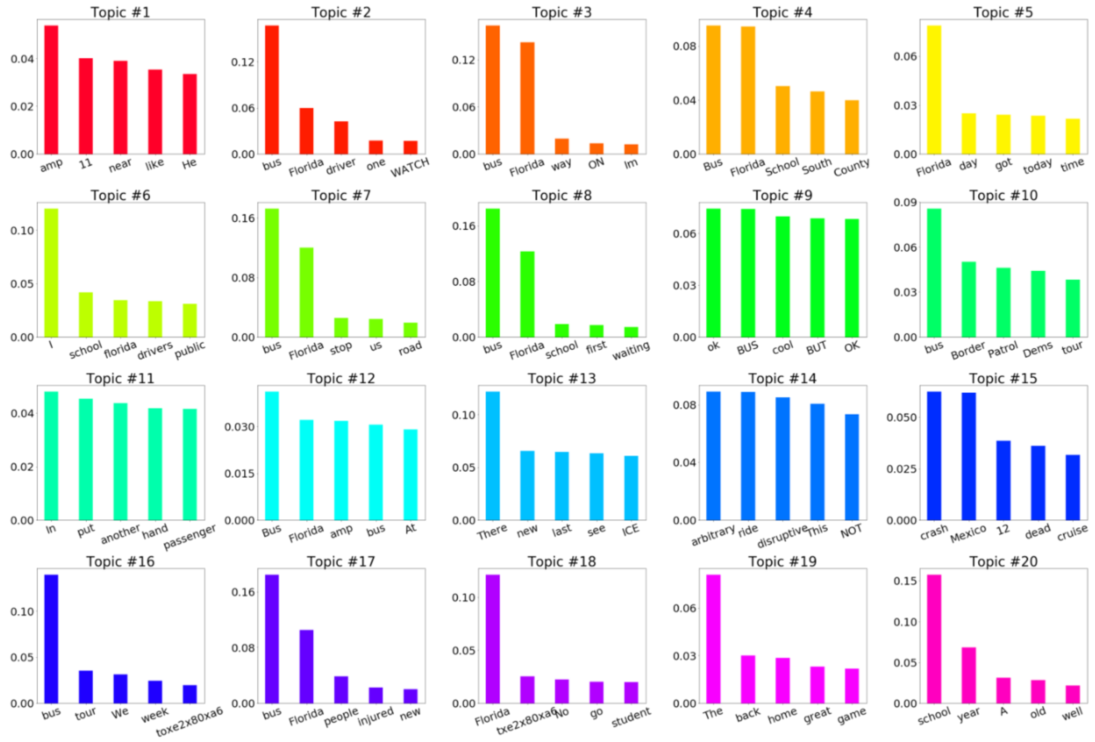


Sentiment Analysis Result – Suntrail

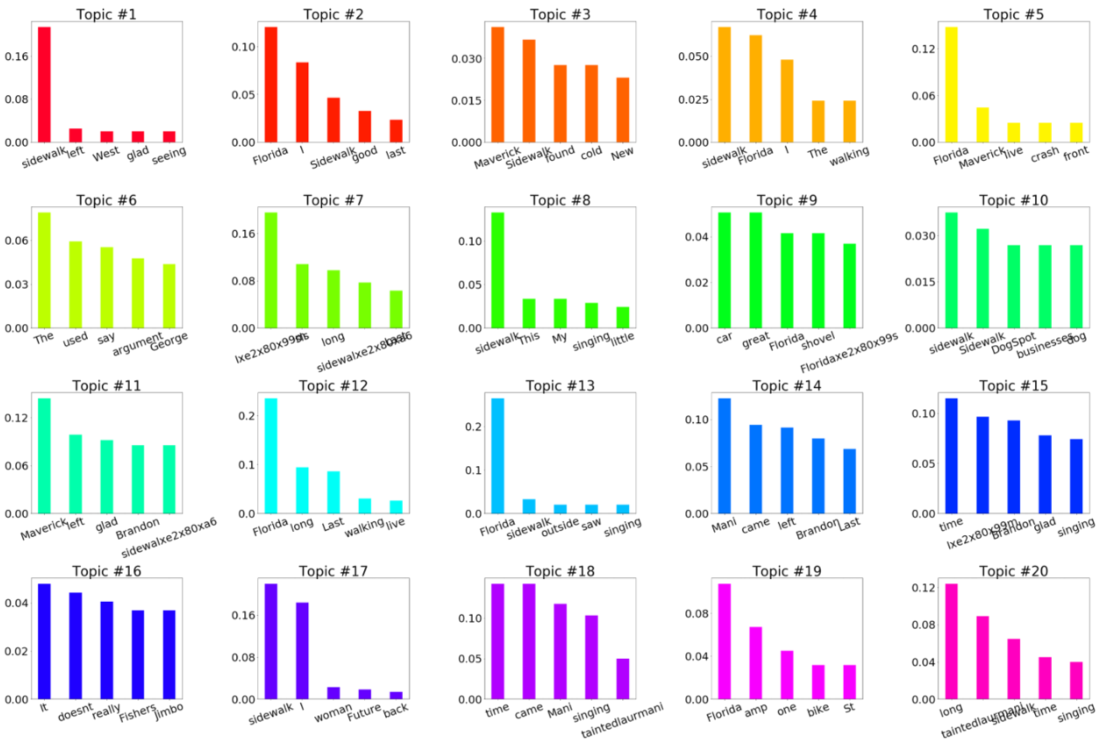


APPENDIX G: TOPIC ANALYSIS RESULTS

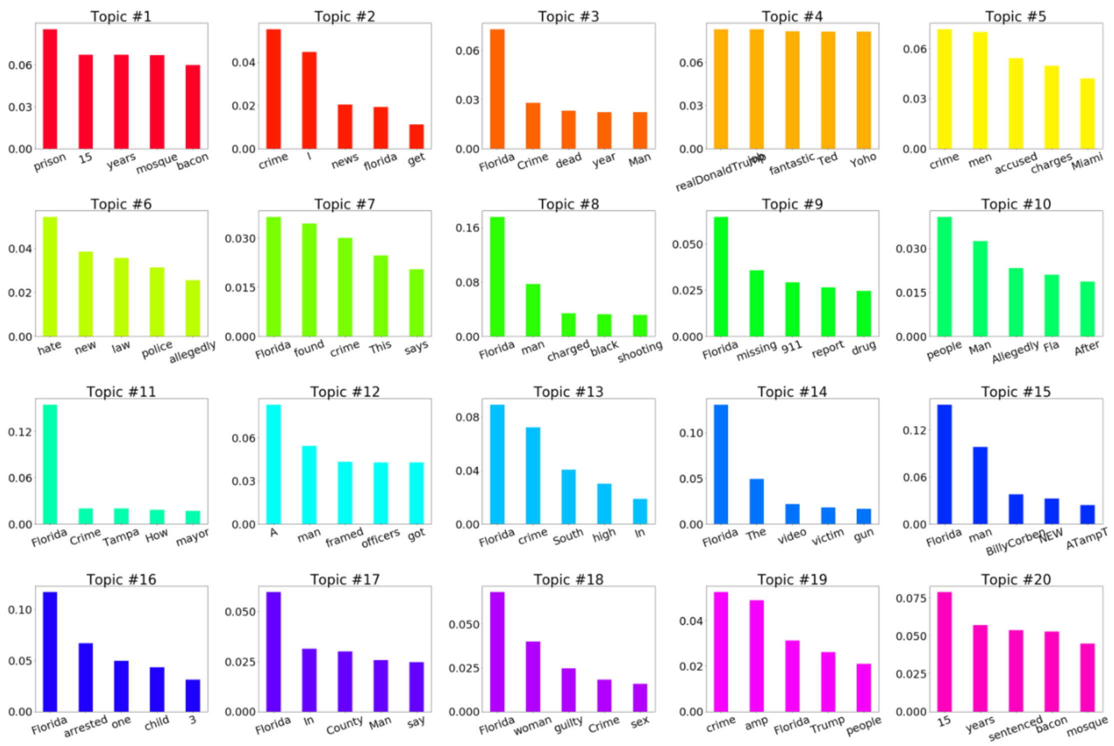
Topic Analysis – Florida Bus



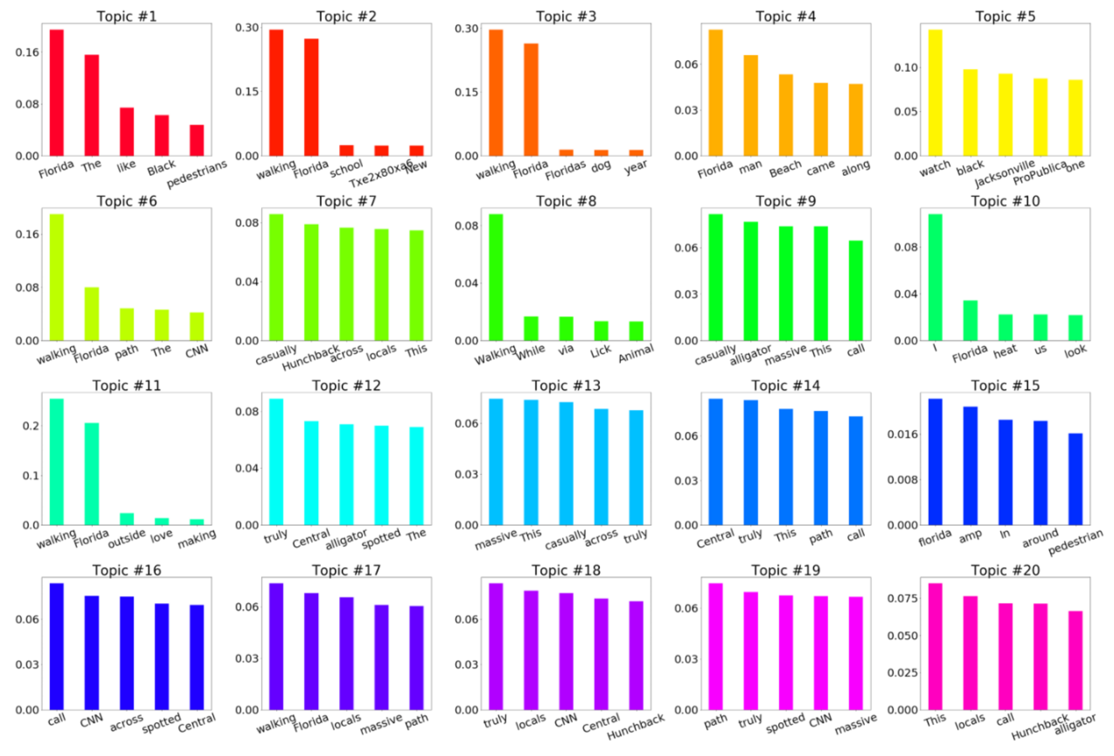
Topic Analysis – Florida Sidewalk



Topic Analysis– Florida Crime



Topic Analysis – Florida Walking



Topic Analysis – Sunshine Skyway