QUANTIFYING IMPACTS OF BROWNFIELD DEVELOPMENT ON PROPERTY VALUE IN MIAMI-DADE COUNTY

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To my parents, Stephen and Shelley Plass

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACS	American Community Survey
BSRA	Brownfield Site Rehabilitation Agreement
CERCLA	Comprehensive Environmental Response Compensation and Liability Act
CLM	Contamination Locator Map (FDEP)
CPI	Consumer Price Index
CSV	Comma-separated value
DERM	Department of Environmental Resources Management
EPA	Environmental Protection Agency
FDEP	Florida Department of Environmental Protection
FDOR	Florida Department of Revenue
FGDB	File Geodatabase
FGDL	Florida Geographic Data Library
FTP	File Transfer Protocol
GIS	Geographic Information Systems
GWR	Geographically-Weighted Regression
MDC	Miami-Dade County
MOA	Memorandum of Agreement
NAL	Name-Address-Legal (FDOR real property roll data)
OLS	Ordinary Least Squares
RCRA	Resource Conservation and Recovery Act
RER	Regulatory and Economic Resources Department (Miami-Dade County)
RLF	Revolving Loan Fund
SARA	Superfund Amendments and Reauthorization Act
SDF	Sales Data Files

SRCO	Site Rehabilitation Completion Order
VCTC	Voluntary Cleanup Tax Credit

Abstract of Thesis Presented to the Graduate School
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In the years preceding the environmental protection regulations of the 1970s, many public and private entities in the United States engaged in practices that introduced large quantities of contaminants into the air, soil, and water. Various public incentive programs designed to remediate contaminated sites have emerged as part of ongoing campaigns aimed at regulating the quantity and spread of contaminants from polluting uses. In consideration of the demands of smart and sustainable growth movements in urban planning and given the rising per-acre value of many urban infill sites, infill development is becoming an increasingly desirable form of development. Despite the potential public health risks stemming from inaction, and profits to be reaped from contaminated site redevelopment, Miami-Dade County has a dearth of ongoing and completed brownfield clean-up projects compared to other municipalities across the country. This may be partly attributable to the widely-held belief that brownfield redevelopment is a high-risk, low-reward venture—a concept this study seeks to address.

The focus of this study is state-designated brownfield sites within Miami-Dade County since such sites are simultaneously the most complex and well-documented classification of contaminated sites in the study area. The study models the impact of five brownfields on

property values from 2010 to 2018. First, an Ordinary Least Squares (OLS) regression model is used to represent the model data, then a decision tree model. The primary objective of the study is to determine whether the redevelopment of county brownfields is desirable and profitable, by examining the economic and social benefits it provides to local governments and private parties.

CHAPTER 1
INTRODUCTION

Urban areas across the United States tend to have high concentrations of land uses that create contaminated sites in low-income and minority communities. The evidence of a relationship between the incidence of contaminated sites and the presence of marginalized groups, likely originates from historical societal discrimination against disenfranchised minorities. This phenomenon, which spawned terms such as "environmental justice," and "environmental equity," is represented by a spectrum of conditions couched in administrative procedure, geography, and social structures (Rosenbaum, 2002, 144). Inequitable and discriminatory practices, coupled with ineffective regulation of pollution until the passage of legislation such as the Clean Air and Clean Water Acts, have generated an urban landscape that is pockmarked with polluted sites. Even now, in the decades following the passage of environmental quality regulations, the combined impact of legal contaminants on residents of areas adjacent to their source is believed to contribute to negative health outcomes (Rosenbaum, 2002, 145). Therefore, despite the efforts of environmental activists, local and national policymakers, and nongovernmental advocacy organizations, and the abundance of popular literature on the subject including, "Silent Spring," (Rachel Carson) "The Color of Law," (Richard Rothstein) and "The Poisoned City," (Anna Clark), contamination continues to threaten disenfranchised communities throughout the United States.

Brownfields represent one species of polluted sites and are defined by the United States Environmental Protection Agency (EPA) as, "real property, the expansion, redevelopment, or reuse of which may be complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant" (EPA, 2019a). As major metropolitan areas approach build-out, brownfield sites have become increasingly desirable for infill development (NLC, 2017). At the same time, state and federal incentives for brownfield cleanup, such as the Voluntary Cleanup Tax Credit (VCTC), and Revolving Loan Funds (RLFs), have improved the economic feasibility of contaminated site redevelopment. But, given the potential liability and costs associated with clean-up, developers and municipalities are still hesitant to redevelop brownfields. For example, in Miami-Dade County (MDC) there are a total of 103 designated brownfield sites, of which only 11 have been remediated as of March 26, 2019 (FDEP, 2019b). Despite this, studies have shown that, "cleanup of brownfield sites alone yields large increases to nearby housing values, and…has unambiguously positive welfare impacts on communities nearby" (Haninger, et.al, 2014, 25).

This study involves modeling the effect of brownfield development on property values in Miami-Dade County for the years 2010 to 2018. The purpose of this study is to quantify the relationship between brownfield site redevelopment and socioeconomic factors such as property values and taxable value in areas proximal to designated brownfield sites. Results will ultimately, inform local governments, developers, urban planners, and members of the general public of the value of brownfield development to affected communities within Miami-Dade County.

This study is divided into seven chapters. It begins with an introduction that provides a general background about brownfield development and the purpose of this study. Chapter 1 also describes a preliminary study's design and methodology, makes some observations about incentive programs for brownfield development and details the existing incentive programs for development in the State of Florida and Miami-Dade County. It also describes the state of brownfield development in Florida and Miami-Dade County, the various impediments to site redevelopment, and the manner in which brownfields impact the communities where they are situated. Chapter 2 focuses on literature review and provides a description and critical discussion of other studies' methods, in addition to their findings. It notes the importance of conventional mapping software and machine learning in improving study outcomes and the incorporation of those tools in this study. Chapter 3 addresses data collection and data analysis. This chapter discusses the sources of data, the results of site visits, and the flaws and limitations of each data source. Chapter 3 also describes the process of cleaning the subject datasets. Chapter 4 outlines the study's methodology, shows how the findings detailed in Chapter 5 were arrived at, and explains in detail the two models created for the study. Chapter 5 reveals the results of the two models and provides insights into the relationships between the variables selected for inclusion within them as they pertain to the research question and study objectives. Chapter 6 discusses the broad implications of the results and describes potential next steps in the research process. Finally, Chapter 7 summarizes the results of the study outlined in Chapter 5 and seeks to answer the research question posed in this chapter while providing a conclusion.

Background

The two dominant federal regulations governing contaminated site cleanup are the Resource Conservation and Recovery Act (RCRA) and the Comprehensive Environmental Response Compensation and Liability Act (CERCLA). The purpose of these statutes is to regulate potentially harmful materials including, "organic materials from industrial processes, heavy metals, biological wastes with bacterial and viral contaminants, sludge, and various chemicals" (Farber, 2014, 204). RCRA was first enacted in 1976 and governs certain aspects of potential contaminants including their storage and disposal. CERCLA, RCRA's retroactive counterpart, was enacted in 1980 and establishes, "broad civil liability" for cleanup of sites where treatment, storage, or disposal of hazardous material has already occurred (Farber, 2014, 205). CERCLA is often referred to as the "Superfund Law," since it established the Superfund program which allows for cleanup of major contaminated sites throughout the United States (Farber, 2014, 222). Though they both contain contaminated material, Superfund sites are distinct from brownfield sites because Superfund sites are considered to have, "the highest level of contamination," or present, "immediate risks" (Ramseur, 2008, CRS-2).

The impetus for the enactment of CERCLA and RCRA came from environmental health disasters caused by a lack of regulation of hazardous substances. One pivotal case that led to the passage of these laws was the now-infamous Love Canal disaster, which occurred in Niagara Falls, New York in the 1970s. Lois Gibbs, an environmental activist and former resident of Love Canal succinctly describes the situation which precipitated countless birth defects and deaths as, "a thousand families who lived near the site of an abandoned toxic chemical waste dump" (Gibbs, 2010, 19). Though the Love Canal disaster is one of the most notorious in environmental law, other cases, including that of Times Beach, Missouri, and "Cancer Alley" in Louisiana also prompted the passage of these regulations.[1]

Literature on environmental regulation tout CERCLA as both broad and dynamic. CERCLA was first amended in 1986 by the Superfund Amendments and Reauthorization Act (SARA), then again in 2002 by the Small Business Liability Relief and Brownfields Revitalization Act, and again in 2018 by the Consolidated Appropriations Act (Farber, 2014,

[1] The Town of Times Beach was the site of dioxin contamination caused by spraying an industrial byproduct from 1972 to 1976. The incident ultimately cost the EPA and State of Missouri $36 million in buyouts and the total costs associated with site cleanup were estimated to be close to $200 million (Hernan, 2010, 99). The Center for Disease Control advised residents of the town to leave following testing in 1982, and by 1997, the entire town of Times Beach had been demolished and buried (Hernan, 2010, 91-100).

"Cancer Alley" is an 85-mile long stretch along the Mississippi River from New Orleans to Baton Rouge. Industrial uses, primarily in the petrochemical sector, are prominent in the region which is also reportedly plagued by, "high unemployment, illiteracy, poverty, and ill health" (Allen, 2003, 2). Due to the ongoing industrial activities in the area, "Cancer Alley" is still a hotbed for environmental activism (Blackwell, Drash, Lett, 2017).

222; Practical Law Real Estate, 2018).[2] The 2002 amendment to CERCLA formalized the EPA's authority to regulate brownfield sites and provided for annual noncompetitive brownfield rehabilitation grants to states as well as competitive individual grants for cleanup of specific brownfield sites nationwide. The 2018 Consolidated Appropriations Act amendment to CERCLA then broadened the scope of financial assistance available to stewards of properties with real or perceived contamination and limited liability for cleanup in an effort to incentivize brownfield remediation and redevelopment (Practical Law Real Estate, 2018). Consequently, developers are afforded more federal assistance for brownfield redevelopment than ever before. In addition to federal regulation, states have also taken steps to assist with brownfield remediation. Florida's regulations serve as an example.

Administrative Procedure for Brownfield Remediation in Florida and Miami- Dade County

The Florida legislature enacted the Brownfields Redevelopment Act in 1997 **(**FDOS, n.d.). According to the Florida Department of Environmental Protection (FDEP), the primary goals of this Act are as follows:

> Reduce public health and environmental hazards on existing commercial and industrial sites that are abandoned or underused due to these hazards; create financial and regulatory incentives to encourage voluntary cleanup and redevelopment of sites, derive cleanup target levels and a process for obtaining a 'No Further Action' letter using Risk-Based Corrective Action Principles; and provide the opportunity for Environmental Equity and Justice. (FDEP, 2019a)

In 2005, the State of Florida executed a Memorandum of Agreement (MOA) with the EPA to, among other things, "facilitate FDEP's implementation of the Florida Brownfield Redevelopment Act" and the associated initiative referred to as the "Brownfield Redevelopment Program" (FDEP & EPA, 2005, 1). This agreement enabled FDEP to receive federal funding for

[2] Known as the "BUILD Act."

brownfield redevelopment, and these funds have been leveraged for over a decade to rehabilitate hundreds of brownfield sites statewide (FDEP & EPA, 2005).

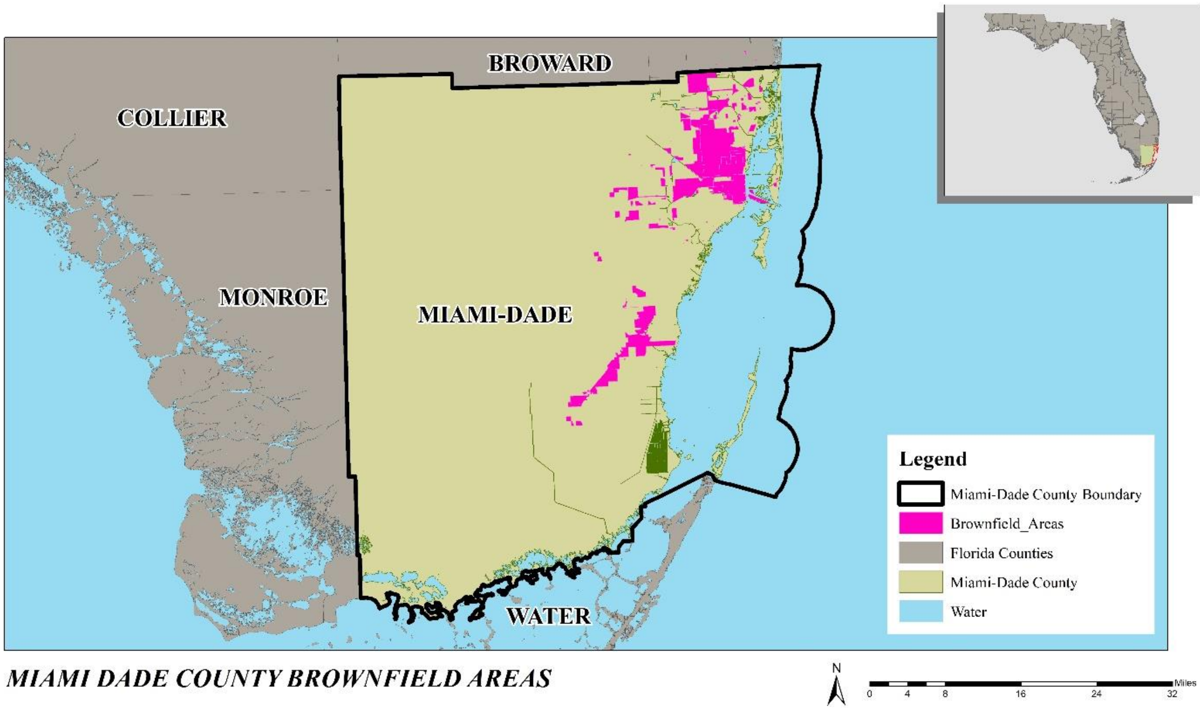


Figure 1-1. Map of Miami-Dade County including designated Brownfield Areas

Before explaining the process for brownfield site designation, an important distinction should be made between "Brownfield Areas" and "Brownfield Sites." According to Florida law, a Brownfield Area is, "a contiguous area of one or more brownfield sites, some of which may not be contaminated, and which has been designated by a local government by resolution..." (F.S. 376.79(5)).[3] A Brownfield Site, by comparison is defined as, "real property, the expansion, redevelopment, or reuse of which may be complicated by actual or perceived environmental contamination" (F.S. 376.79(4)). Therefore, state-designated brownfield sites are expected to fall within designated brownfield areas as depicted in Figure 1-1 for Miami-Dade County. In order to receive federal, state, or local assistance for brownfield remediation, property owners must

[3] "…Such areas may include all or portions of community redevelopment areas, enterprise zones, empowerment zones, other such designated economically deprived communities and areas, and Environmental Protection Agency-designated brownfield pilot projects" (F.S.376.79(4)).

enter into an agreement with the county or brownfields district in which the contaminated site is situated, in addition to making a separate agreement with the local government (Davis, 2002, 524). These agreements, referred to as Brownfield Site Rehabilitation Agreements (BSRAs), contain information about the amount and type of pollution on-site, as well as the requirements for remediation. Once the requirements in the agreement have been satisfied, the county or district issues a Site Rehabilitation Completion Order (SRCO) attesting to the successful completion of remediation requirements in the BSRA.

Each year, FDEP releases an annual report on the performance of the Florida Brownfields Redevelopment Program in accordance with Florida Statutes section 376.85. According to this report, a total of 354 BSRAs were executed in the State of Florida from 1997 to 2018. Of those 354 agreements, 25 were executed in 2018 alone, down from 30 in the previous year. According to the State's 2018-2019 annual report, in total, 137 SRCOs have been issued since 1997, and 15 were issued in 2018 compared with 14 in the previous year. Like FDEP, Miami-Dade County also issues an annual report documenting the performance of its district's brownfields program (RER, 2019). According to their 2019 report, which covers program performance from June 1, 2018 to June 1, 2019, 10 new BSRAs were executed, and 2 sites were issued SRCOs. The county also reported a total of 43 BSRAs executed and 10 SRCOs issued in Miami-Dade County since the program's inception.

A survey of the publicly-available data concerning contaminated site cleanup in Florida revealed the presence of thousands of contaminated sites throughout the state. According to the EPA's data, Miami-Dade County contains 399 contaminated sites, of which 367 are brownfields. FDEP notes the presence of 1,244 cleanups in the county, 57 of which are brownfield cleanups. Finally, Miami-Dade County's contaminated sites dataset contains 2,483 records, 145 of which likely correspond to brownfield sites.[4] The differences in the number of total contaminated sites and brownfield sites between each agency results from the type of cleanup project. The EPA's records correspond to sites that have received federal funding of some kind for cleanup-related activities. FDEP's records correspond to sites that, at a minimum, have executed BSRAs, and Miami-Dade County's records are associated with permits pulled in connection with site cleanup. Table 1-1 sets forth state and county totals for each dataset referenced herein.

Table 1-1. Summary of Agency Data for Contaminated Sites (FL v. MDC)

	State of Florida	Miami-Dade County
EPA Cleanups ("Cleanups in Your Community") *		
All Cleanups	1,936	399
Superfund Sites	81	14
Brownfield Cleanups	1,583	367
FDEP Cleanups ("DEP Cleanup Sites") **		
All Cleanups	11,947	1,244
Brownfield Cleanups	318	57
MDC Cleanups ("Contaminated Sites")		
All Records	N/A	2,483
All Contaminated Sites in Phase Range 09-11	N/A	145

* EPA does not standardize county names. Figure based on count of counties with names similar to Miami-Dade County

** Dataset last updated October 2018

This study initially identified 11 sites in Miami-Dade County for which SRCOs were issued. Compared to other municipal regions including Milwaukee and Minneapolis, the number of available remediated sites for consideration in this study is low (DeSousa, 2009). Nonetheless, this study can provide important insights even if it only confirms the findings of other studies. This study is also important because it will provide specific answers for the geographic area under consideration. Like the numerous other studies that were conducted to determine the social and economic impacts of brownfield redevelopment, this one is area-specific, but may

[4] Brownfield sites of interest in this study with records in the Contaminated Sites dataset are tagged with Phase numbers 09-11

yield results that show a trend. Continued research in this manner will increase the knowledge base about the benefits of brownfield redevelopment, and potentially persuade stakeholders and investors that their redevelopment projects will be safe and profitable. Given the risks and costs associated with brownfield redevelopment, this study can also help stakeholders evaluate the cost-reduction incentives provided for redevelopment projects (Bacot & O'Dell, 2006, 145-146).

Preliminary Study Overview

As major metropolitan areas approach build-out, brownfield sites become increasingly desirable locations for infill development (NLC, 2017). At the same time, state and federal incentives for brownfield cleanup, such as the Voluntary Cleanup Tax Credit (VCTC) and various Revolving Loan Funds (RLF), have made it more economically feasible to redevelop contaminated sites. However, given the stigma, liability, and costs associated with clean-up, developers and municipalities are hesitant to build on lands designated as brownfields. While numerous studies have been conducted to determine the social and economic impacts of brownfield redevelopment, their generalizability is often limited by the unique characteristics of the properties studied in each municipality. Since it can be hard to identify variables and metrics that contribute to success of redevelopment projects in varied municipal regions, it is still difficult to persuade stakeholders and investors that specific redevelopment projects are safe and profitable (Bacot & O'Dell, 2006). Continued study of brownfield developments' impacts upon communities is therefore necessary to broaden our understanding of the conditions that make it economically sensible to develop a particular site.

To better understand existing conditions within Miami-Dade County, a preliminary study was carried out in the fall of 2018 in a limited geographic area to gauge the feasibility of this study. Since the methodology of the preliminary study helped shape the conceptual framework and methodology of this one, it is worthwhile to describe the preliminary study's findings and flaws. The preliminary study sought to answer the question of whether development of brownfields in Miami-Dade communities within a one-mile radius of an interstate highway impacts property value. This preliminary study applied the hedonic price method, using a total of 23 variables, to predict change in adjusted property values from the year 2002 to the year 2017. These variables, specifically land use, change in land use, distance to the nearest remediated brownfield, and fitted values from previous years, are derived from publicly-available data found in the Miami-Dade County Open Data Portal, and the Florida Geographic Data Library (FGDL). The structure of this analysis is centered on examining the local impacts of brownfield site remediation over time. As such, the model includes 8 dummy variables to capture the impacts from 9 remediated sites. Ideally this would not only control for differences in the types of brownfield redevelopment, but also provide granular data about how such development might positively or negatively affect property value.

The first flaw in the preliminary study design was the decision to include all uses (e.g., municipal, condominium, low and high density residential, etc.) in the OLS model. As a consequence, the input data failed tests for normality, thereby challenging the validity of the final model's output. Second, the brownfield sites selected were not valid for the study. Specifically, most sites selected did not have executed BSRAs associated with them—let alone SRCOs. This flaw was discovered following correspondence with Miami-Dade County staff who then recommended more appropriate sources of data and helped to identify the sites that met the minimum requirements for inclusion in the study. Third, the variables that were included in the model had values that were too similar to one another.[5] However, this was eventually recognized and accounted for. Despite these limitations, results were still valuable since they

[5] This model included variables which were autocorrelated and therefore had an inflated R^2 value

allowed for critical examination of the factors in the study including datasets and methodology. For example, prior to conducting the preliminary study, the implications of a negative impact from development on property value were never considered.

Though conclusions drawn from the results of this study warranted further investigation, the model's predictive capacity is very promising. This is not only because results were ultimately found to be significant, but also because of the characteristics of the dependent and independent variables. For example, the adjusted property value itself seemed to be divided into tiers influenced by land use, and some remediated brownfield sites impacted property value positively while others did so negatively. There are a wide array of variables that influence change in property value. Consequently, the model's independent variables' influence upon the dependent variables in this geographic context was unique.

CHAPTER 2
LITERATURE REVIEW

A review of findings and methodology in existing literature on the subject of modeling impacts from development on property value reveals that many studies have quantified the effects of brownfield redevelopment on communities. The prevalence of these studies seems to be partially attributable to the existence of federal, state, and local brownfield development incentive programs, coupled with a general interest in evaluating the efficacy of allocating public funds to assist with brownfield clean-up. Many of the studies that were surveyed utilize the hedonic price method, which involves, “using the value of a surrogate good or service to measure the implicit price of a non-market good” (CBABuilder, n.d.). Moreover, many of these studies consider a variety of physical and social factors in order to account for more variation in the data.

A mixed-methods study by De Sousa, Wu & Westphal (2009) oriented its hedonic price model around variables including median household income, distance to roads, percentage of poverty, and African American population percentage. This large study used 26 variables to predict the impact of brownfield redevelopment on property value, and encompassed redeveloped brownfields in Minneapolis, Minnesota and Milwaukee, Wisconsin from 1996 to 2004. These cities are unique because they both have robust brownfield redevelopment programs. For instance, Minneapolis alone initiated more than 100 successful site cleanups from 1994 to 2009 (De Sousa, Wu, Westphal, 2009, 98). The results of this study’s hedonic price model demonstrated net positive impacts stemming from brownfield redevelopment in both municipalities (De Sousa, Wu, Westphal, 2009, 104). Two notable findings from this study are that the type of redevelopment, and the properties’ distance from the brownfield site affect the degree to which property values increase. The adjusted R^2 for the pre-redevelopment (1994) model is 0.52 (De Sousa, Wu, Westphal, 2009, 104).[1] The adjusted R^2 for the post-redevelopment model is 0.63 (De Sousa, Wu, Westphal, 2009, 104).

A nationwide study by Haninger, Ma, & Timmins (2014), used a combination of social survey data, and state and municipal quantitative data, to accomplish essentially the same objective as De Sousa, Wu & Westphal in their 2009 study. The Haninger, Ma & Timmins study took a somewhat different approach to a hedonic price model by accounting for, "unobservables that may be correlated with cleanup activities," and by, "controlling for brownfield, house, and neighborhood characteristics" (Haninger, Ma & Timmins, 2014, 22). Understandably, given the scope of the study, the R^2 values produced by the Haninger et al. study appear generally lower than those of studies that examine smaller geographic areas.

While much research on this subject involves a geographic component, researchers have seldom used conventional mapping software. One notable exception is a report by Sun & Jones in 2013 that incorporated GIS technology by Esri to model the spatial relationship between brownfield development and property value. Sun & Jones' research methodology is a good example of the capacity of GIS technology for modeling spatial relationships between variables. This study, like De Sousa, Wu & Westphal's, examines the City of Milwaukee, and applies the hedonic price method to measure and predict the impact of brownfield development on property value in the area. The Sun & Jones study employs the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) tools supplied in Esri's ArcMap Geostatistical Analyst Extension, to obtain and visualize predicted outcomes for the city. The resulting property-level OLS, based on 11 variables, yielded predictions with R^2 values of 0.625 for 1996,

[1] The R^2 statistic is described as, 'the proportion of total variation about the mean…explained by the regression' (Draper & Smith, 1998, 33). The adjusted R^2 statistic represents the R^2 value adjusted for the number of observations in the dataset (Draper & Smith, 1998, 104).

and 0.649 for 2004. The research described in this paper draws heavily from the work of De Sousa, Wu & Westphal's methodology, but uses some of the techniques and software applied by Sun & Jones, in order to better leverage new technology and visualization tools while still obtaining useful insights into the impact of brownfields on property value in Miami-Dade County.

The decision to utilize GIS technology in the research methodology alludes to a central issue in this study's design: geographic scope of data. This factor introduces yet another layer of complexity into the analysis of brownfields' impacts upon communities. Economist Raymond Palmquist notes in "Property Value Models" (2005), that US Census data aggregates population demographics in a way that can muddle results of hedonic price modeling, necessitating use of higher resolution data to obtain more accurate results (784). Moreover, much of the literature reviewed includes discussion of geographic scope (Haninger, et.al, 2014, 25; DeSousa Wu & Westphal, 2009; Bacot & O'Dell, 2006; Dubin, Pace, & Thibodeu, 1999). For instance, the aforementioned study by Haninger et al. (2014) uses a control group that consists of a home that is outside of a brownfield's radius of potential influence, but within a particular radius of the site. Those involved in the study assumed that properties that are located between these two radii are similar enough to be compared to properties within the radius of each brownfields' area of influence. Meanwhile, other studies were limited in scope to a couple urban areas (Bäing & Wong, 2018; Mashayekh, Hendrickson & Matthews, 2012). The existence of such case studies may be necessitated by the variability between metropolitan regions. Despite regional differences, however, positive economic and social outcomes stemming from brownfield redevelopment seem to be universal (Mueller, 2005).

An additional challenge to modeling the impact of an intervention (e.g., contamination clean-up and redevelopment) on property values within a geographic region is spatial autocorrelation. It is often assumed that things that are close together are likely to be alike. In some cases, this idea translates into bias in model prediction. There are many types of data which may be influenced by spatial autocorrelation, including housing data, demographic data, or data pertaining to natural disasters such as hurricanes. Robin Dubin, in his article published in the Journal of Housing Economics, aptly states, "spatial autocorrelation is likely to be present in any situation in which location matters" (1998). Dubin also explains that failure to account for spatial autocorrelation may result inaccurate model output and biased prediction variance (1998, 305). Similarly, spatial autocorrelation poses a challenge in modeling impacts of redevelopment and contaminated site cleanup. This factor may be accounted for by weighting observations in a dataset using a spatial weights matrix. A spatial weights matrix is a "NxN" matrix representing the spatial relationships between observations in a dataset (Dubin, 1998, 306). Tools in ArcMap such as GWR allow the user to input a spatial weights matrix in order to account for existing or emerging spatial relationships between variables in regression models. Due to the chosen methodology and the physical distribution of remediated brownfields sites in Miami-Dade County, the presence of spatial autocorrelation have influenced the results of this study.

Of all the methods for quantifying impacts of brownfields redevelopment, none applied machine learning techniques for model optimization. This omission is significant given the expansive body of research attesting to the potential of such methods to improve prediction accuracy of models derived from data affected by a wide array of variables. To improve the quality of research results, this study employed machine learning—specifically recursive partitioning, to attempt to optimize model prediction accuracy using contemporary methods.

This machine learning method is described in a paper published by Strobl, Malley & Tutz which discusses how to carry out recursive partitioning using R (2009).

It is difficult to overstate the importance of parallel academic literature to bolstering the methodology applied by this study and others cited in this chapter. In addition to studies concerned with the impact of brownfield development on property value and other social and economic factors, this study also considered several publications concerning methods for prioritizing brownfield development based on various criteria (Pizzol, et al., 2016). These documents provided a useful range of possible externalities and defining metrics for assessing the success of brownfield redevelopment programs. For example, consider Bacot & O'Dell's findings about the importance of cost-incentives, and the alternative methods for modeling spatial and temporal variables in the hedonic price model discussed by Dube & Legros (2009; 2014).

CHAPTER 3
DATA

Reliable results in this study are heavily dependent on collection of equally reliable data, and application of proper data cleaning methodology. This chapter outlines the data collection and data cleaning processes used in this study, and explains the choices of particular sources of data for representation of contaminated sites over others. It also describes parcel data sources, and outlines the methods and underlying principles of the data cleaning process. Specifically, the “Data Collection” subsection, in addition to clarifying the data collection process, also summarizes the rationale for data source selection. The “Data Management” subsection enumerates and explains the treatments used in each table alongside the source of the data selected. This subsection also provides important documentation of methods for validation and ground-truthing alongside a detailed list of the sites and variables ultimately selected for inclusion in the models. This “Data” chapter precedes the chapter concerning modeling methodology because data cleaning methodology and study design principles have a substantial impact on model results. For reference, further information about the data used in this study is located in Appendix G.

Data Collection

The EPA is a major source of data on brownfield redevelopment. Among other things, their data represents site characteristics and cleanup status of polluted sites nationwide. However, state agencies such as FDEP and individual municipalities including Miami-Dade County are also sources of detailed information about brownfields located within their jurisdictional bounds. Municipalities sometimes have data and documentation that is not readily available through the EPA. For example, unlike the EPA, the Florida Department of Environmental Protection enables the general public to access the digitized copies of executed SRCOs and BSRAs that contain details such as the nature of pollution on-site, and the terms of the BSRA. For this study, it was easier to validate data obtained from FDEP directly through FDEP and Miami-Dade County since FDEP and Miami-Dade County staff were both very responsive to questions about the state and district brownfield programs. Since FDEP and Miami-Dade County offered higher resolution data and support, these agencies' datasets were used in place of the EPA's.

To elaborate, Miami-Dade County's Department of Regulatory and Economic Resources (RER) includes a designated brownfields program, and the State of Florida maintains a comprehensive database of BSRAs. Environmental data is publicly-available on the Miami-Dade County Open Data Portal and FDEP websites, so contaminated site and environmental permit tables and shapefiles were downloaded from both of these sources. Other geospatial data used in this study are hosted by the Florida Geographic Data Library (FGDL), a repository for geographic data within the State of Florida. To expound on the specific datasets used in this study, brownfield site locations and characteristics are available in the "Contaminated Site" shapefile, described as follows on the Miami-Dade County Open Data site:

> A point feature class of open DERM Contaminated sites - see phase code for the status of the site.[1] Contaminated Sites, identifies properties where environmental contamination has been documented in the soil or groundwater. Facilities get listed as a contaminated site by a DERM inspector who finds a violation on the property. Facilities that store potentially contaminated materials are permitted and/or tracked by DERM. A site is removed from the active contaminated sites layer/list when the site is found by DERM to be cleaned up.

Further information about the five sites included in this study was downloaded from FDEP's Contamination Locator Map (CLM). The DEP Cleanup Sites dataset, which is the specific

[1] DERM refers to the Department of Environmental Resources Management of Miami-Dade County. According to Section 1-4.3 (c) of the Miami-Dade County Code of Ordinances, the powers, functions, and responsibilities of this department have been transferred to the Department of Regulatory and Economic Resources (2011).

dataset hosted on the FDEP Open Data Portal, is the dataset from which the specific site locations and details were obtained. This dataset was last updated in August of 2019.

The Miami-Dade County "Contaminated Sites" and "Environmental Permits" datasets, hosted on the Miami-Dade County Open Data Portal, were used to corroborate the DEP Cleanup Sites dataset. According to the open data portal, the "Contaminated Sites" dataset is updated on a monthly basis. Though the "Environmental Permits," table was used in the preliminary study to vet the brownfield sites selected from the "Contaminated Site" shapefile, and to determine each site's approximate year of redevelopment as shown in Table 3-1, use of the "Environmental Permits" table was discontinued once the individual SRCO agreements for the county were located. The "Environmental Permits" table is described as a "list of open and closed permits issued or tracked by DERM". Once the SRCO records were located, viable sites were aggregated in a single shapefile containing only the locations of the contaminated sites selected for inclusion in the study (Appendix A provides a summary of results from site visits as well as a copy of the site visit questionnaire).

Locating the source data for this study proved to be a difficult undertaking. Shapefiles containing property values were not available for free through Miami-Dade County's Open Data site, but they could be downloaded from the Public Access Bulletin Board (a file hosting site maintained by the County) for a fee. Ultimately, it was discovered that the Florida Department of Revenue (FDOR) maintains tables called, "Name – Address – Legal", or NAL, which includes county property appraisers' "Just Value" and the variables used in property value calculations. The agency also hosts year-to-year parcel geometry for the entire State of Florida on their File Transfer Protocol (FTP) site. This data can be obtained free of charge through an email request to department staff. However, the NAL tables are only available in comma-separated values (CSV) format and parcel geometry is only available as a shapefile. For the sake of expediency, it was decided that for the years 2012, 2014, 2017, and 2018, Florida Geographic Data Library (FGDL) parcel data that includes both parcel geometry and NAL table variables would be used in place of the FDOR data. FDGL also provided supplemental data used to generate the maps for this study.

Data Management

Data analysis began with Miami-Dade County's "Contaminated Sites" dataset. In the preliminary study, a number of contaminated sites were selected from the dataset based on their "complete" status. Upon speaking with representatives of FDEP and after meeting with County employees managing the brownfields program, it was discovered that the "Contaminated Sites" dataset alone would not provide adequate information to select properties for inclusion in the study. Consequently, the list of brownfield sites was revisited and improved upon using the aforementioned Contamination Locator Map data and other documentation provided by FDEP. Several variables were added to the subsetted "Contaminated Sites" dataset that described the year the original contaminated parcels received their SRCOs as well as each site's BSRA ID number, and name (e.g., "Mandy's Market"). Data from FDEP also informed the removal and addition of several sites from the original list since the list maintained by the state had more reliable and comprehensive documentation. To ensure that all the sites selected for this study met minimum criteria defined in the methodology, site visits were conducted.

Several sites were omitted as a result of these visits due to their state of development. Site visit results are provided in Appendix A alongside rationale for omitting particular sites from the study. The five sites selected for inclusion in the study were added to a second subset of the contaminated site dataset and set aside for later steps of the data analysis process. Figure 3-1 depicts the study area as well as the spatial distribution of the selected sites. Table 3-1 outlines the eleven sites within Miami-Dade County for which SRCOs were issued at the time of the study. Sites labelled "INCLUDED" represent sites with conditions which met minimum criteria for inclusion in the study at the time of the survey.

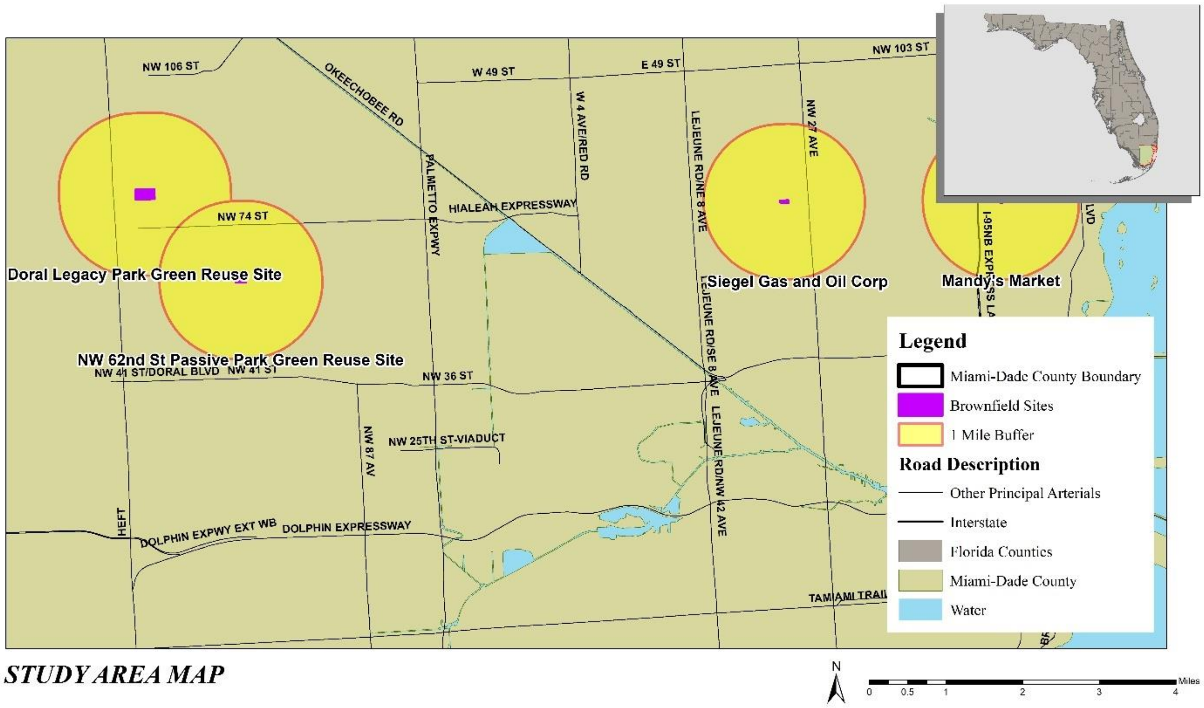


Figure 3-1. Map of the brownfield sites included in this study

Table 3-1. Brownfield Sites Selected for Study

Site Number	Site Name	Brownfield Site ID (FDEP)	Date of SRCO Issuance	Included / Omitted
1	5th & Alton Shopping Center	BF130001001	3/14/2012	OMITTED
2	Wynwood N. Miami	BF139801009	10/29/2015	OMITTED
3	BHG St. Martins Pl. LTD	BF139801008	12/18/2014	INCLUDED
4	Wagner Square	BF129801003	10/7/2005	OMITTED
5	Jackson West Hospital Brownfield Site	BF131104000, BF13104002	7/25/2018	OMITTED
6	Beacon Lakes Property…	BF130301001	5/9/2012	OMITTED
7	NW 62ND Street Passive Park Green Reuse Site	BF131601001	6/25/2018	INCLUDED

Table 3-1. Continued

Site Number	Site Name	Brownfield Site ID (FDEP)	Date of SRCO Issuance	Included / Omitted
8	Doral Legacy Park Green Reuse Site	BF131502001	12/10/2018	INCLUDED
9	Land South Partners I, Brownfield Site	BF131301001	8/24/2016	OMITTED
10	Mandy’s Market, LLC	BF139801007	9/28/2017	INCLUDED
11	Siegel Gas and Oil Corp	BF139904001	5/16/2011	INCLUDED

As previously stated, the parcel data, namely the NAL tables and parcel geometry for the years 2010, 2011, 2013, 2015 and 2016, were obtained from FDOR. However, parcel data for the remaining years (2012, 2014, 2017, and 2018) were obtained from FGDL for the sake of expedience. It should be noted that the FGDL dataset is derived directly from the NAL tables. Since the parcel datasets used in this study contain hundreds of thousands of records, it was difficult to analyze the entire dataset in its original form. To conduct the analysis, the parcel dataset was subsetted several times. First, where necessary, the parcel data for Miami-Dade County was extracted from that of the entire State of Florida using the “Select By Attributes” tool in ArcGIS Pro. Then, the parcel dataset was subsetted a second time using a buffer of one mile around each of the selected brownfield sites. The one mile buffer was selected based on results from the literature review and the preliminary study.[2] A third subset of the master dataset was generated to obtain parcels within a quarter mile of the subject property to model the effects of redevelopment at a closer range, in an attempt to reduce noise.

Table 3-2 of this study describes the fields included in the dataset. Some fields were calculated based on the parcel geometry and other dataset variables. The decision to include

[2] Research by De Sousa, Wu & Westphal (2009) utilized different buffers around brownfield sites to gauge their effects.

many of the NAL dataset variables described in Table 3-2 was made based on the documentation provided in the "2018 User's Guide" for NAL and Sales Data Files (SDF)" provided on FDOR's website (FDOR, 2018). Pertinent variable definitions from the user's guide are provided in Appendix B.

Table 3-2. Model Variable Table

Variable Type	Variable Alias	Original Variable(s)	Variable Description	Data Type
DV	ADJV2	JV, Parcel Acreage, CPI (Base 2018)	Adjusted Just Value calculated as follows: $log_{10}[\frac{\left(\frac{JV_n}{CPI_n}\right) CPI_{2018}}{Acres_n}]$	Double
IV	ACTYRBLT	ACT_YR_BLT	Actual year of construction for structure	Long Integer
IV	TOTLVGAREA	TOT_LVG_AREA	Total area of all floors in a structure	Long Integer
IV	DIFDOR	DOR_UC	Dummy variable representing a change in DOR code from one year to the next	Long Integer
IV	JVCNG	JV	Dummy variable representing a change in Just Value from one year to the next	Float
IV	NEAR_DIST	Latitude, Longitude	Distance to the nearest brownfield site included in the study	Double
IV	SETYR	N/A	Dataset year	Long Integer
IV	DORUC1_1…DORUC8_1*	DOR_UC	DOR Code Category based on Polk County Property Appraiser website table	Long Integer
IV	SRCO_YR	N/A	Year of SRCO execution for the nearest brownfield site included in the study	Long Integer

* DORUC Classifications based on Polk County code descriptions: DORUC1_1 – Residential, DORUC2_1 – Condominium (omitted), DORUC3_1 – Commercial, DORUC4_1 – Industrial, DORUC5_1 – Agricultural, DORUC6_1 – Institutional, DORUC7_1 – Government/Exempt (omitted), DORUC8_1 – Vacant

The variables included in this model were selected based on the results of the literature review as well as those of the preliminary study. To reduce the influence of outliers and other confounding variables on the data, some land use classifications and data were omitted from the model. First, condominiums, represented by variable, “DORUC2_1” were omitted due to the fact that the Miami-Dade County Property Appraiser represents condominiums with “pancake polygons,” which are overlapping polygons in a dataset with the same geometry but different values. Since all but one polygon in the pancake contains a “Just Value,” condominiums appear to have disproportionately low average Just Values. While it is possible to extract the Just Value polygon for each condominium located in the study area, it is a time consuming venture with very little payoff since the multifamily character of condominiums is captured by the variables, “DORUC1_1” (residential parcels) and “TOTLVGAREA”. Second, Government/Exempt parcels were omitted because such parcels are outside the scope of this study which primarily evaluates the impact of brownfield redevelopment on the Just Value and estimated total taxable value of land. Including government-owned parcels complicates matters because the owners of these parcels may not pay property taxes. Third, all parcels with Adjusted Just Value equal to 0 were removed from consideration since such parcels skew models’ predicted values and lack monetary value. The breakdown of DOR Code reclassification is shown in Table 3-3.

Table 3-3. DOR Code Variable Reclassification

Variable Name	Type of Use	Range of DOR Code Values
DORUC1_1	Residential	001, 003, 004, 005, 006, 007, 008, 009
DORUC2_1	Condominium	002
DORUC3_1	Commercial	010, 011, 012, 013, 014, 015, 016, 017, 018, 019, 020, 021, 022, 023, 024, 025, 026, 027, 028, 029, 030, 031, 032, 033, 034, 035, 036, 037, 038, 039

Table 3-3. Continued

Variable Name	Type of Use	Range of DOR Code Values
DORUC4_1	Industrial	040, 041, 042, 043, 044, 045, 046, 047,048, 049
DORUC5_1	Agricultural	050, 051, 052, 053, 054, 055, 056, 057, 058, 059, 060, 061, 062, 063, 064, 065, 066, 067, 068, 069
DORUC6_1	Institutional	070, 071, 072, 073, 074, 075, 076, 077, 078, 079
DORUC7_1	Governmental	080, 081, 082, 083, 084, 085, 086, 087, 088, 089
DORUC8_1	Vacant	000, 010, 040, 070, 080

The Adjusted Just Value ("ADJV2") variable used as the independent variable in this model was produced by converting each parcel's Just Value figure into 2018 dollars and dividing the value by parcel acreage. To adjust parcel Just Value for inflation, the national Consumer Price Index (CPI) was used, and to further normalize the data, $\log_{10}$ was taken of the quotient of inflation-Adjusted Just Value divided by parcel acreage. Alternative modes of conceptualizing the Adjusted Just Value were considered. One alternative shown below uses the CPI for the Miami-Fort Lauderdale-West Palm Beach area in lieu of the national CPI provided by the Bureau of Labor Statistics. It should be noted that the OLS model results, the average Adjusted Just Value, and the Adjusted Just Value standard deviation were not greatly affected by these alternate methods of calculating the Adjusted Just Value. In fact, the Adjusted Just Values for both figures are well within one standard deviation of each other. For reference, Table C-5 in Appendix C compares CPIs and Adjusted Just Values between the study model and the alternate model shown on the following page.

$$ln\left[\frac{\left(\frac{JV_n}{CPI_n}\right)CPI_{2018}}{Acres_n}\right] \tag{3-1}$$

Data for each year of the study was not aggregated when it was in its original form. Consequently, the rows from each dataset had to be joined into a single master dataset in order to run the models described in the following section. To do this, each year's parcel polygons were converted into points. However, the 2018 parcel geometry retained its original form until the final step of the data-cleaning process since it was used as the basis for a number of spatial joins used to calculate the DIFDOR and JVCNG fields.[3] Descriptive statistics for the master dataset are provided in Appendix C, and two visualizations of the data are displayed in Figure 3-2 and Figure 3-3. Figure 3-2 depicts aggregate Adjusted Just Values within the 1-mile buffer surrounding each brownfield site for all years in the study. Figure 3-3 shows the percentage of population below poverty level categorized by quantile according to the 2013-2017 American Community Survey (ACS) census block group estimates. Note that every brownfield site is located in a Block Group with a relatively high percentage of the population living below the poverty line.

[3] The final step of the data cleaning process involved appending 2010-2017 parcel data to the 2018 point data.

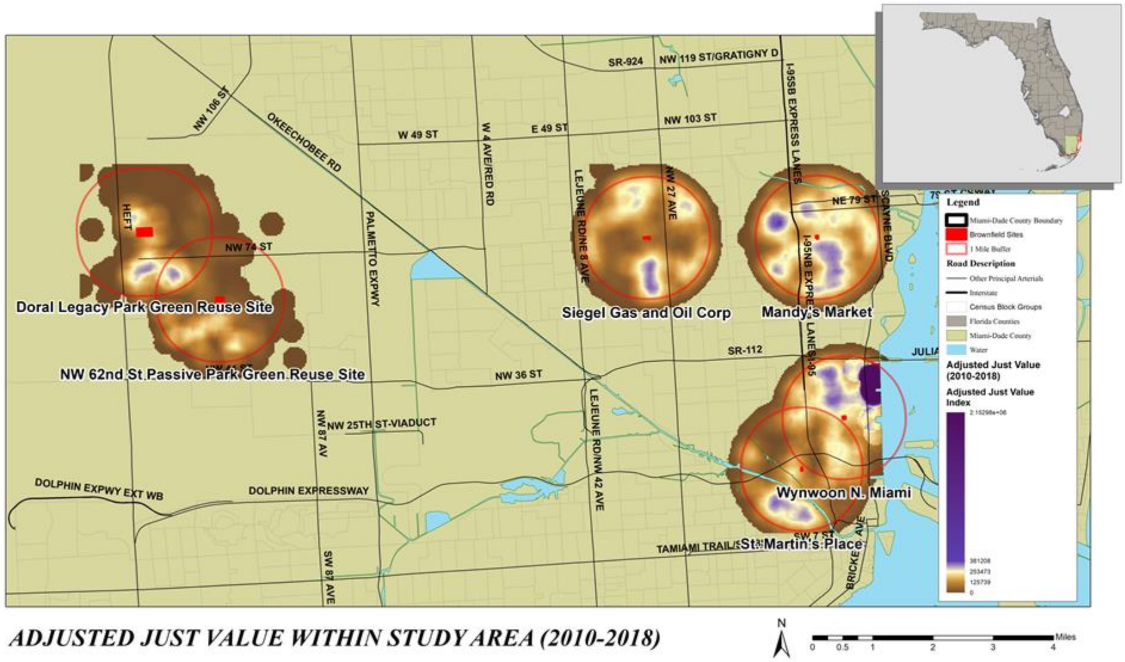


Figure 3-2. Map of Adjusted Just Value (“ADJV2”) in Study Area

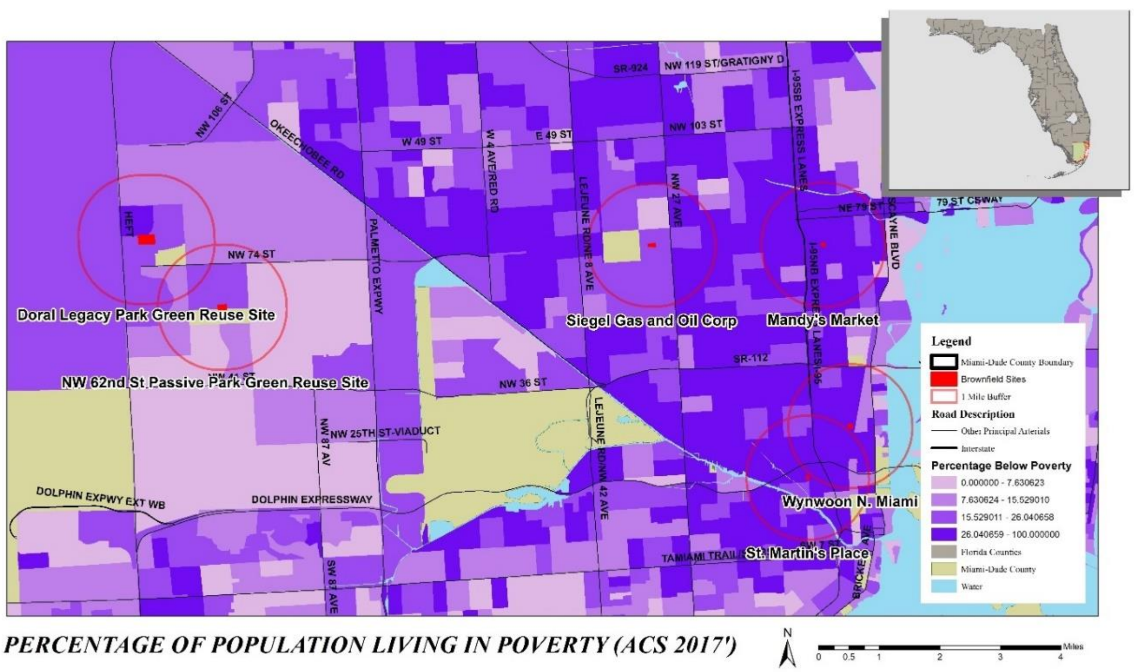


Figure 3-3. Map of percentage of population living in poverty by census block group according to ACS 2013-2017.

CHAPTER 4
METHODOLOGY

Formulating Model 1 and Model 2

This study applies two independent hedonic price models to fulfill two objectives. First, the models measure the effect of existing brownfield redevelopment projects in Miami-Dade County on the assessed value of nearby properties. Second, the models predict the effect of brownfield redevelopment projects on parcels in the County. The two models employed in this study are referred to as, “Model 1” and “Model 2”. Model 1 was generated using ordinary least squares regression, while Model 2 was generated using recursive partitioning. Figure 4-1 illustrates the modeling workflow at a high level.

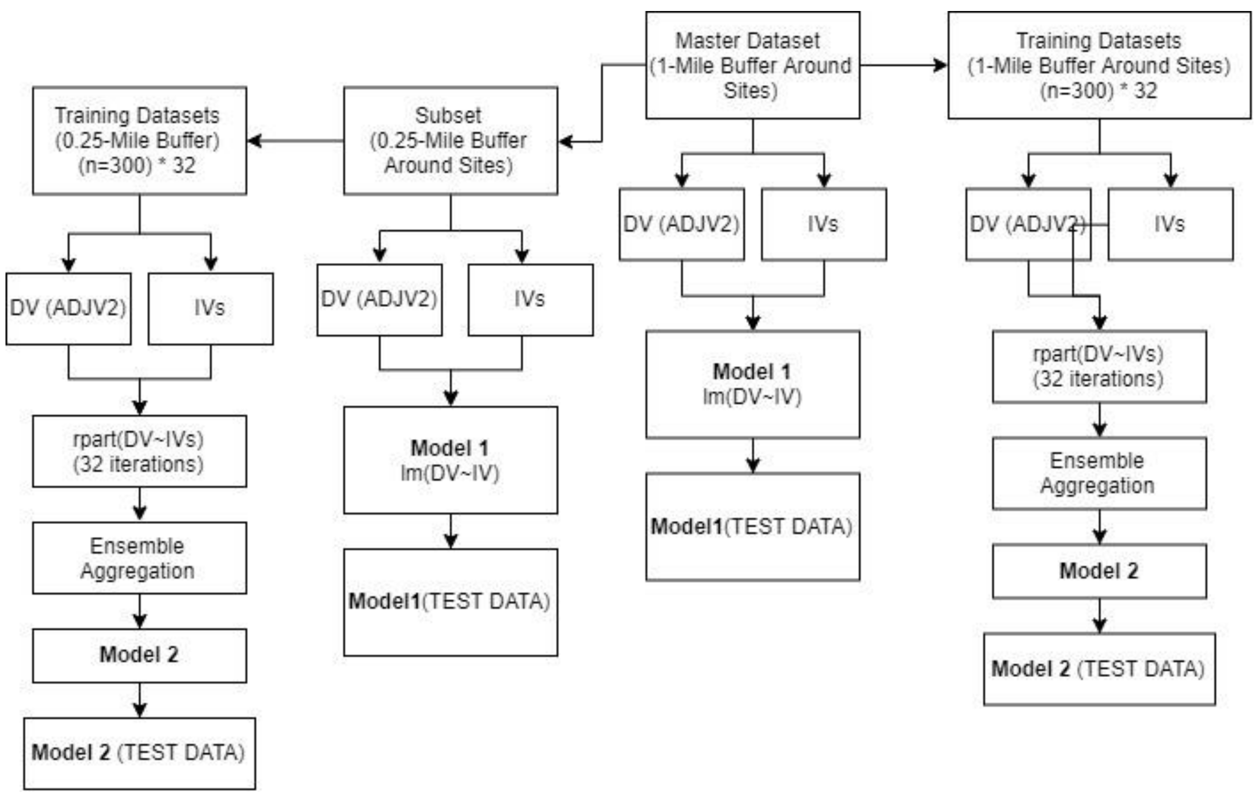


Figure 4-1. High-level modeling workflow

During the data cleaning process, the variables in the master dataset used in both models were standardized between datasets. Descriptive statistics for each of the variables helped ensure that the data cleaning process went smoothly, and that model inputs were reasonable and representative of conditions within the study areas. The master dataset was exported from ArcMap as a CSV for analysis in R.[1] One significant modification was made to the dataset at this point to correct a source of bias in the "ACTYRBLT" variable. Specifically, all observations in which the ACTYRBLT is equal to 0 were removed in order to prevent stratification. Unfortunately, this affected vacant parcels ("DORUC8_1") of which many were coded with an ACTYRBLT equal to 0. Additional analysis included obtaining model summary statistics that enumerated the model coefficients, their contribution to the model, and the degree of confidence associated with the coefficient value, among other things (Appendix D). Results from a separate test for autocorrelation were reviewed prior to running both iterations of Model 1 (Appendix D). For the purpose of gauging replicability of the OLS performed in R, OLS was run a second time in ArcMap. After reviewing results from further analysis, a linear model was constructed:

$$ADJV_i = \alpha + ACTYRBLTx_1 + TOTLVGAREAx_2 + DIFDORx_3 + JVCNGx_4 + NEAR_{DISTx_5} + SETYRx_6 + DORUC1\_1_1x_7 + DORUC4\_1x_8 + DORUC5\_1x_9 + DOCUR6\_1x_{10} + DORUC8\_1x_{11} + SRCO\_YRx_{13} + \varepsilon_i \tag{4-1}$$

Summary statistics for the linear model were obtained and results were recorded. No observations were removed from the dataset. Maps of the predicted parcel values as well as maps of the residuals were generated based on Model 1 (Figure 5-2 and Figure 5-3).

[1] "R is a language and environment for statistical computing and graphics" (The R Foundation, n.d.).

To obtain a reliable model using the decision tree approach it was necessary to analyze an ensemble of trees. As Figure 4-1 indicates, Model 2 is produced after aggregating an ensemble of 32 decision tree models produced from random samples of data (n=300). The process for this began with construction of a second regression model using the "rpart" package:[2]

```
singlesample<-MASTERSET[sample(nrow(MASTERSET),300,replace=TRUE),]
names(singlesample)<-c('ADJV2','ACTYRBLT', 'TOTLVGAREA', 'DIFDOR', 'JVCNG', 'NEAR_DIST','SETYR', 'DORUC1_1', 'DORUC3_1', 'DORUC4_1', 'DORUC5_1', 'DORUC6_1','DORUC8_1', 'SRCO_YR')
dtreetest<-rpart ( ADJV2 ~ DORUC1_1 + DORUC3_1 + NEAR_DIST + DORUC4_1 + DORUC5_1 + DORUC6_1 + DORUC8_1, data = singlesample)
```

After performing a few tests on output from this single iteration, a function was created to loop the test a total of 32 times and store the resulting trees, model summary, and predicted ADJV2 values for each observation in the table in JPEG, TXT, and CSV format respectively. The test was iterated 32 times because 30 samples or more is generally considered the minimum number of observations needed to establish significance in a population that follows a normal distribution. Since the training datasets were derived from relatively small random samples from the master dataset, it is assumed that the resulting models will be randomly distributed.

For reference, the output summaries from each iteration are provided in Appendix E. The predicted values were subsequently assigned an identifier (e.g., 1, 2, or 3) and stored as a CSV. Each model's CSV containing predicted values was joined as a column into a single dataset called "Model2". The average of each model's predicted value was taken, resulting in the predicted values for Model 2 shown in Figure 5-5 and described in the "Results" chapter.

[2] "MASTERSET" is the placeholder object name for the dataset containing all observations.

The process of averaging the results of decision tree model output is known as "the Ensemble Method" or "Bagging" (Strobl, Malley & Tutz, 2009**)**. Bagging has been proven effective on, "'unstable' learning algorithms where small changes in the training set result in large changes in predictions" (Strobl, Malley & Tutz, 2009**).** When applied in Model 2, this method involved taking the average estimated value for each parcel in the master dataset. This method was selected for the study because the diagrams and summaries of the models shown in Appendix D indicate variability in prediction outcomes. Run time for Model 2 was exceedingly long since there are over 6 million estimated values to process and there is no automatic multicore processing functionality in R. Therefore, estimated values for a sample of parcels (n=500) were drawn to produce interim model results.

Both Model 1 and Model 2 were also run on a subset of the master dataset where the Near Distance is less than or equal to 0.25 miles. This additional step was performed in order to attempt to better isolate the effect of redevelopment on adjacent property values. In addition, the scripts for Model 1 and Model 2 are included in Appendix H. Input lines have been commented out for ease of use.

Modeling Impact on Estimated Total Taxable Value

Central to this study is the idea that continued investment in brownfield redevelopment will yield benefits to stakeholders. Among the beneficiaries of brownfield redevelopment are municipal governments who enjoy increased property tax revenue. As such, this study applies Model 1 to demonstrate the estimated increase in total taxable value from brownfield redevelopment projects on the Mandy's Market brownfield site. This site was selected because its 1-mile buffer did not overlap with other sites' and it was redeveloped in 2017 which enabled comparison between total taxable value in the year prior to SRCO issuance (2016) and the year following SRCO issuance (2018). The Mandy's Market site is located in a low-income neighborhood and its current use is retail.

To begin, an estimated Total Taxable Value was derived from the original Just Value of parcels with centroids in the 2016 and 2018 datasets within the 1-mile buffer around the Mandy's Market site. This 2018 inflation-adjusted Just Value was calculated using the millage rate (*M*) from each year, actual homestead exemption amount (*H*; 2016) or a placeholder constant of 50,000 (2018). The following equations describe the calculation for properties with homestead exemptions for 2016 and 2018 respectively:

$$\left(\frac{M_{2016}}{1000} * (JV_{2016} - H)\right) * 1.040595998 \tag{4-2}$$

$$\frac{M_{2018}}{1000} * (JV_{2018} - 50000) \tag{4-3}$$

The following equations describe the calculation for properties without homestead exemptions for 2016 and 2018 respectively.

$$\left(\frac{M_{2016}}{1000}\right) * JV_{2016}) * 1.040595998 \tag{4-4}$$

$$\left(\frac{M_{2018}}{1000}\right) * JV_{2018} \tag{4-5}$$

The variable, "NEAR_DIST" was selected to represent the overall impact of brownfield redevelopment on property value, and by extension, estimated total taxable value. The relative contribution of this variable to the output of the Model 1 OLS regression was used to calculate the estimated increase in total taxable value attributable to the brownfield's redevelopment.

CHAPTER 5
RESULTS

Linear Model Results ("Model 1")

Model 1 represents the linear model that results from the dataset subsetted to exclude observations where ACTYRBLT is equal to 0. This necessitated the removal of 51,804 observations from the dataset (a 25% reduction) resulting in n=157,543 for Model 1. Parcels with DORUC8_1 values equal to 1 were significantly impacted by this exclusion with nearly 98% of observations removed.

The final Model 1 summary report is provided in Table 5-1 below. Results indicate some dispersion of residuals, however, a plot of the residuals versus actual values indicates positive correlation between predicted and actual values (Figure 5-1).[1] Most variables are retained in this model, and those that are not are assigned values of "NA" for results in the initial summary report. Specifically, agricultural parcels ("DORUC5_1" equal to 1) are excluded from the model due to their low count (Appendix C for descriptive statistics for each variable). Notably, the coefficients that were found to have the lowest confidence for predicted Adjusted Just Value were residential parcels (DORUC1_1 at 0.127), and vacant parcels (DORUC8_1 at 0.739). Standardized betas were calculated for each variable (Table 5-2), and the two variables that appear to have the greatest sway on the model predictions are ACTYRBLT and SRCO_YR which contribute a 10% and 9% increase in Adjusted Just Value respectively.

Since there are a large number of observations in the dataset, the adjusted R^2 value (0.2214) appears unchanged despite there being 14 variables in the model. According to this

[1] The primary measure of correlation in this study is the Pearson's Correlation Coefficient, a common test which allows for comparison of relationships between variables in the dataset using a matrix. The Pearson's Correlation Coefficient is used throughout this study to represent the, "strength and direction of linear relationships between pairs of continuous variables" (Kent State, 2019).

adjusted R^2 value, the model accounts for approximately 22% of variation in the data with a statistically significant p value of 2.2 e^{-16}. Once parameters are finalized, the model was replicated in ArcMap and estimated values and residuals were visualized using the Point Density tool (Figure 5-2).

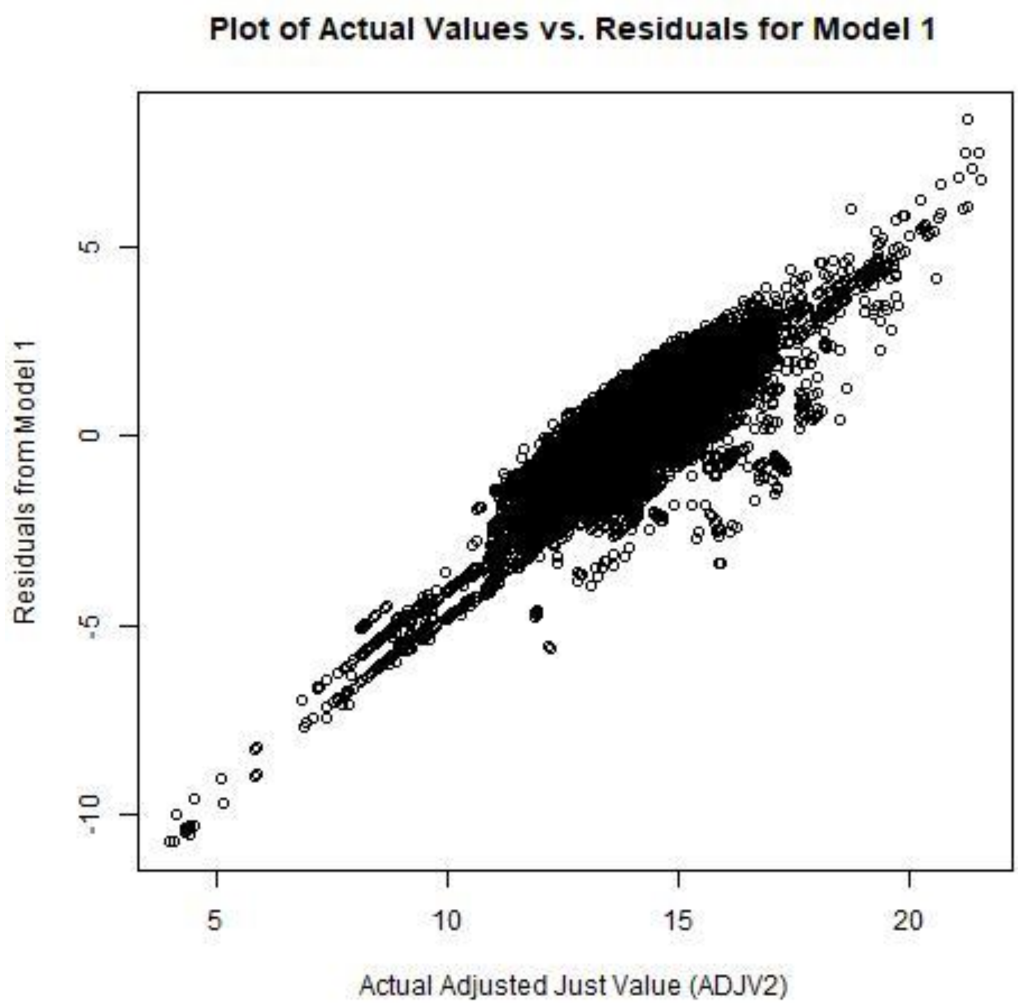


Figure 5-1. Plot of Adjusted Just Values versus Residuals (Model 1)

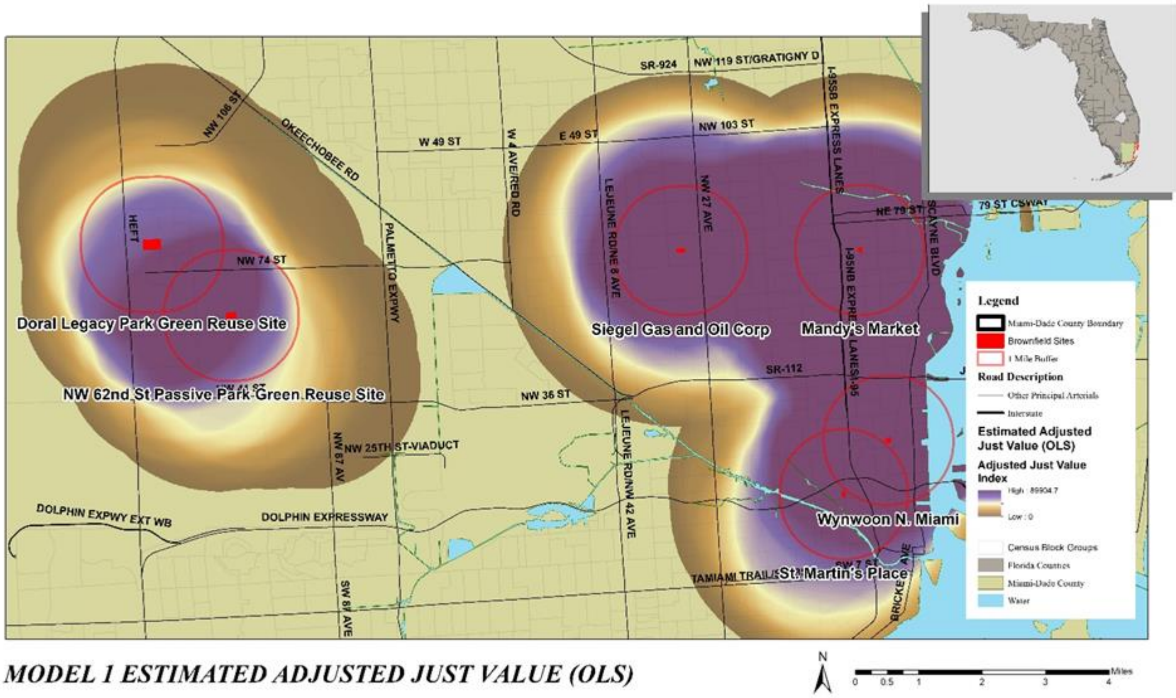


Figure 5-2. Map of predicted values from OLS Regression

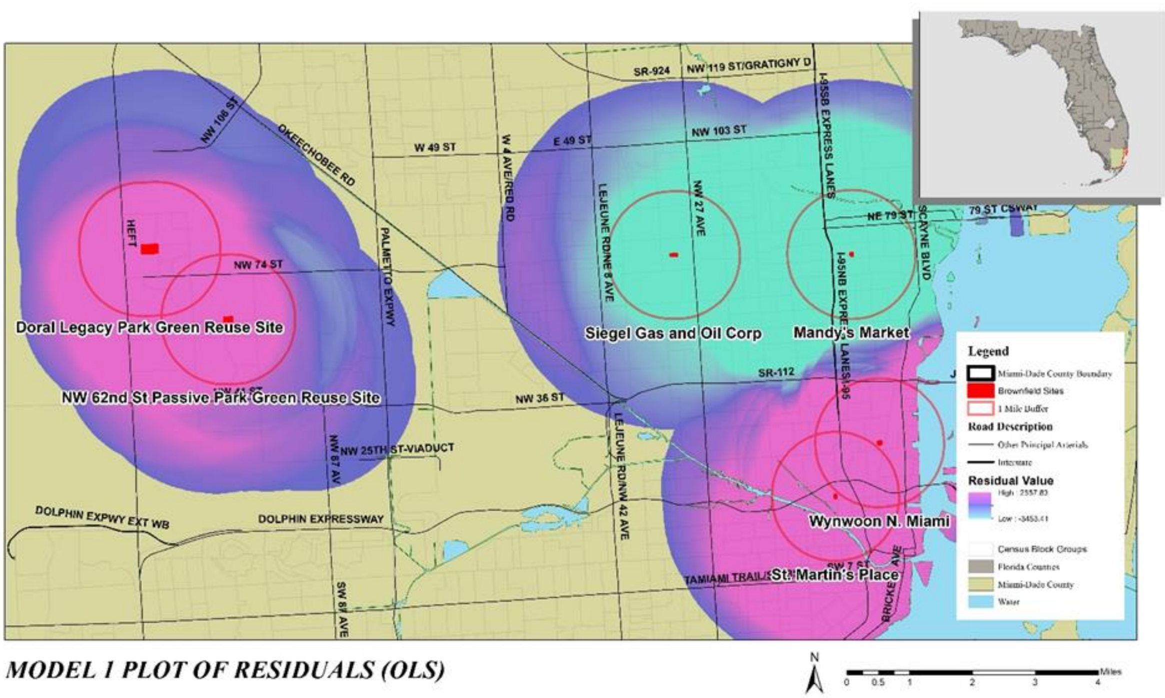


Figure 5-3. Map of residuals versus predicted values from OLS regression

Table 5-1. Model 1 Summary Report

Residuals:

Min	1Q	Median	3Q	Max
-10.7052	-0.5288	0.0163	0.5860	8.3430

Coefficients:

	Estimate	Std. Error	t value	Pr (>|t|)
(Intercept)	-2.024e+02	1.918e+00	-105.543	< 2e-16 ***
ACTYRBLT	1.001e-02	9.642e-05	103.857	< 2e-16 ***
TOTLVGAREA	4.113e-06	8.364e-08	49.179	< 2e-16 ***
DIFDOR	-8.416e-01	1.309e-02	-64.285	< 2e-16 ***
JVCNG	1.334e-01	5.164e-03	25.824	< 2e-16 ***
NEAR_DIST	-7.446e-05	1.869e-06	-39.848	< 2e-16 ***
SETYR	-9.698e-04	4.840e-05	-20.036	< 2e-16 ***
DORUC1_1	-7.030e-02	4.603e-02	-1.527	0.127
DORUC3_1	4.113e-01	4.654e-02	8.837	< 2e-16 ***
DORUC4_1	2.238e-01	4.671e-02	4.791	1.66e-06 ***
DORUC6_1	4.687e-01	4.947e-02	9.474	< 2e-16 ***
DORUC8_1	1.826e-02	5.475e-02	0.334	0.739
SRCO_YR	9.863e-02	9.699e-04	101.695	< 2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.9426 on 157530 degrees of freedom
Multiple R-squared: 0.2214
Adjusted R-squared: 0.2214
F-statistic: 3733 on 12 and 157530 DF
p-value: < 2.2e-16

Table 5-2. Model Standardized Betas

Variable	Standardized Beta
(Intercept)	0.000000000
ACTYRBLT	0.242771342
TOTLVGAREA	0.111657088
DIFDOR	-0.149117982
JVCNG	0.062345407
NEAR_DIST	-0.095661691
SETYR	-0.050915137
DORUC1_1	-0.026030982
DORUC3_1	0.111616604
DORUC4_1	0.055285557
DORUC6_1	0.055831854
DORUC8_1	0.001354328
SRCO_YR	0.236672562

OLS model results from the subsetted master dataset did not show any improvement over the first iteration of Model 1 that was constructed using the master dataset. Cursory comparison between the two datasets reveals that the two have somewhat different characteristics which are magnified by the significantly-reduced sample size. While the model itself is significant with a p-value of 2.2 e^{-16}, its adjusted R^2 is 0.16, compared to 0.22 obtained from assessment of the master dataset. The three variables that appear to exert the most influence over the model results are DIFDOR, ACTYRBLT, and DORUC4_1 (Industrial). This contrasts the results from Model 1 run on the master dataset which identified ACTYRBLT and SRCO_YR as the two major contributing variables to the model. Table 5-3 shows the performance of this model's variables and Table 5-4 elucidates each variables' relative influence on the model. Though results of the Moran's I test for spatial autocorrelation indicated a lower degree of autocorrelation, this effect may be attributed to other factors such as the reduced sample size or the natural clustering produced by the study design itself. More detailed results from this iteration of Model 1 may be found in the latter half of Appendix C as well as in Appendix D.

Table 5-3. Model 1 Summary Report (0.25-Mile Buffer)

Residuals:

Min	1Q	Median	3Q	Max
-9.6469	-0.6308	0.1363	0.6178	3.9262

Coefficients:

	Estimate	Std. Error	t value	Pr (>|t|)
(Intercept)	2.846e+01	1.424e+01	1.999	0.045681
ACTYRBLT	1.001e-02	9.642e-05	17.097	< 2e-16 ***
TOTLVGAREA	4.967e-06	5.278e-07	9.411	< 2e-16 ***
DIFDOR	-1.351e+00	5.477 e-02	-24.672	< 2e-16 ***
JVCNG	4.004 e-01	2.505 e-02	15.982	< 2e-16 ***
NEAR_DIST	-5.234e-04	1.070 e-04	-4.892	1.01 e-06 ***

Table 5-3. Continued

	Estimate	Std. Error	t value	Pr (>|t|)
SETYR	-1.850e-02	4.186 e-03-	4.419	1.00 e-05 ***
DORUC1_1	-1.911e-01	1.476 e-01	-1.295	0.195509
DORUC3_1	4.677e-01	1.519 e-01	3.080	0.002075 *
DORUC4_1	-5.256e-01	1.489 e-01	-3.530	0.000418 ***
DORUC6_1	6.911e-01	1.766 e-01	3.915	9.12 e-05 ***
DORUC8_1	-8.169e-01	2.162 e-01-	3.779	0.000159 ***
SRCO_YR	4.328e-03	6.070 e-03	0.713	0.475846

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.087 on 9736 degrees of freedom
Multiple R-squared: 0.1637
Adjusted R-squared: 0.1626
F-statistic: 158.8 on 12 and 9736 DF
p-value: < 2.2 e-16

Table 5-4. Model Standardized Betas (0.25-Mile Buffer)

Variable	Standardized Beta
(Intercept)	0.0000000
ACTYRBLT	0.1874543
TOTLVGAREA	0.0908807
DIFDOR	-0.2479433
JVCNG	0.1583003
NEAR_DIST	-0.046382
SETYR	-0.0430701
DORUC1_1	-0.0740161
DORUC3_1	0.1076906
DORUC4_1	-0.1767491
DORUC6_1	0.0654883
DORUC8_1	-0.0486555
SRCO_YR	0.0077259

Decision Tree Model Results ("Model 2")

Model 2, which utilizes a decision tree model to predict Adjusted Just Value, does not rely on a subset of the master dataset to remove values where ACTYRBLT is equal to 0; the model uses the dataset as-is. Predictions from this model constituted a near 14% improvement in R^2 over those from Model 1 resulting in an R^2 value of ~0.36. Of note is the graph of residuals versus predicted values for Model 2 compared to Model 1 (Figure 5-4). While Model 1 shows a positive linear trend, Model 2 displays a strange stratification of predicted values which results from the selected modeling method which places data with particular ranges of value in predictive categories.

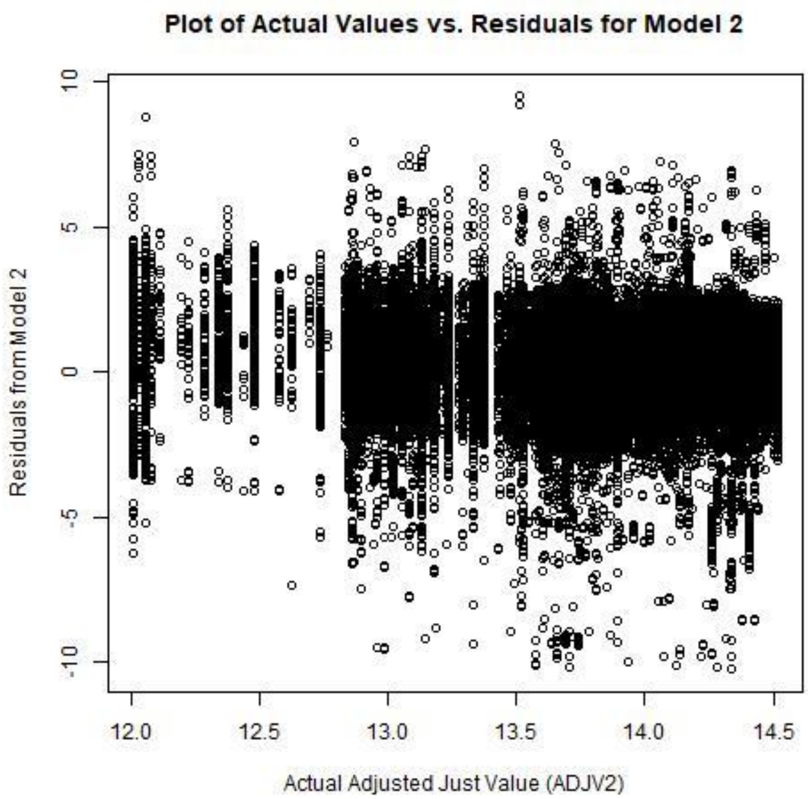


Figure 5-4. Plot of Adjusted Just Values versus Residuals (Model 2)

Maps of Model 2 results (predicted values and residuals) are displayed in Figures 5-5 and 5-6, and details for each model that comprised a single iteration of Model 2 are provided in Appendix E. Note that each iteration of Model 2 produced using the bagging method generally accounts for more variation in the data than the linear model represented by Model 1. This is evidenced by the sample model output plots included in Appendix E.

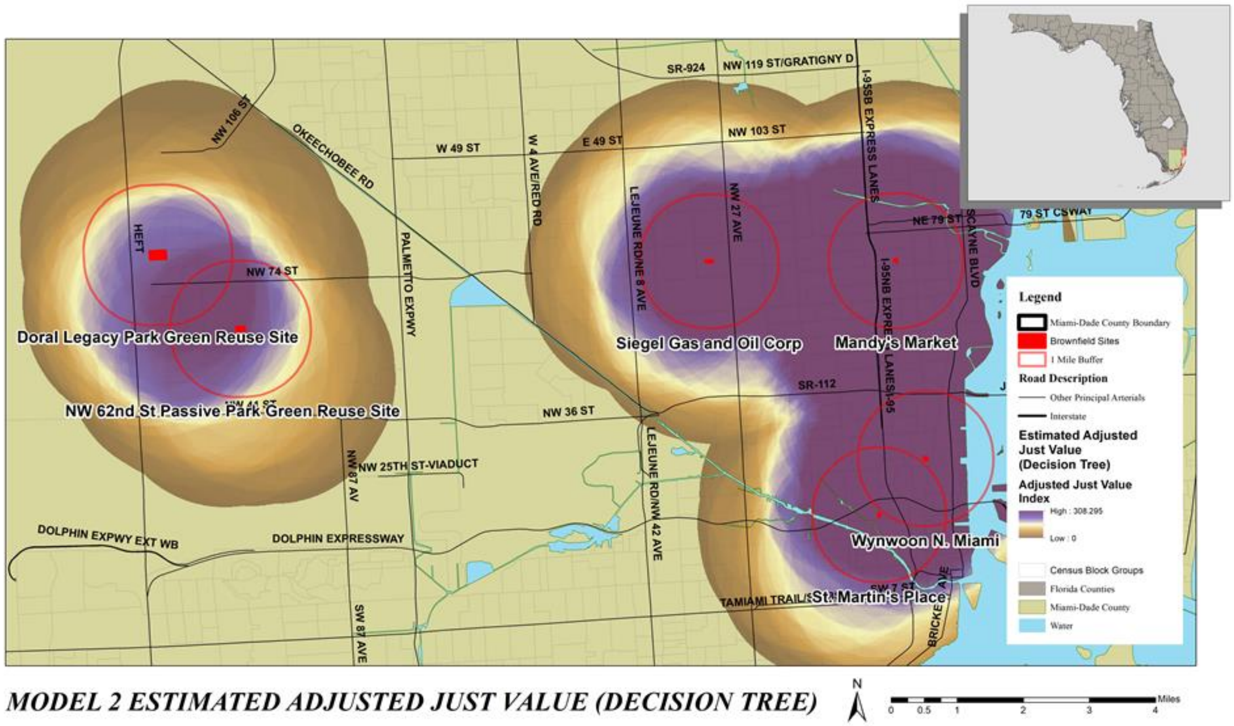


Figure 5-5. Map of predicted values from from Model 2

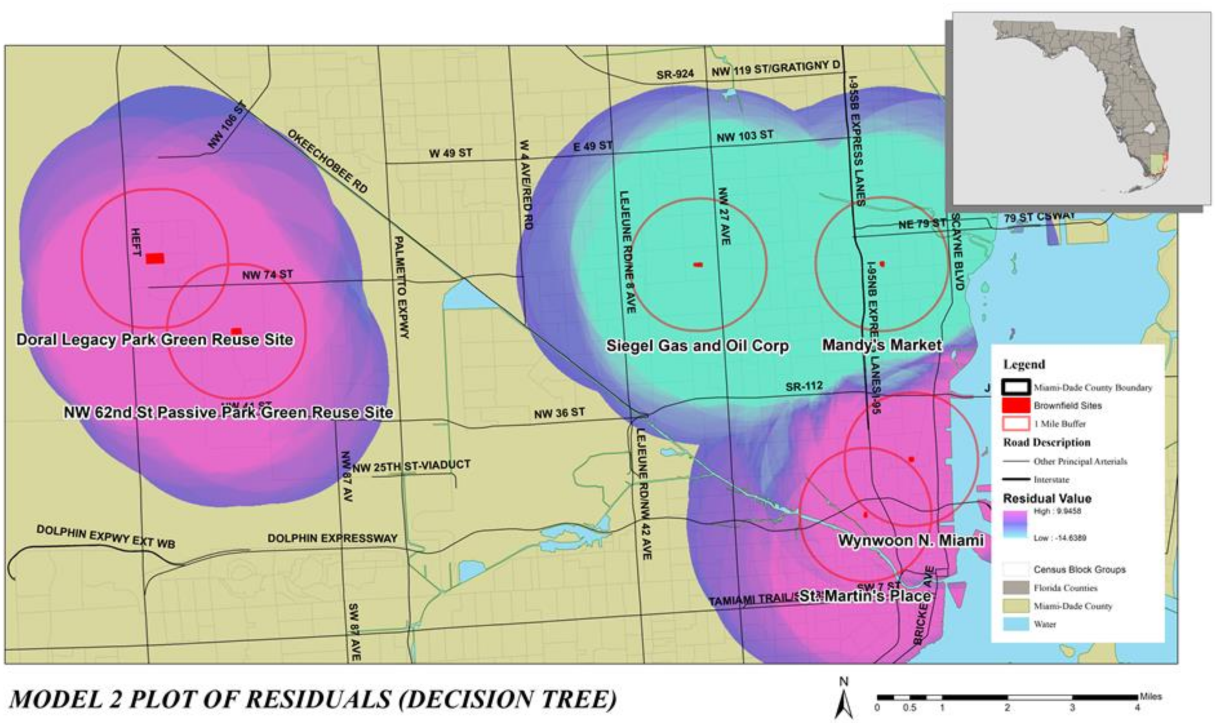


Figure 5-6. Map of residuals versus predicted values from Model 2

Unlike results from Model 1 applied to the 0.25-mile subset dataset, results from Model 2 demonstrate a marginal improvement over the 1-mile buffer dataset. To elaborate, the R^2 resulting from Model 2 is approximately 0.39. The reason for this improvement is unclear, however, results may have been affected by the fact that the training datasets comprised a larger proportion of the model input data in this application of Model 2 methodology than they did in the 1-mile buffer trial. In sum, results from applications of Model 2 were consistently better than those from Model 1.

Total Taxable Value Impacts

The OLS results from the Mandy's Market site allude to a trend in the data that does not reflect the global model's results. Specifically, a positive correlation exists between the distance from the brownfield site ("NEAR_DIST") and the estimated total taxable value. Moreover, in this case, the distance from the site only accounts for 0.006% of variation in the data compared with the estimated 2.5% effect noted in the global model. It should be noted that research suggests that lower property values in the area may be linked to the present commercial use on the subject site.[2] For reference, summary statistics for this model are provided in Table 5-3.

[2] Research by the Institute for Local Self-Reliance (ISLR) indicates dollar stores have a negative impact on social and economic factors in the communities in which they are located (Donahue & Mitchell, 2018).

Figure 5-7. Site photo from 2019 Brownfields Report (Miami-Dade County Regulatory and Economic Resources. 2019, June 1. Miami-Dade County's Brownfields Program 2019 Annual Report, from https://floridadep.gov/waste/waste-cleanup/documents/miami-dade-county-2019-annual

Table 5-5. Summary of OLS Results

Variable Coefficients (a)	StdError	t-Statistic	Probability [b]	Robust SE	Robust P	r[b]
Intercept						
5417.188973	175.370920	30.889893	0.00000*	187.289017	28.924221	0.000000*
NEAR_DIST						
-0.547715	0.064271	-8.522013	0.00000*	0.050517	-10.842086	0.000000*

OLS Diagnostics

Number of Observations	12,340	Aikake’s Information Criterion (AICc) [d]:	265009.148386
Multiple R-Squared [d]	0.005852	Adjusted R-Squared [d]:	0.005771
Joint F-Statistic [e]	72.624703	Prob(>F), (1,12338) degrees of freedom:	0.000000*
Joint Wald Statistic [e]	117.550821	Prob(>chi-squared), (1) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]	3.650631	Prob(>chi-squared), (1) degrees of freedom:	0.056048
Jarque-Bera Statistic [g]	189008633.429554	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Table 5-5. Continued

Notes on Interpretation

* An asterisk next to a number indicates a statistically significant p-value ($p < 0.01$).

[a] Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent variable.

[b] Probability and Robust Probability (Robust_Pr): Asterisk (*) indicates a coefficient is statistically significant ($p < 0.01$); if the Koenker (BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coefficient significance.

[c] Variance Inflation Factor (VIF): Large Variance Inflation Factor (VIF) values (> 7.5) indicate redundancy among explanatory variables.

[d] R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance.

[e] Joint F and Wald Statistics: Asterisk (*) indicates overall model significance ($p < 0.01$); if the Koenker (BP) Statistic [f] is statistically significant, use the Wald Statistic to determine overall model significance.

[f] Koenker (BP) Statistic: When this test is statistically significant ($p < 0.01$), the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). You should rely on the Robust Probabilities (Robust_Pr) to determine coefficient significance and on the Wald Statistic to determine overall model significance.

[g] Jarque-Bera Statistic: When this test is statistically significant ($p < 0.01$) model predictions are biased (the residuals are not normally distributed).

WARNING 000851: Use the Spatial Autocorrelation (Moran's I) Tool to ensure residuals are not spatially autocorrelated.

CHAPTER 6
DISCUSSION

Before discussing the results of this study, a few important distinctions should be made. First, Miami-Dade County differs from other locales for which similar studies have been carried out. The county is a coastal municipality that never developed a strong industrial sector like those of Milwaukee and Minneapolis. This is evidenced by a cursory comparison of both the number of cleanups and the total number of remediated brownfield sites located within the county bounds compared to other municipalities with larger industrial sectors. Consequently, variables identified as reliable predictors for property value in these studies may not hold as much water when applied elsewhere. Moreover, having fewer redeveloped sites for comparison may have introduced bias into the results— especially if the impacts upon property value were heavily influenced by the type of redevelopment as findings on the subject seem to suggest (DeSousa, 2009).

In addition to the number of brownfield sites selected for inclusion in the study, other factors such as the heterogeneity of conditions surrounding each site may have influenced the results described in this study. Findings outlined in the subsection, "Total Taxable Value Impacts," allude to wide variation in performance of variables within each buffer, and results from OLS models run in ArcGIS also allude to issues of spatial autocorrelation. The uses that brownfield redevelopment projects have produced in Miami-Dade County have been diverse, and include commercial, public park, and multifamily residential. Unfortunately, the fact that they are diverse and few in number makes it difficult to apply a generalized model of their impacts across the county since they pull the data in various directions. Though the preliminary study included dummy variables representing the nearest brownfield site, this study did not include site identification or classification because it was assumed that there would be too many sites to represent individually with dummy variables.

The social and economic context of this study is another potential influencer of results in this study. The Great Recession of 2008 was a significant downturn in the American economy, that resulted in decreased property values across the nation. The Great Recession had radiating impacts on personal wealth and welfare, public services, and economic productivity among other things (Oliff, Mai & Palacios, 2012). By 2010, the first year of this study, the economy in Florida had not recovered, and property values remained depressed (McNichol & Johnson, 2010). Comparison of Just Value of property in the study area in a pre-recession year (2004) and Just Value of property in a sample of the years covered by this study, namely 2010, 2016, 2017, and 2018, suggest that property values in the study area still have not recovered to pre-recession highs. Instead, as Figure 6-1 indicates, values have remained relatively constant for at least the past four years.[1]

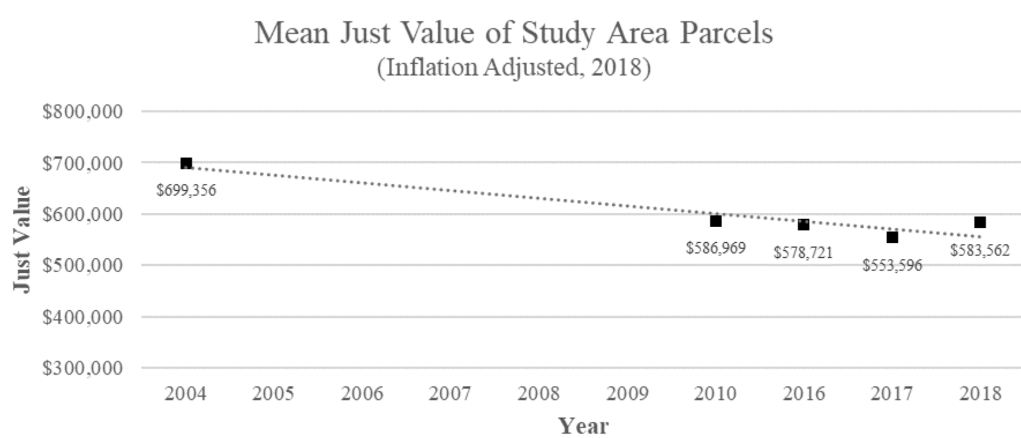


Figure 6-1. Graph representing mean just value of parcels within the study area over time

[1] The mean Just Values shown represent all parcels within the study area's 1-mile buffer—they do not exclude parcels with Just Value equal to zero nor do they omit parcels based on land use. Therefore, standard deviations for each figure are high.

Studies suggest that property values are affected by factors including the price of land, population, household size, income, and neighborhood amenities (DiPasquale & Wheaton, 1996). Therefore, it may be helpful to examine the performance of some of these variables in the study area and county. According to ACS data, in 2017, Miami-Dade County had an estimated total population of 2,702,602. This constitutes an increase of 4.8% since 2010. In 2017, the study area itself had an estimated total population of 245,850 which was 9.1% of the total county population in that year. According to decennial census data, in 2010, the study area population was 223,136 which was 9.2% of the study area population in 2017. With regard to racial composition, in Miami-Dade County 75.6% of the population identified themselves as white according to 2017 ACS data. Approximately 13% of this population indicate that they are not Hispanic—a precipitous decline since 2010 where 36% of those who identified as white also identified as "Not Hispanic." The study area appears to have a racial composition that is somewhat different from that of the overall county. To elaborate, in 2017, the study area was predominantly white, however, only 60% of the population within the study area has identified as white while 33% of the area identified as black.

The notion that conditions within the study area are distinct is supported further by the distribution of owner-versus renter-occupied housing units. Overall, there were a larger share of renter-occupied housing units in the study area compared to the county. That is, 71% of housing units in the study area were renter-occupied in 2017 (up from 55.22% in 2010) compared to 47.8% countywide. For reference, additional census tract data for the study area was summarized and provided in Appendix F. These historical trends in demographic characteristics and economic growth in the county have likely colored the results of this study. This begs the question of how models might be adapted in light of these factors to better represent the impact of redevelopment on property value.

Model Optimization

The process of data cleaning and collection and development of the recursive partitioning model were two of the most demanding aspects of this study. Efforts in these phases contributed to this study's insights on federal dataset organization and alternative methods for modeling brownfield impacts. In retrospect, there are a number of variables which were excluded from this study due to limited time and resources which might be included in future models to improve their performance. These variables are listed below in Table 7-1. Census tract and block group-level data are data that have been aggregated for a particular geographic area. Single census tracts and block groups comprise large portions of the 1-mile buffers around each brownfield site. Figure 3-3 illustrates the reality that given the limited number of remediated sites included in this study, incorporating demographic variables such as those marked with "**" in Table 7-1 is infeasible due to the resolution of the dataset. If more observations were obtained, or if the study design was modified, it might be possible to include US Census data in either of the two models.

In reference to model optimization within Model 2, the bagging method applied is intended to compensate for overfitting, which is a common concern in machine learning models. While it was assumed that the reported predictions would minimize this, there is nonetheless some concern that the training dataset sample size (n=300) may be too small given the size of the overall dataset. Future studies that employ Model 2 should revise the sample sizes used in each iteration of the "rpart" function to reflect an optimal standard for selecting samples for training datasets unique to recursive partitioning. Furthermore, the processing time for the entire master dataset was fairly long. While there are packages that enable multicore processing, which may expedite this process on computers with greater capacity, the alternative option is to run the script on a smaller sample. For instance, in this study, the most expeditious way to gain insights about the machine learning model's accuracy was to average a random sample of 500 rows of the dataset which contain results from each of the 32 models. Though the prediction was not as accurate, it still produced a higher value than predictions generated using OLS.[2]

R^2 is used throughout this study to quantify prediction accuracy, but there are other metrics for accuracy not discussed that could change the way results are interpreted. Therefore, detailed results from the models are included in the appendices to this study to allow for independent interpretation.

Table 6-1. Other Potential Model Variables*

Variable Description	Potential Data Source
Age of the housing stock (Year of construction minus year of dataset)	Parcel Dataset
Number of bathrooms	-
Garage capacity	-
African American (%) **	US Census Data
Annual income **	US Census Data
Commuting time (min) **	US Census Data
Whether located in floodzone	FEMA Flood Maps
Below poverty (%) **	US Census Data
Number of brownfields within the buffer	MDC, FDEP, or EPA Brownfields Data
Number of parks within the buffer	MDC OpenData Portal, Parcel Dataset
Number of industrial sites within the buffer	Parcel Dataset
Number of residential sites within the buffer	Parcel Dataset
Number of commercial sites within the buffer	Parcel Dataset
Parcel Dataset Adjacent to redeveloped	Parcel Dataset, FDEP and MDC Data
Years since site redevelopment	MDC, FDEP, or EPA Brownfields Data

* Based on results of literature review, primarily the study by DeSousa, Wu & Westphal
** US Census data is aggregated over large areas and may not represent the reality of

[2] Note that this issue with processing time is only relevant for predictions for a large number of parcels.

Emergent Public Policy and Applications of Findings

In 2017, Congress passed the Tax Cuts and Jobs Act which created the Opportunity Zone tax incentive program. This program is described as an incentive which, "offers capital gains tax relief to investors for new investment in designated areas" (US Department of Treasury, 2018). The purpose of this program is to encourage economic growth and investment in designated distressed communities by providing Federal income tax benefits to taxpayers who invest in businesses located within these zones. In Miami-Dade County, 31% of Brownfield Area acreage is within an Opportunity Zone (Figure 7-1). While this new program may not revolutionize brownfield redevelopment in Miami-Dade County, it may incentivize it further. This in turn would create more opportunities to study trends in development impacts since more developers may elect to execute BSRAs.

The Opportunity Zone program is a multi-billion-dollar investment by the federal government, but local governments have taken additional measures to maximize the benefits of this program. This includes hiring designated staff for coordinating development in municipal Opportunity Zones, developing plans for sites located in Opportunity Zones, and commissioning informational and promotional materials for prospective developers. The findings of this study may improve Opportunity Zone program performance in Miami-Dade County by providing some justification for deployment of public funds to further this new economic development initiative. Specifically, the study's findings support the idea that proximity to a remediated brownfield site positively impacts property values, and by extension, tax revenue. Study findings may be extended to other comparable economic development programs and models for Miami-Dade County as well.

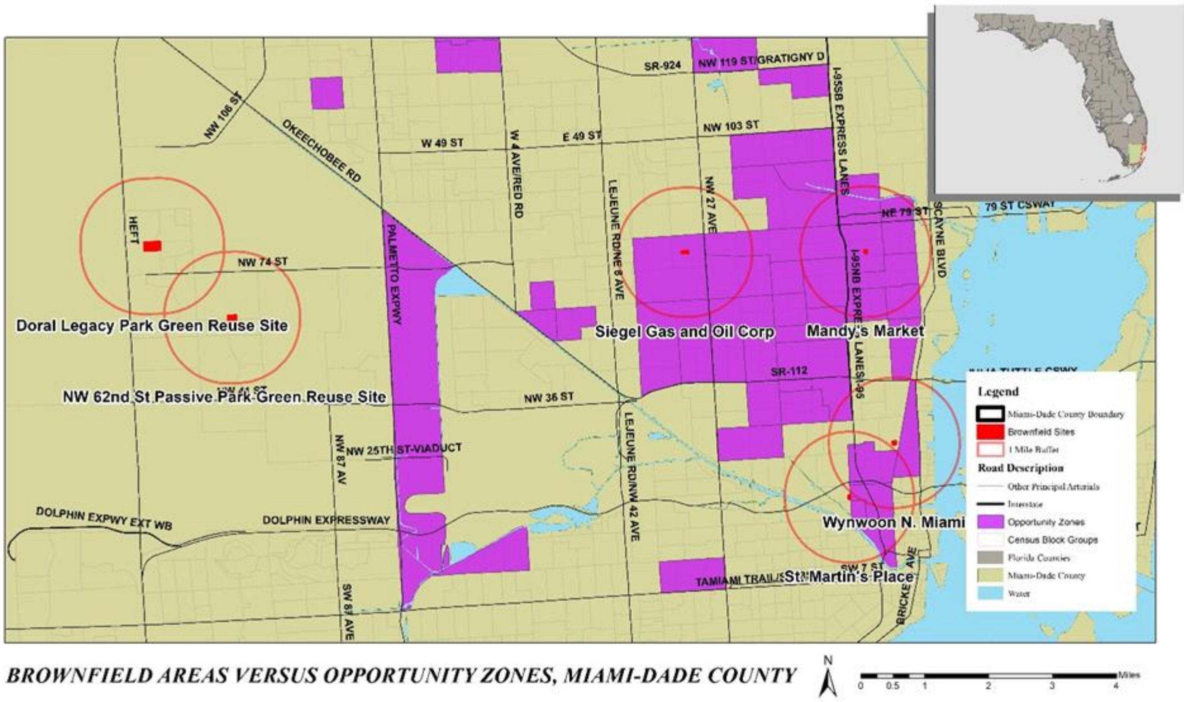


Figure 7-1. Map of Brownfield Areas versus Opportunity Zones in Miami-Dade County

CHAPTER 7
CONCLUSION

As cities approach build-out, infill sites become increasingly desirable locations for redevelopment. Brownfield sites, which are often urban infill, by extension also become more attractive. Federal, state, and local brownfield cleanup incentive programs increase the appeal of redeveloping these often-stigmatized properties by lowering the up-front cost associated with cleanup. Coupled with other economic development incentives (e.g., the Opportunity Zone Program), developers are presented with the opportunity to offset project costs significantly. Furthermore, in recent years, federal regulations pertaining to cleanup liability have been relaxed which contributes to reduced risk, and thereby cost. Since public dollars have been consistently invested into brownfield redevelopment programs for decades, and the private sector has an interest in the appreciated value of property, there is a question of what sore of impact brownfield redevelopment has on its surrounding area. This study sought to quantify the relationship between brownfield site redevelopment and socioeconomic factors (particularly property value) in Miami-Dade County, an area with limited brownfield redevelopment activity.

Following review of literature pertaining to policy and methods for modeling brownfield redevelopment, it was decided that two versions of hedonic price model would be used to demonstrate the impact of fifteen variables on the $\log_{10}$ of property value adjusted for site acreage and inflation. The first model (Model 1) used the more traditional OLS regression approach employed by most other studies surveyed. The second model (Model 2) used recursive partitioning, a machine learning method, to determine whether results could be improved using other methodology. The data collection and cleaning process for this study was demanding since the study involved examination of parcel data for the years 2010 to 2018. Each brownfield site included in the study was selected from a shortlist of redeveloped sites with executed SRCOs following a site inspection. Once a sufficiently clean master dataset consisting of all parcels within 1 mile of a brownfield site (with some omissions including government parcels and condominiums) was created, the data was inputted into both Model 1 and Model 2 and results were recorded. The master dataset was then subsetted to include only parcels within 0.25 miles of each site, and the models were run again to ascertain whether decreasing the distance from residential parcels would improve prediction accuracy by reducing noise in the data.[1] Additionally, an attempt was made to estimate the impact that brownfield development had on taxable value by estimating tax revenue from a particular site and running OLS using the same input variables as before. The site in question, "Mandy's Market," had an unanticipated outcome that emerging research suggests is tied to its current use as a dollar store.

Model 1 was found to account for approximately 22% of variation in Adjusted Just Value. Of the variables selected for inclusion in the model, two were specific to the presence of brownfields in the area, namely NEAR_DIST and SRCO_YR. NEAR_DIST, representing the distance of each parcel in the 1-mile buffer around the site to the nearest remediated brownfield site had a negative coefficient, indicating that as distance increased, Adjusted Just Value decreased. This implied that closeness to a redeveloped brownfield site produced higher property values. The SRCO_YR variable represents the year that the SRCO was executed. This variable has a positive coefficient indicating that as time passed, (2010-2018) the Adjusted Just Value of the property also increased.

The initial study design did not include a variable representing pre-development value and post development value. It was anticipated that such values would improve the prediction accuracy and overall reliability of the model. These values were calculated and included in

[1] R^2 was only marginally improved in Model 2.

separate variables in one cursory trial, but yielded no significant improvements in Model 1.[2] On the whole, predictions from this OLS model are questionable because the model results do not display a normal distribution of residuals, and there are a number of unresolved issues with autocorrelation. Issues with autocorrelation are not limited to the variables included in Model. l. Specifically, spatial autocorrelation resulted from the decision to subset parcels in Miami-Dade County based on a 1-mile buffer around the five brownfield sites. Since there were only five sites that were not evenly dispersed throughout the county, clustering occurred. This clustering is not accounted for by the adjusted R^2 statistic. To illustrate this point, Global Moran's I was run twice using a fixed distance band on the parcels in the dataset, and in both instances, results reflected clustering (Appendix C for reports). [3]

Results from Model 2 demonstrate an improvement in prediction accuracy over Model 1. When run on the master dataset (1-mile buffer) a 14% improvement over the OLS model was noted. Prediction accuracy was improved slightly by narrowing the buffer to 0.25 miles which yielded a 3% increase in the R^2 value. Model 2 also accounts for some of the issues introduced by the dataset tied to normal distribution of residuals, modeling of time series data, and the like. By sorting data into unique buckets, it becomes possible to compensate for issues introduced by autocorrelation. While the current model configuration does not account for spatial autocorrelation, it may be improved upon in the future to do so.

[2] When these two variables are included in Model 2, the R^2 value calculated using the expedient method was approximately 0.54. This is a tremendous improvement over the original Model 2 described at length in this study. It is recommended that this be investigated further.

[3] Moran's I, specifically the "Spatial Autocorrelation (Global Moran's I)" tool by Esri, "measures spatial autocorrelation based on both feature locations and feature values simultaneously. Given a set of features and an associated attribute, it evaluated whether the pattern expressed is clustered, dispersed, or random" (Esri, n.d.)

The bagging technique employed makes it difficult to discuss the relative variable importance for each model. Results from models produced from the test data show great variation in model prediction values, so each output model cannot be viewed as representative of the larger trends in the data. Given a larger selection of redeveloped brownfield sites, it might be possible to obtain better results. In general, Model 1 is well-suited for demonstrating the relative overall effect of variables upon actual values, while Model 2, with further refinement, is better equipped to provide predictions for property value increase due to development.

APPENDIX A

SUMMARY OF RESULTS FROM SITE VISITS AND SITE VISIT QUESTIONNAIRE

5th & Alton Shopping Center *** OMITTED DUE TO URBAN CONTEXT***

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
5th & Alton Shopping Center	**1**	BF130001001	12/29/2000	3/14/2012	1	1	0	0	0	0	0	0	0	0	0	0	0	Gas Station and Vehicle Repair	Mixed Use Commercial	2/21/2001	Block Group 2, Census Tract 44.05	0	CMRCL

(**From left:** North entrance, Southeastern corner, Buildings south of site)

Questionnaire Field	Questionnaire Results
Site Number	1
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	The site has been developed and to the East there is a new building under construction.
From the list below, select the type(s) of use(s) observed on the site:	Commercial
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential;Condominium;Commercial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	Police presence on the SE corner of the building--stopped a driver-- was in a heated discussion.
Are there police present in the area?	Yes
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	< 25 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	No. However, most of the trees planted were palms
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	High traffic commercial/residential area. Lot of new construction, close to a park.

Wynwood N. Miami * OMITTED DUE TO STATE OF DEVELOPMENT*****

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Wynwood N. Miami	**2**	BF139801009	6/24/2014	10/29/2015	0	0	1	1	0	0	0	0	0	0	0	0	0	Onsite soakage pit, and Other	Vacant	3/1/2014	Block Group 2, Census Tract 28	1	VACANT

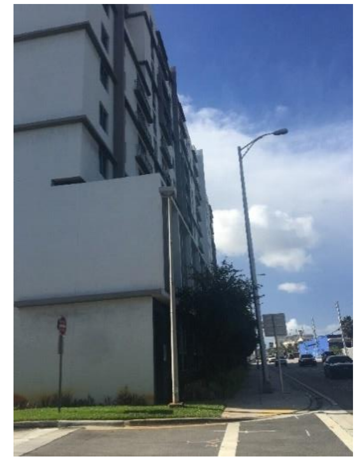


(**From left:** East side of property, Southwest corner from across street, Buildings southwest of site)

Questionnaire Field	**Questionnaire Results**
Timestamp	2019/05/04 6:43:29 PM AST
Site Number	2
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	Yes
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Miscellaneous
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Commercial;Industrial;Institutional
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	No
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	Yes
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	> 50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	None, but most trees planted are palms

BHG St. Martins Pl. LTD

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
BHG St. Martins Pl. LTD	**3**	BF139801008	3/17/2014	12/18/2014	0	0	0	0	0	1	0	0	0	0	0	0	0	Unknown	Residential (Multifamily)	11/21/2013	Block Group 2, Census Tract 30.01	0	RESID

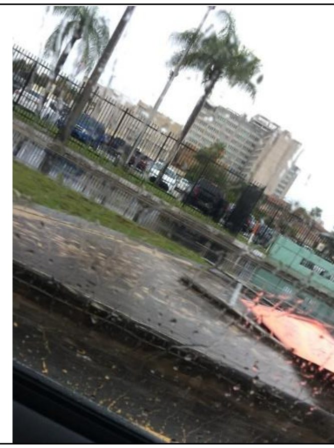


(**From left:** East side of property, Southwest corner from across street, Buildings southwest of site)

Questionnaire Field	**Questionnaire Results**
Timestamp	2019/05/04 6:43:29 PM AST
Site Number	2
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	Yes
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Miscellaneous
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Commercial;Industrial;Institutional
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	No
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	Yes
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	> 50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	None, but most trees planted are palms

Wagner Square ***OMITTED DUE TO STATE OF DEVELOPMENT***

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
BHG St. Martins Pl. LTD	**4**	BF129801003		10/7/2005	NP	NP	NP	NP	NP	NP	NP	NP	NP	NP	NP	NP	NP	NP	Vacant (Parking)	NP		1	VACANT

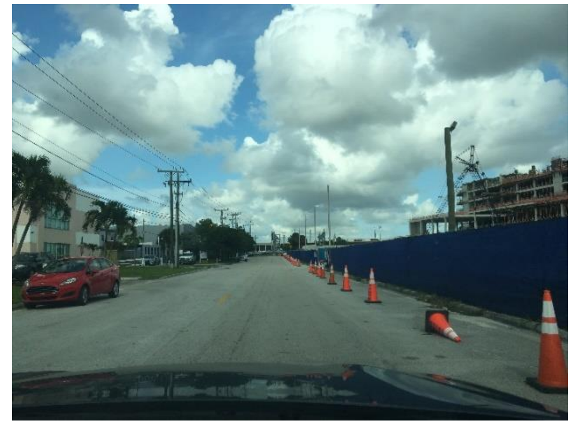

(**From left:** East to west view of street abutting site to the south, area to the north of site, area to the northwest of site)

Questionnaire Field	Questionnaire Results
Timestamp	5/8/2019 0:11:18
Site Number	4
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	Yes
From the list below, select the type(s) of use(s) observed on the site:	Miscellaneous
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Commercial, Miscellaneous
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	Yes
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	> 50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Too much hardscape
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	Vacant lot surrounded by many residential properties of varied densities near a low density commercial area and massive parking lots. Few pedestrians were observed possibly due to inclement weather and/or time of day.

***Note**: This site was supposed to be used for residential housing according to the October 7, 2005 SRCO.

Jackson West Hospital Brownfield Site ***OMITTED DUE TO STATE OF DEVELOPMENT***

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Jackson West Hospital Brownfield Site	5	BF131104000, BF13104002	3/28/2017	7/25/2018	0	0	0	0	1	1	0	0	0	0	0	0	0	Mixing of soil and horse manure, improper disposal of construction and demolition debris	Institutional	NP	Block Group 3, Census Tract 90.10	1	INSTL



(**From left:** Photo of site progress, area south of site south to east view of site)

Questionnaire Field	Questionnaire Results
Timestamp	5/10/2019 0:45:25
Site Number	5
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	The site is presently undergoing construction. No portion of it is open to the public at this time.
From the list below, select the type(s) of use(s) observed on the site:	Institutional
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Commercial, Industrial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	No
Are there boarded-up or closed buildings in the area?	Yes
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	25-50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Ongoing construction on-site. Trees present in swales on opposite side of street.
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	Site was heavily commercial/industrial with poor pedestrian access. In addition, it abutted a major highway as well as a major road. The area gave the impression of being relatively well-maintained with minimal activity.

Beacon Lakes Property…* OMITTED DUE TO STATE OF DEVELOPMENT*****

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Jackson West Hospital Brownfield Site	**6**	BF130301001	11/24/2003	5/9/2012	1	0	0	1	1	0	0	0	0	0	0	0	0	Unknown	Vacant	11/24/2003	Block Group 1, Census Tract 141	1	VACANT


(**From left:** Shopping plaza southwest of the site, south to north view to the site, warehouses to the west of the site)

Questionnaire Field	**Questionnaire Results**
Timestamp	5/10/2019 0:57:19
Site Number	6
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Commercial, Industrial, Institutional
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Commercial, Industrial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	Yes
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	< 25 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Abundant hardscape
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	Large commercial, industrial, institutional area. No indication of ongoing construction.

NW 62ND Street Passive Park Green Reuse Site

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Jackson West Hospital Brownfield Site	7	BF131601001	7/25/2018	6/25/2018	0	0	0	0	1	0	0	0	0	0	0	0	0	Naturally-occurring muck soils	Commercial, Institutional	6/25/2015	Block Group 1, Census Tract 90.34	0	CMRCL

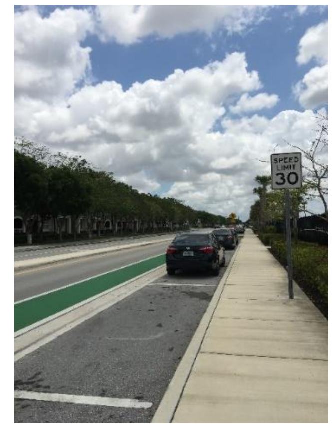


(**From left:** Ikea located to west of site, Keiser University campus to west, adjacent road on west side)

Questionnaire Field	Questionnaire Results
Timestamp	5/10/2019 1:12:20
Site Number	7
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	The site itself is presently being developed
From the list below, select the type(s) of use(s) observed on the site:	
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Commercial, Industrial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	No
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	> 50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Ongoing construction, abundant hardscape
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	Site has yet to be redeveloped (ongoing). Surrounding area has abundant new construction (residential and commercial). Notable absence of major chains.

Doral Legacy Park Green Reuse Site

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Jackson West Hospital Brownfield Site	**8**	BF131502001	3/13/2013	12/10/2018	0	0	0	0	1	0	0	0	0	0	0	0	0	Naturally Occurring in Soil	Municipal (Park)	3/13/2015	Block Group 4, Census Tract 90.43	0	MNCPL

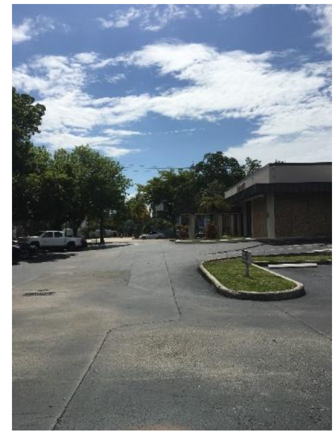


(**From left:** Community center to the east, west side of the park from elevated walkway, west to east view of on street parking)

Questionnaire Field	**Questionnaire Results**
Timestamp	5/10/2019 1:00:51
Site Number	8
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Governmental
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Condominium
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	Yes
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	< 25 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Abundant hardscape
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	This is a large park and community center containing fitness facilities in the center of a suburban neighborhood.. There was heavy foot traffic, and many children were at play at the time of the inspection (summer afternoon)

Land South Partners I, Brownfield Site ***OMITTED DUE TO STATE OF DEVELOPMENT***

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Land South Partners I, Brownfield Site	**9**	BF131301001	3/13/2013	8/24/2016	1	0	0	1	0	0	1	1	0	0	0	0	0	USTs, dispensers, piping, oil-water separator	Vacant	3/28/1998	Block Group 4, Census Tract 12.03	1	VACANT

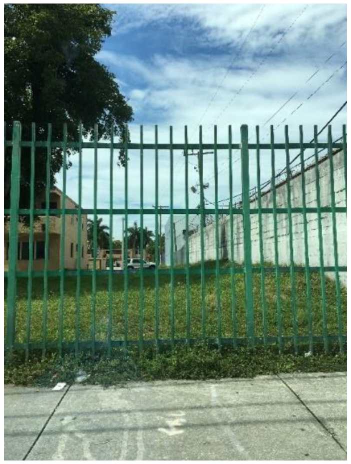


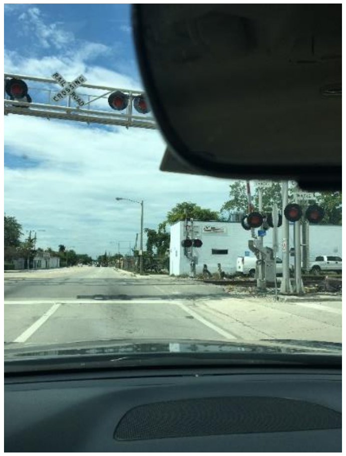
(**From left:** Area east of site with commercial center, vacant site adjacent to bank, surrounding area to the south)

Questionnaire Field	Questionnaire Results
Timestamp	5/8/2019 0:17:40
Site Number	9
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Miscellaneous
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Condominium, Commercial, Institutional, Governmental
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	25-50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Hardscape abundant
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	Vacant lot adjacent to a bank, near a community center, a Whole Foods, and a strip mall. Heavy vehicle traffic from intersection of major roads, moderate foot traffic from commercial and residential uses as well as bus stop.

Mandy's Market, LLC

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Mandy's Market, LLC	**10**	BF139801007		9/28/2017	1	0	0	0	0	0	0	0	1	1	1	1	1	Petroleum storage onsite in underground tanks	Commercial	9/10/2012	Block Group 2, Census Tract 14.01	0	DEVPT





(**From left:** Residential area to the west of site, railroad tracks west of site, Southwest corner of block)

Questionnaire Field	Questionnaire Results
Timestamp	5/8/2019 0:00:24
Site Number	10
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	No
From the list below, select the type(s) of use(s) observed on the site:	Commercial
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Commercial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	Yes
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	> 50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Too much impervious area and soil compaction

In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	High concentration of high-density residential and low density commercial adjacent to a major road near railroad tracks. Not much pedestrian traffic.

Siegel Gas and Oil Corp

Site Name	Site Number	Brownfield Site ID (FDEP)	Date of BSRA Execution	Date of SRCO Issuance	Petroleum	Metals	Isopropylbenzen	Polycyclic	Arsenic	Benzo(a)pyrene	Volatile Organic Compounds	Lead	Benzene	Ethylbenzene	Napthalene	toluene	Total xylenes	Polluting Use/Activities	Land Use	Date of Contamination Discovery	2017 Census tract number	OMIT	Description
Siegel Gas and Oil Corp	**11**	BF139904001	2/24/2004	5/16/2011	1	0	0	1	0	0	1	0	0	0	0	0	0	Above ground petroleum storage and transport	Industrial	11/9/2001	Block Group 1, Census Tract 9.03	0	INDST



(**From left:** South to north view of block, residential area adjacent to site, north to south view of area)

Questionnaire Field	Questionnaire Results
Timestamp	5/7/2019 23:54:06
Site Number	11
Could you locate this site?	Yes
Is there any indication that clean-up is still ongoing?	No
Is there new development observed in the vicinity of the site?	Yes
From the list below, select the type(s) of use(s) observed on the site:	Industrial
From the list below, select the type(s) of use(s) observed in the area surrounding the site	Residential, Commercial, Industrial
Are there street lights present in the area?	Yes
Are there bus stops present in the area?	No
Are there sidewalks present in the area?	Yes
Are there boarded-up or closed buildings in the area?	No
Did you observe any incidents of crime?	No
Are there police present in the area?	No
Describe the tree canopy in the area by checking the box next to the list below (please approximate)	25-50 feet between each tree on a block
If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible	Compaction by heavy vehicle traffic
In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.	High traffic industrial/commercial use across the street from multifamily residential. Some pedestrian activity, lots of garbage in unkempt swales. Large multifamily unit adjacent to highway to the west.

Site Visit Questionnaire

1. **Site Number**
   Mark only one oval.

   - ◯ 1
   - ◯ 2
   - ◯ 3
   - ◯ 4
   - ◯ 5
   - ◯ 6
   - ◯ 7
   - ◯ 8
   - ◯ 9
   - ◯ 10
   - ◯ 11

2. **Could you locate this site?**
   Mark only one oval.

   - ◯ Yes
   - ◯ No

3. **Is there any indication that clean-up is still ongoing?**
   Mark only one oval.

   - ◯ Yes
   - ◯ No

4. **Is there new development observed in the vicinity of the site?**
   Mark only one oval.

   - ◯ Yes
   - ◯ No
   - ◯ Other: ____________________

5. **From the list below, select the type(s) of use(s) observed on the site:**
Check all that apply.

- [ ] Residential
- [ ] Condominium
- [ ] Commercial
- [ ] Industrial
- [ ] Agricultural
- [ ] Institutional
- [ ] Governmental
- [ ] Miscellaneous

6. **From the list below, select the type(s) of use(s) observed in the area surrounding the site**
Check all that apply.

- [ ] Residential
- [ ] Condominium
- [ ] Commercial
- [ ] Industrial
- [ ] Agricultural
- [ ] Institutional
- [ ] Governmental
- [ ] Miscellaneous

7. **Are there street lights present in the area?**
Mark only one oval.

- ( ) Yes
- ( ) No

8. **Are there bus stops present in the area?**
Mark only one oval.

- ( ) Yes
- ( ) No

9. **Are there sidewalks present in the area?**
Mark only one oval.

- ( ) Yes
- ( ) No
- ( ) Other: ______________________

10. **Are there boarded-up or closed buildings in the area?**
    Mark only one oval.
    - ( ) Yes
    - ( ) No

11. **Did you observe any incidents of crime?**
    Mark only one oval.
    - ( ) Yes
    - ( ) No
    - ( ) Other: ____________________

12. **Are there police present in the area?**
    Mark only one oval.
    - ( ) Yes
    - ( ) No

13. **Describe the tree canopy in the area by checking the box next to the list below (please approximate)**
    Mark only one oval.
    - ( ) < 25 feet between each tree on a block
    - ( ) 25-50 feet between each tree on a block
    - ( ) > 50 feet between each tree on a block

14. **If there are any physical conditions that would prevent planting of trees, please describe them below and include photos where possible**

    ____
    ____
    ____
    ____
    ____

15. **In no more than three sentences, describe your impression of the site and its surrounding area as well as any observations made that were not encompassed by this questionnaire.**

    ____
    ____
    ____
    ____
    ____

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APPENDIX B
SELECTED VARIABLE DESCRIPTIONS FROM THE 2018 NAL USER'S GUIDE

Table B-1. Selected Variable Descriptions

Variable Alias	2018 User Guide Definition
JV	This field contains the property appraiser's opinion of market value after an adjustment for the criteria defined in s. 193.011, F.S. Counties must annually notify the Department of the percentage adjustment they make for each use code. This entry has a variable length and can contain up to 12 digits. Note: Adjustment rates are available on the Department's website.
DOR_UC	DOR Land Use Code. This field indicates the land use code associated with each type of property. The property appraiser assigns the use code based on Department guidelines. If a parcel has more than one use, the appraiser assigns a code according to property's predominant use. This entry has a fixed length and should appear as a three-digit number ranging from 000 through 099.
ACT_YR_BLT	This field indicates the year the parcel's primary structure was built. This field is required for all improved use codes. This field will be blank if not applicable. This entry has a fixed length and should appear as a four-digit number.
TOT_LVG_AREA	Total Living or Usable Area. This field reflects the total effective area of all improvements on the property, excluding improvements classified as special features. This is the total area of all floors on any multi-story building and the total area of all property record cards that share the same unique parcel number. The effective building area is measured in square feet and begins with the building's base area, which is the building type's major area. Property appraisers may apply percentage factors to the square footages of other building areas such as attached garages, attached carports, porches, utility rooms, and offices. These percentage factors may be less than or greater than one, depending on the unit cost of the other area(s) relative to that of the base area. For example, the percentage factor for a garage attached to a single-family home typically would be less than one, while the percentage factor for an enclosed office area in a warehouse typically would be greater than one. The effective base area is the sum of the base area's square footage and the adjusted square footages of all other attached building areas. This field is left blank if not applicable. This entry has a variable length and can contain up to 12 digits.
TAX_VAL	Taxable Value. This field reflects the total taxable value of all tangible personal property. This entry has a variable length and can contain up to 12 digits.

APPENDIX C
VARIABLE DESCRIPTIVE STATISTICS

Table C-1. Selected Descriptive Statistics

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
8	2010	12460	3.3077849	3.0918941	0	0	1102.5457	14.321443	12460	0	0	0	0	0	0	0	12460	2018
8	2012	3839	126.91456	772.91144	1199	3834	980.21188	13.215064	3839	0	0	0	0	0	0	0	3839	2018
8	2013	3852	169.36241	1790.3505	856	1734	3157.8385	13.177545	3852	0	0	0	0	0	0	0	3852	2018
8	2014	4014	24.040359	344.49975	571	1965	958.79661	13.398354	4014	0	0	0	0	0	0	0	4014	2018
8	2015	3807	156.12241	2211.3241	241	2793	994.23124	13.574189	3807	0	0	0	0	0	0	0	3807	2018
8	2016	3581	19.043843	63.668808	490	379	3198.3467	12.920019	3581	0	0	0	0	0	0	0	3581	2018
8	2017	6681	1.2058075	1.3924562	861	5329	1017.1217	12.545729	6681	0	0	0	0	0	0	0	6681	2018
8	2018	6393	4.1013609	2.8320038	169	1975	1009.7626	12.553109	6393	0	0	0	0	0	0	0	6393	2018
6	2010	668	1875.1287	6430.7395	0	0	1178.988	14.272724	668	0	0	0	0	0	668	0	0	2018
6	2011	255	1879.451	14360.471	24	52	3366.3092	14.180693	255	0	0	0	0	0	255	0	0	2018
6	2012	271	1882.9926	13629.524	83	271	1035.4048	14.248657	271	0	0	0	0	0	271	0	0	2018
6	2013	260	1798.9038	14053.888	71	72	3444.5721	14.05138	260	0	0	0	0	0	260	0	0	2018
6	2014	254	1903.0551	20345.854	27	99	1009.907	14.309825	254	0	0	0	0	0	254	0	0	2018
6	2015	251	1887.5418	21338.976	10	214	998.02458	14.429832	251	0	0	0	0	0	251	0	0	2018
6	2016	250	1917.188	14837.96	29	48	3341.5825	14.136948	250	0	0	0	0	0	250	0	0	2018
6	2017	237	1959.1603	23600.068	38	221	1001.9466	14.631395	237	0	0	0	0	0	237	0	0	2018
6	2018	234	1960.2821	25037.872	7	94	966.29724	14.657091	234	0	0	0	0	0	234	0	0	2018
5	2010	3	0	0	0	0	841.47083	13.620967	3	0	0	0	0	3	0	0	0	2018
5	2011	4	0	0	2	2	2038.8849	13.273883	4	0	0	0	0	4	0	0	0	2018
5	2012	4	0	0	2	4	621.63129	12.893909	4	0	0	0	0	4	0	0	0	2018
5	2013	2	0	0	0	2	1445.0711	12.845154	2	0	0	0	0	2	0	0	0	2018
5	2014	4	0	0	0	1	621.62034	13.253991	4	0	0	0	0	4	0	0	0	2018

Table C-1. Continued

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
5	2015	4	0	0	1	1	759.73106	13.766875	4	0	0	0	0	4	0	0	0	2018
5	2016	4	0	0	1	1	2039.0025	13.206378	4	0	0	0	0	4	0	0	0	2018
5	2017	4	0	0	1	3	759.67227	13.96047	4	0	0	0	0	4	0	0	0	2018
5	2018	4	0	0	1	1	466.90762	14.296101	4	0	0	0	0	4	0	0	0	2018
4	2010	1267	1953.6093	20055.557	0	0	949.56827	14.351471	1267	0	0	0	1267	0	0	0	0	2018
4	2011	1274	1926.3477	20087.238	60	148	3129.6052	14.066545	1274	0	0	0	1274	0	0	0	0	2018
4	2012	1251	1936.5819	19938.9	153	1251	948.14166	14.182349	1251	0	0	0	1251	0	0	0	0	2018
4	2013	1266	1915.2599	21388.58	129	320	3119.3229	14.062441	1266	0	0	0	1266	0	0	0	0	2018
4	2014	1248	1949.2532	20344.366	45	835	951.54361	14.230938	1248	0	0	0	1248	0	0	0	0	2018
4	2015	1246	1915.0514	19255.145	22	975	957.1356	14.491292	1246	0	0	0	1246	0	0	0	0	2018
4	2016	1263	1936.7846	21324.598	65	115	3133.851	14.011055	1263	0	0	0	1263	0	0	0	0	2018
4	2017	1582	1969.1384	16157.871	439	1540	842.24383	13.98767	1582	0	0	0	1582	0	0	0	0	2018
4	2018	1583	1969.8073	16333.806	8	602	789.54671	14.026408	1583	0	0	0	1583	0	0	0	0	2018
3	2010	1960	1578.5689	13421.534	0	0	1025.7867	14.512462	1960	0	0	1960	0	0	0	0	0	2018
3	2011	1879	1557.6354	11135.625	220	361	3364.7558	14.236283	1879	0	0	1879	0	0	0	0	0	2018
3	2012	1907	1537.6371	11214.137	452	1904	1031.3676	14.312962	1907	0	0	1907	0	0	0	0	0	2018
3	2013	1927	1534.7436	10664.445	287	591	3333.5706	14.162207	1927	0	0	1927	0	0	0	0	0	2018
3	2014	1909	1538.5746	10304.242	114	1008	1023.2939	14.394588	1909	0	0	1909	0	0	0	0	0	2018
3	2015	1874	1495.3084	10805.988	73	1528	1027.9411	14.63421	1874	0	0	1874	0	0	0	0	0	2018
3	2016	1858	1568.0081	10584.14	122	281	3368.3583	14.184829	1858	0	0	1858	0	0	0	0	0	2018
3	2017	2397	1663.2123	9173.7747	750	2304	1048.45	13.955222	2397	0	0	2397	0	0	0	0	0	2018
3	2018	2399	1674.7912	9626.8128	52	938	1013.4934	14.040261	2399	0	0	2399	0	0	0	0	0	2018
1	2010	21271	1953.16	4008.5311	0	0	1124.4746	14.226776	21271	21271	0	0	0	0	0	0	0	2018
1	2011	13106	1959.2841	3107.532	216	3407	3497.6418	13.667273	13106	13106	0	0	0	0	0	0	0	2018

Table C-1. Continued

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
1	2012	13118	1947.1705	2830.2254	633	13115	1065.9936	13.741959	13118	13118	0	0	0	0	0	0	0	2018
1	2013	13139	1944.264	2910.392	539	4312	3497.679	13.625719	13139	13139	0	0	0	0	0	0	0	2018
1	2014	13236	1958.5212	2981.1894	146	10905	1065.896	13.806698	13236	13236	0	0	0	0	0	0	0	2018
1	2015	13213	1916.9006	3041.8657	135	12699	1065.3909	13.968003	13213	13213	0	0	0	0	0	0	0	2018
1	2016	13137	1960.1355	3113.1222	177	562	3492.3394	13.608962	13137	13137	0	0	0	0	0	0	0	2018
1	2017	13606	1964.1599	3263.1886	701	13277	1062.8984	14.084275	13606	13606	0	0	0	0	0	0	0	2018
1	2018	13711	1965.1812	3328.4873	136	9973	1047.2462	14.198159	13711	13711	0	0	0	0	0	0	0	2018
0	0	147	1669.2041	1775.3129	147	0	2227.4037	15.980014	147	0	0	0	0	0	0	0	0	2018
0	2010	37	1855.2973	12000.054	0	0	832.03206	13.323726	37	0	0	0	0	0	0	0	0	2018
0	2011	3825	53.121569	491.89333	1055	934	3203.6297	13.020088	3825	0	0	0	0	0	0	0	0	2018
0	2012	55	1426.4364	9551.6182	24	55	909.64225	13.638917	55	0	0	0	0	0	0	0	0	2018
0	2013	80	1100.85	5447.55	21	50	3302.1341	12.504127	80	0	0	0	0	0	0	0	0	2018
0	2014	48	1636.9792	19751.229	10	20	883.94108	13.381335	48	0	0	0	0	0	0	0	0	2018
0	2015	43	1691.5116	21207.93	3	30	875.60113	13.910403	43	0	0	0	0	0	0	0	0	2018
0	2016	50	1804.02	15427.5	8	6	3019.6589	13.034851	50	0	0	0	0	0	0	0	0	2018
0	2017	46	1626.1739	27885.348	11	34	881.3753	13.970202	46	0	0	0	0	0	0	0	0	2018
0	2018	49	1529.9184	31259.857	3	22	835.0445	14.017644	49	0	0	0	0	0	0	0	0	2018

Table C-2. Variable Summary Statistics(R Output)

OID	ACTYRBLT	TOTLVGAREA	DIFDOR	JVCNG	NEAR_DIST	ADJV2	SETYR	DORUC1_1	DORUC2_1	DORUC3_1	DORUC4_1	DORUC5_1	DORUC6_1	DORUC7_1	DORUC8_1	SRCO_YR	ORIG_FID
Min. :-1	Min. :1902	Min. : 0	Min. :0.00000	Min. :0.0000	Min. : 0.0	Min. : 3.991	Min. : 0	Min. :0.0000	Min. :0	Min. :0.00000	Min. :0.00000	Min. :0	Min. :0.00000	Min. :0	Min. :0.000000	Min. :2011	Min. : 0
1st Qu.:-1	1st Qu.:1941	1st Qu.: 1274	1st Qu.:0.00000	1st Qu.:0.0000	1st Qu.: 940.6	1st Qu.:13.246	1st Qu.:2011	1st Qu.:1.0000	1st Qu.:0	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0	1st Qu.:0.00000	1st Qu.:0	1st Qu.:0.000000	1st Qu.:2014	1st Qu.: 5388
Median :-1	Median :1954	Median : 1878	Median :0.00000	Median :1.0000	Median :1310.5	Median :13.894	Median :2014	Median :1.0000	Median :0	Median :0.00000	Median :0.00000	Median :0	Median :0.00000	Median :0	Median :0.000000	Median :2015	Median :11294
Mean :-1	Mean :1961	Mean : 5749	Mean :0.03721	Mean :0.5246	Mean :1800.6	Mean :13.969	Mean :2012	Mean :0.8058	Mean :0	Mean :0.09263	Mean :0.07532	Mean :0	Mean :0.01647	Mean :0	Mean :0.006316	Mean :2015	Mean :11895
3rd Qu.:-1	3rd Qu.:1984	3rd Qu.: 3087	3rd Qu.:0.00000	3rd Qu.:1.0000	3rd Qu.:2175.8	3rd Qu.:14.754	3rd Qu.:2016	3rd Qu.:1.0000	3rd Qu.:0	3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0	3rd Qu.:0.00000	3rd Qu.:0	3rd Qu.:0.000000	3rd Qu.:2017	3rd Qu.:17020
Max. :-1	Max. :2018	Max. :1157536	Max. :1.00000	Max. :1.0000	Max. :6495.0	Max. :21.524	Max. :2018	Max. :1.0000	Max. :0	Max. :1.00000	Max. :1.00000	Max. :0	Max. :1.00000	Max. :0	Max. :1.000000	Max. :2018	Max. :37665

Table C-3. PPM Correlation (R Output)

	ACTYRBLT	TOTLVGAREA	DIFDOR	JVCNG	NEAR_DIST	ADJV2	SETYR	DORUC1_1	DORUC3_1	DORUC4_1	DORUC6_1	DORUC8_1	SRCO_YR
ACTYRBLT	1	0.08186786	0.043317042	0.095961321	-0.075007835	0.31805874	-0.048236864	0.019810943	-0.041714365	0.005311468	-0.033803319	0.070977322	0.268982393
TOTLVGAREA	0.08186786	1	0.046146296	-0.001214442	-0.000784249	0.144350885	0.003505437	-0.175921598	0.083005131	0.13481007	0.04360877	0.03934125	-0.016504705
DIFDOR	0.043317042	0.046146296	1	0.096672576	-0.019916087	-0.090463957	-0.139357442	-0.188179078	0.127708416	0.052670303	0.041764385	0.14053468	0.014242213
JVCNG	0.095961321	-0.001214442	0.096672576	1	-0.362366772	0.110410252	0.046706278	0.038694048	-0.021396727	-0.023231302	-0.031353353	0.024866437	0.056743008
NEAR_DIST	-0.075007835	-0.000784249	-0.019916087	-0.362366772	1	-0.160105123	-0.012478732	0.036229676	-0.00698335	-0.041950553	-0.00856036	-0.007249118	-0.095616666
ADJV2	0.31805874	0.144350885	-0.090463957	0.110410252	-0.160105123	1	-0.044004659	-0.119131818	0.093963931	0.048953216	0.041946632	0.009349094	0.302123388
SETYR	-0.048236864	0.003505437	-0.139357442	0.046706278	-0.012478732	-0.044004659	1	0.054316805	0.011096721	0.009727402	0.002463456	0.001758477	-0.030249065
DORUC1_1	0.019810943	-0.175921598	-0.188179078	0.038694048	0.036229676	-0.119131818	0.054316805	1	-0.650856926	-0.581382556	-0.263569963	-0.162402645	0.072736066
DORUC3_1	-0.041714365	0.083005131	0.127708416	-0.021396727	-0.00698335	0.093963931	0.011096721	-0.650856926	1	-0.091187832	-0.041340032	-0.02547229	-0.0256796
DORUC4_1	0.005311468	0.13481007	0.052670303	-0.023231302	-0.041950553	0.048953216	0.009727402	-0.581382556	-0.091187832	1	-0.036927276	-0.022753303	-0.083461286
DORUC6_1	-0.033803319	0.04360877	0.041764385	-0.031353353	-0.00856036	0.041946632	0.002463456	-0.263569963	-0.041340032	-0.036927276	1	-0.010315217	-0.013732568
DORUC8_1	0.070977322	0.03934125	0.14053468	0.024866437	-0.007249118	0.009349094	0.001758477	-0.162402645	-0.02547229	-0.022753303	-0.010315217	1	0.023755457
SRCO_YR	0.268982393	-0.016504705	0.014242213	0.056743008	-0.095616666	0.302123388	-0.030249065	0.072736066	-0.0256796	-0.083461286	-0.013732568	0.023755457	1

Table C-4. 0.25 Mile Subset Selected Descriptive Statistics

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
8	2010	3	1959.666667	1302.333333	0	0	257.2468713	10.82117987	6030	0	0	0	0	0	0	0	3	2018
8	2012	25	1951.6	3401.84	22	25	217.5610739	13.54142518	50300	0	0	0	0	0	0	0	25	2018
8	2013	1	2007	11097	1	1	331.2952919	13.66102606	2013	0	0	0	0	0	0	0	1	2018
8	2014	2	1964.5	582	0	1	203.1009527	8.699219066	4028	0	0	0	0	0	0	0	2	2018
8	2015	16	1986.6875	44371.875	9	8	187.4549883	13.64840677	32240	0	0	0	0	0	0	0	16	2018
8	2016	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	2017	1	2005	0	0	0	227.0302285	4.333098431	2017	0	0	0	0	0	0	0	1	2018
8	2018	1	2005	0	0	0	201.3005568	4.313994224	2018	0	0	0	0	0	0	0	1	2018
6	2010	18	1951.611111	21484.22222	0	0	224.4416363	14.65672217	36180	0	0	0	0	0	18	0	0	2017
6	2011	3	1960.333333	10087.33333	0	1	279.0407619	14.73866787	6033	0	0	0	0	0	3	0	0	2017
6	2012	18	1951.611111	21484.22222	4	18	224.4416337	14.57546068	36216	0	0	0	0	0	18	0	0	2017
6	2013	3	1960.333333	10087.33333	2	3	279.0407574	14.70650497	6039	0	0	0	0	0	3	0	0	2017
6	2014	18	1951.611111	22799.33333	2	10	224.4416376	14.66375349	36252	0	0	0	0	0	18	0	0	2017
6	2015	17	1953.117647	22001.94118	0	15	218.9293549	14.93666726	34255	0	0	0	0	0	17	0	0	2017
6	2016	3	1960.333333	10087.33333	1	0	279.0407574	14.67116266	6048	0	0	0	0	0	3	0	0	2017
6	2017	19	1954.842105	32501.31579	5	19	220.3278776	15.37184056	38323	0	0	0	0	0	19	0	0	2017
6	2018	26	1960.846154	36323.15385	1	9	235.8290129	15.35653801	52468	0	0	0	0	0	26	0	0	2018
4	2010	212	1956.476415	17485.28302	0	0	228.1101845	14.46109906	426120	0	0	0	212	0	0	0	0	2018
4	2011	44	1953.431818	15356.38636	2	10	213.5750843	14.24711644	88484	0	0	0	44	0	0	0	0	2017
4	2012	211	1956.800948	17891.61611	22	211	228.7154097	14.32120424	424532	0	0	0	211	0	0	0	0	2018
4	2013	42	1954.619048	15620.38095	0	17	214.56951	14.19066651	84546	0	0	0	42	0	0	0	0	2017
4	2014	215	1956.860465	17711.05581	7	142	229.1679163	14.4526536	433010	0	0	0	215	0	0	0	0	2018
4	2015	209	1956.995215	17318.57895	2	169	228.2269129	14.82884899	421135	0	0	0	209	0	0	0	0	2018
4	2016	44	1953.431818	15356.38636	0	9	212.7610316	14.17961123	88704	0	0	0	44	0	0	0	0	2017

Table C-4. Continued

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
4	2017	419	1981.785203	9557.852029	222	409	240.6577806	13.17089916	845123	0	0	0	419	0	0	0	0	2018
4	2018	544	1986.387868	9503.316176	1	112	206.4319804	12.83372274	1097792	0	0	0	544	0	0	0	0	2018
3	2010	117	1952.333333	9898.452991	0	0	220.0006126	14.47187438	235170	0	0	117	0	0	0	0	0	2018
3	2011	29	1951.551724	6399.413793	1	5	197.4099034	14.1473167	58319	0	0	29	0	0	0	0	0	2018
3	2012	107	1952.280374	10401.78505	31	107	228.0416789	14.26699361	215284	0	0	107	0	0	0	0	0	2018
3	2013	30	1948.166667	6470.366667	8	10	192.6324749	14.17094656	60390	0	0	30	0	0	0	0	0	2017
3	2014	111	1953.198198	10662.84685	13	80	226.4987087	14.45589868	223554	0	0	111	0	0	0	0	0	2018
3	2015	107	1955.336449	12968.06542	8	90	232.7097519	14.80189182	215605	0	0	107	0	0	0	0	0	2018
3	2016	28	1952.321429	6456.428571	6	4	199.3194825	14.04845119	56448	0	0	28	0	0	0	0	0	2018
3	2017	125	1961.328	10870.672	40	118	252.5403848	14.93085113	252125	0	0	125	0	0	0	0	0	2018
3	2018	139	1963.043165	12711.59712	1	46	246.7133033	15.04940861	280502	0	0	139	0	0	0	0	0	2018
1	2010	1064	1975.651316	2436.778195	0	0	252.5609787	14.17758441	2138640	1064	0	0	0	0	0	0	0	2018
1	2011	134	1991.485075	3895.216418	0	101	216.7988898	14.44716526	269474	134	0	0	0	0	0	0	0	2018
1	2012	1060	1976.808491	2480.133019	39	1060	253.4699327	14.04594653	2132720	1060	0	0	0	0	0	0	0	2018
1	2013	134	1991.485075	3895.216418	3	115	216.8001106	14.41500237	269742	134	0	0	0	0	0	0	0	2018
1	2014	1068	1976.821161	2720.98221	7	909	253.0576123	14.17016516	2150952	1068	0	0	0	0	0	0	0	2018
1	2015	1035	1978.246377	2887.299517	9	990	252.7791547	14.3241017	2085525	1035	0	0	0	0	0	0	0	2018
1	2016	134	1991.485075	3895.216418	0	1	216.8001112	14.37966005	270144	134	0	0	0	0	0	0	0	2018
1	2017	1051	1977.571836	2985.549001	15	1041	252.441063	14.51378712	2119867	1051	0	0	0	0	0	0	0	2018
1	2018	1107	1976.903342	2976.543812	0	648	246.0712678	14.54818975	2233926	1107	0	0	0	0	0	0	0	2018
0	2010	9	1959.888889	4980.222222	0	0	253.3420143	14.14378908	18090	0	0	0	0	0	0	0	0	2017
0	2011	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
0	2012	10	1960.7	4491.8	2	10	260.5683266	14.00532635	20120	0	0	0	0	0	0	0	0	2017
0	2013	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
0	2014	9	1964.222222	3878	0	7	261.2512835	14.17233326	18126	0	0	0	0	0	0	0	0	2017

Table C-4. Continued

DORUC	SETYR	FREQUENCY	MEAN_ACTYRBLT	MEAN_TOTLVGAREA	SUM_DIFDOR	SUM_JVCNG	MEAN_NEAR_DIST	MEAN_ADJV2	COUNT_SETYR	COUNT_DORUC1_1	COUNT_DORUC2_1	COUNT_DORUC3_1	COUNT_DORUC4_1	COUNT_DORUC5_1	COUNT_DORUC6_1	COUNT_DORUC7_1	COUNT_DORUC8_1	MAX_SRCO_YR
0	2015	8	1965	3747.125	0	7	267.6309416	14.32683773	16120	0	0	0	0	0	0	0	0	2017
0	2016	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
0	2017	9	1970.555556	23181.33333	0	8	270.5092266	14.74583778	18153	0	0	0	0	0	0	0	0	2017
0	2018	10	1974.3	20912.1	1	6	234.1865065	14.77090883	20180	0	0	0	0	0	0	0	0	2018

Table C-5. CPI Comparison Table

Year	Miami-Fort Lauderdale-WPB	Percent Changed Since 2018	National CPI	Percent Changed Since 2018
2004	185.6	-0.42815194	188.9	-0.329311805
2005	194.3	-0.364204838	195.3	-0.285750128
2006	203.9	-0.299975478	201.6	-0.245570437
2007	212.39	-0.248010735	207.342	-0.211076386
2008	222.119	-0.19334681	215.303	-0.166295871
2009	221.387	-0.197292524	214.537	-0.170460107
2010	223.062	-0.188301907	218.056	-0.151571156
2011	230.851	-0.148208152	224.939	-0.116333762
2012	235.207	-0.126943501	229.594	-0.093700184
2013	238.179	-0.112881488	232.957	-0.077911374
2014	243.147	-0.090143	236.736	-0.060704751
2015	245.419	-0.080050852	237.017	-0.059447213
2016	249.79	-0.061151367	240.007	-0.046248651
2017	256.681	-0.032663111	245.12	-0.024424772
2018	265.065	0	251.107	0

Table C-6. 0.25 Mile Subset Variable Summary Statistics (R Output)

OID	ACTYRBLT	TOTLVGAREA	DIFDOR	JVCNG	NEAR_DIST	ADJV2	SETYR	DORUC1_1	DORUC2_1	DORUC3_1	DORUC4_1	DORUC5_1	DORUC6_1	DORUC7_1	DORUC8_1	SRCO_YR	ORIG_FID
Min. :-1	Min. :1917	Min. : 0	Min. :0.00000	Min. :0.0000	Min. : 0.0	Min. : 4.314	Min. :2010	Min. :0.0000	Min. :0	Min. :0.00000	Min. :0.000	Min. :0	Min. :0.00000	Min. :0	Min. :0.000000	Min. :2011	Min. : 0
1st Qu.:-1	1st Qu.:1947	1st Qu.: 1549	1st Qu.:0.00000	1st Qu.:0.0000	1st Qu.:172.8	1st Qu.:13.513	1st Qu.:2012	1st Qu.:0.0000	1st Qu.:0	1st Qu.:0.00000	1st Qu.:0.000	1st Qu.:0	1st Qu.:0.00000	1st Qu.:0	1st Qu.:0.000000	1st Qu.:2015	1st Qu.: 5388
Median :-1	Median :1971	Median : 2392	Median :0.00000	Median :1.0000	Median :256.1	Median :14.444	Median :2015	Median :1.0000	Median :0	Median :0.00000	Median :0.000	Median :0	Median :0.00000	Median :0	Median :0.000000	Median :2017	Median :11294
Mean :-1	Mean :1974	Mean : 5983	Mean :0.04995	Mean :0.6721	Mean :242.6	Mean :14.218	Mean :2014	Mean :0.6962	Mean :0	Mean :0.08134	Mean :0.199	Mean :0	Mean :0.01282	Mean :0	Mean :0.005026	Mean :2016	Mean :11895
3rd Qu.:-1	3rd Qu.:2006	3rd Qu.: 3629	3rd Qu.:0.00000	3rd Qu.:1.0000	3rd Qu.:326.7	3rd Qu.:14.990	3rd Qu.:2017	3rd Qu.:1.0000	3rd Qu.:0	3rd Qu.:0.00000	3rd Qu.:0.000	3rd Qu.:0	3rd Qu.:0.00000	3rd Qu.:0	3rd Qu.:0.000000	3rd Qu.:2018	3rd Qu.:17020
Max. :-1	Max. :2017	Max. :565961	Max. :1.00000	Max. :1.0000	Max. :402.3	Max. :18.303	Max. :2018	Max. :1.0000	Max. :0	Max. :1.00000	Max. :1.000	Max. :0	Max. :1.00000	Max. :0	Max. :1.000000	Max. :2018	Max. :37665

Table C-7. 0.25 Mile Subset PPM Correlation (R Output)

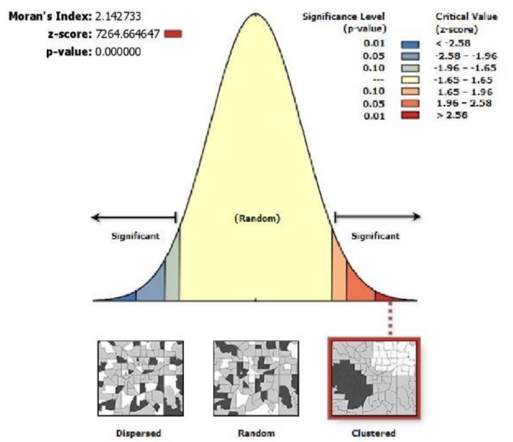
	ACTYRBLT	TOTLVGAREA	DIFDOR	JVCNG	NEAR_DIST	ADJV2	SETYR	DORUC1_1	DORUC3_1	DORUC4_1	DORUC6_1	DORUC8_1	SRCO_YR
ACTYRBLT	1	0.009983345	0.023343397	-0.035519999	-0.149093653	0.158265934	0.088249174	0.183474408	-0.177243727	-0.063077597	-0.072007824	-0.015739323	0.474920051
TOTLVGAREA	0.009983345	1	0.008882469	-0.015145338	-0.011630909	0.085448562	0.007957175	-0.220668824	0.065364261	0.171313022	0.103363469	0.034588545	-0.139706464
DIFDOR	0.023343397	0.008882469	1	0.136104526	0.005614393	-0.231798441	0.070074235	-0.272366279	0.117793303	0.187623085	0.036644156	0.196765983	0.024128391
JVCNG	-0.035519999	-0.015145338	0.136104526	1	0.046697665	0.107848436	0.231438885	0.144267873	-0.058309243	-0.123034257	-0.017495529	0.006391446	0.016983048
NEAR_DIST	-0.149093653	-0.011630909	0.005614393	0.046697665	1	-0.064276175	-0.015644751	0.101156819	-0.03296909	-0.088212123	-0.014320529	-0.020828847	-0.024882035
ADJV2	0.158265934	0.085448562	-0.231798441	0.107848436	-0.064276175	1	-0.019972528	0.110847061	0.101283116	-0.203719971	0.069504527	-0.082572183	0.074455279
SETYR	0.088249174	0.007957175	0.070074235	0.231438885	-0.015644751	-0.019972528	1	-0.099044202	-0.01070252	0.127458864	0.001672432	-0.033108924	0.061246568
DORUC1_1	0.183474408	-0.220668824	-0.272366279	0.144267873	0.101156819	0.110847061	-0.099044202	1	-0.45042859	-0.75448316	-0.172513703	-0.107586696	0.232625701
DORUC3_1	-0.177243727	0.065364261	0.117793303	-0.058309243	-0.03296909	0.101283116	-0.01070252	-0.45042859	1	-0.14831419	-0.033912261	-0.021149092	-0.134344867
DORUC4_1	-0.063077597	0.171313022	0.187623085	-0.123034257	-0.088212123	-0.203719971	0.127458864	-0.75448316	-0.14831419	1	-0.056804188	-0.035425446	-0.15490461
DORUC6_1	-0.072007824	0.103363469	0.036644156	-0.017495529	-0.014320529	0.069504527	0.001672432	-0.172513703	-0.033912261	-0.056804188	1	-0.008100081	-0.021654857
DORUC8_1	-0.015739323	0.034588545	0.196765983	0.006391446	-0.020828847	-0.082572183	-0.033108924	-0.107586696	-0.021149092	-0.035425446	-0.008100081	1	-0.018553157
SRCO_YR	0.474920051	-0.139706464	0.024128391	0.016983048	-0.024882035	0.074455279	0.061246568	0.232625701	-0.134344867	-0.15490461	-0.021654857	-0.018553157	1

Moran's I Spatial Autocorrelation Report (1-Mile Buffer) 25.00 Meter

Distance Threshold

9/24/2019 Spatial Autocorrelation Report

Spatial Autocorrelation Report



Given the z-score of 7264.66464734, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	2.142733
Expected Index:	-0.000005
Variance:	0.000000
z-score:	7264.664647
p-value:	0.000000

Dataset Information

Input Feature Class:	_MERGED2018
Input Field:	ADJV2
Conceptualization:	FIXED_DISTANCE
Distance Method:	MANHATTAN
Row Standardization:	False
Distance Threshold:	25.0000 Meters
Weights Matrix File:	None
Selection Set:	False

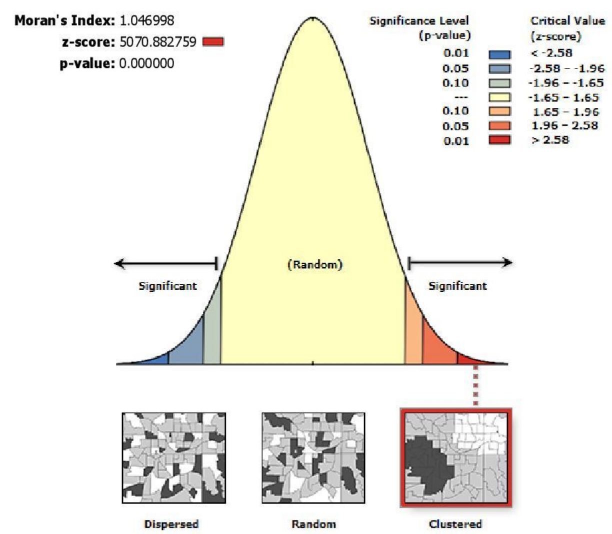
file:///C:/Users/Lian Plass/Documents/ArcGIS/MoransI_Result_15204_2728_.html 1/2

9/24/2019 Spatial Autocorrelation Report

file:///C:/Users/Lian Plass/Documents/ArcGIS/MoransI_Result_15204_2728_.html 2/2

Moran's I Spatial Autocorrelation Report (1-Mile Buffer) 50.00 Meter Distance Threshold

Spatial Autocorrelation Report



Given the z-score of 5070.88275877, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	1.046998
Expected Index:	-0.000005
Variance:	0.000000
z-score:	5070.882759
p-value:	0.000000

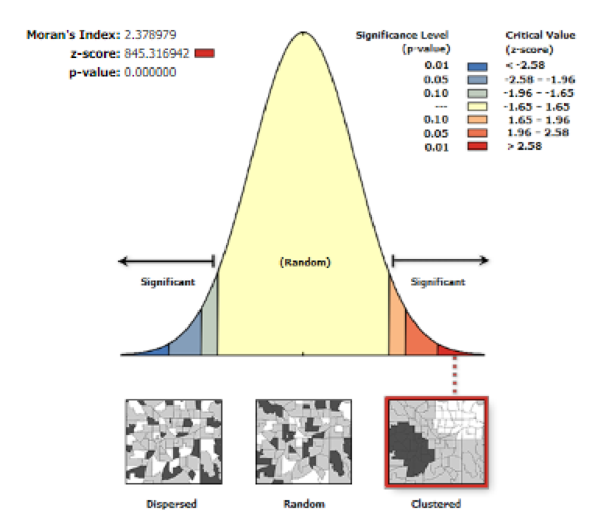
Dataset Information

Input Feature Class:	_MERGED2018
Input Field:	ADJV2
Conceptualization:	FIXED_DISTANCE
Distance Method:	MANHATTAN

Row Standardization:	False
Distance Threshold:	50.0000 Meters
Weights Matrix File:	None
Selection Set:	False

Moran’s I Spatial Autocorrelation Report (0.25-Mile Buffer)

Spatial Autocorrelation Report



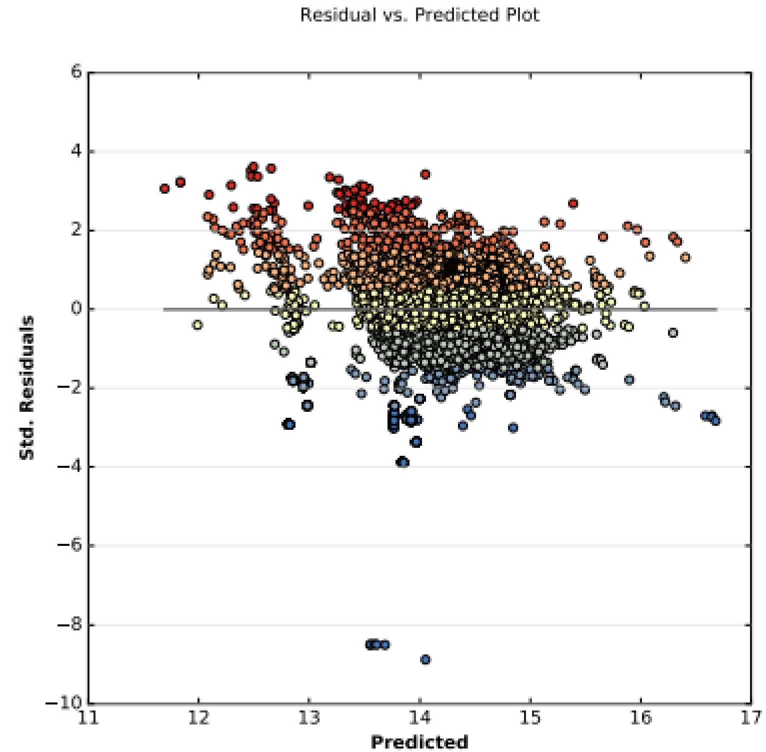
Given the z-score of 845.31694175, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

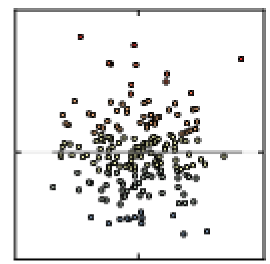
Moran's Index:	2.378979
Expected Index:	-0.000103
Variance:	0.000008
z-score:	845.316942
p-value:	0.000000

Dataset Information

Input Feature Class:	master252019116
Input Field:	ADJV2
Conceptualization:	INVERSE_DISTANCE
Distance Method:	MANHATTAN
Row Standardization:	False
Distance Threshold:	777.0925 Meters
Weights Matrix File:	None
Selection Set:	False



This is a graph of residuals (model over and under predictions) in relation to predicted dependent variable values. For a properly specified model, this scatterplot will have little structure, and look random (see graph on the right). If there is a structure to this plot, the type of structure may be a valuable clue to help you figure out what's going on.



APPENDIX D
SUPPLEMENTAL INFORMATION FOR LINEAR MODEL

Table D-1. ArcMap OLS Model Results (1-Mile Buffer)

Variable	Coefficient [a]	StdError	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-202.404765	1.917745	-105.543118	0.000000*	1.420614	-142.476987	0.000000*	--------
ACTYRBLT	0.010014	0.000096	103.857377	0.000000*	0.000110	90.982932	0.000000*	1.105551
TOTLVGAREA	0.000004	0.000000	49.178962	0.000000*	0.000000	23.431859	0.000000*	1.042972
DIFDOR	0.841606	0.013092	-64.284881	0.000000*	0.028613 -	29.413480	0.000000*	1.088682
JVCNG	0.133361	0.005164	25.824177	0.000000*	0.005352	24.920382	0.000000*	1.179274
NEAR_DIST	-0.000074	0.000002	-39.847863	0.000000*	0.000002 -	41.146093	0.000000*	1.166070
SETYR	-0.000970	0.000048	-20.036361	0.000000*	0.000044 -	22.110736	0.000000*	1.306516
DORUC1_1	-0.070296	0.046028	-1.527243	0.126718	0.072467 -	0.970043	0.332013	58.779162
DORUC3_1	0.411274	0.046538	8.837371	0.000000*	0.073424	5.601381	0.000000*	32.275288
DORUC4_1	0.223785	0.046712	4.790721	0.000003*	0.073132	3.060000	0.002227*	26.945131
DORUC6_1	0.468673	0.049468	9.474208	0.000000*	0.074385	6.300644	0.000000*	7.026465
DORUC8_1	0.018262	0.054754	0.333536	0.738743	0.088385	0.206621	0.836302	3.335953
SRCO_YR	0.098632	0.000970	101.694973	0.000000*	0.000729	135.323210	0.000000*	1.095861

OLS Diagnostics

Input Features: ols_set Dependent Variable: ADJV2
Number of Observations: 157543 Akaike's Information Criterion (AICc) [d]: 428484.780498
Multiple R-Squared [d]: 0.221418 Adjusted R-Squared [d]: 0.221358
Joint F-Statistic [e]: 3733.270420 Prob(>F), (12,157530) degrees of freedom: 0.000000*
Joint Wald Statistic [e]: 57318.455315 Prob(>chi-squared), (12) degrees of freedom: 0.000000*
Koenker (BP) Statistic [f]: 14528.043455 Prob(>chi-squared), (12) degrees of freedom: 0.000000*
Jarque-Bera Statistic [g]: 560596.545237 Prob(>chi-squared), (2) degrees of freedom: 0.000000*

Notes on Interpretation
* An asterisk next to a number indicates a statistically significant p-value (p < 0.01).
[a] Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent variable.
[b] Probability and Robust Probability (Robust_Pr): Asterisk (*) indicates a coefficient is statistically significant (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coeffi
[c] Variance Inflation Factor (VIF): Large Variance Inflation Factor (VIF) values (> 7.5) indicate redundancy among explanatory variables.
[d] R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance.
[e] Joint F and Wald Statistics: Asterisk (*) indicates overall model significance (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Wald Statistic to determine overall model significance.
[f] Koenker (BP) Statistic: When this test is statistically significant (p < 0.01), the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). You should rely on the Robust Probabilities (Robust_Pr) to determine coef
[g] Jarque-Bera Statistic: When this test is statistically significant (p < 0.01) model predictions are biased (the residuals are not normally distributed).

Table D-2. ArcMap OLS Model Results (0.25-Mile Buffer)

Variable	Coefficient [a]	StdError	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	28.457740	14.238917	1.998589	0.045672*	14.813847	1.921023	0.054754	--------
ACTYRBLT	0.007289	0.000426	17.097385	0.000000*	0.000414	17.624053	0.000000*	1.399383
TOTLVGAREA	0.000005	0.000001	9.411312	0.000000*	0.000001	4.725098	0.000004*	1.085546
DIFDOR	-1.351333	0.054773	-24.671712	0.000000*	0.092802 -	-14.561448	0.000000*	1.175741
JVCNG	0.400360	0.025051	15.981659	0.000000*	0.026928	14.867605	0.000000*	1.142155
NEAR_DIST	-0.000523	0.000107	-4.892363	0.000002*	0.000106-	-4.937247	0.000001*	1.046327
SETYR	-0.018499	0.004186	-4.418971	0.000013*	0.004374 -	-4.228893	0.000029*	1.105898
DORUC1_1	-0.191083	0.147607	-1.294541	0.195518	0.146811 -	-1.301556	0.193108	38.056237
DORUC3_1	0.467747	0.151863	3.080055	0.002089*	0.151896	3.079380	0.002094*	14.231277
DORUC4_1	-0.525636	0.148910	-3.529883	0.000433*	0.149987	-3.504536	0.000475*	29.187634
DORUC6_1	0.691127	0.176552	3.914589	0.000101*	0.172703	4.001824	0.000071*	3.258074
DORUC8_1	-0.816911	0.216199	-3.778516	0.000170*	0.561852	-1.453959	0.146005	1.930304
SRCO_YR	0.004328	0.006070	0.713027	0.475839	0.005325	0.812890	0.416288	1.366749

OLS Diagnostics

Input Features:	master252019116	Dependent Variable:	ADJV2
Number of Observations:	9749	Akaike's Information Criterion (AICc) [d]:	29299.730703
Multiple R-Squared [d]:	0.163675	Adjusted R-Squared [d]:	0.162644
Joint F-Statistic [e]:	158.783586	Prob(>F), (12,9736) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	1589.504250	Prob(>chi-squared), (12) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	2152.763105	Prob(>chi-squared), (12) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	7872.388393	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Notes on Interpretation

* An asterisk next to a number indicates a statistically significant p-value (p < 0.01).

[a] Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent variable.

[b] Probability and Robust Probability (Robust_Pr): Asterisk (*) indicates a coefficient is statistically significant (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coeffi

[c] Variance Inflation Factor (VIF): Large Variance Inflation Factor (VIF) values (> 7.5) indicate redundancy among explanatory variables.

[d] R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance.

[e] Joint F and Wald Statistics: Asterisk (*) indicates overall model significance (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Wald Statistic to determine overall model significance.

[f] Koenker (BP) Statistic: When this test is statistically significant (p < 0.01), the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). You should rely on the Robust Probabilities (Robust_Pr) to determine coef

[g] Jarque-Bera Statistic: When this test is statistically significant (p < 0.01) model predictions are biased (the residuals are not normally distributed).

Table D-3. Assessment of Variable Performance (1-Mile Buffer)

	Relative Variable Strength	Variables' Contributions to the Model
	Standardized Beta	Adjusted R^2
ACTYRBLT	0.242771342	0.1012
TOTLVGAREA	0.111657088	0.0208
DIFDOR	-0.149117982	0.0082
JVCNG	0.062345407	0.0122
NEAR_DIST	-0.095661691	0.0256
SETYR	-0.050915137	0.0019
DORUC1_1	-0.026030982	0.0142*
DORUC3_1	0.111616604	0.0088*
DORUC4_1	0.055285557	0.0024*
DORUC6_1	0.055831854	0.00175*
DORUC8_1	0.001354328	8.106e-05*
SRCOYR	0.236672562	0.09127

* These results are for the linear model generated from the subsetted dataset excluding values for which ACTYRBLT is equal to 0. There is a notable improvement in R^2 for DOR code dummy variables when the ACTYRBLT variable is removed and/or included as-is, however, overall model performance diminishes.

Shapiro-Wilk normality test

data: sample(dadelmres, 5000, replace = TRUE)
W = 0.90515, p-value < 2.2e-16

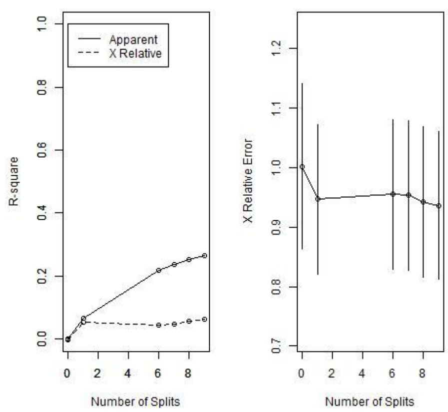
Figure D-1. Distribution of Residuals

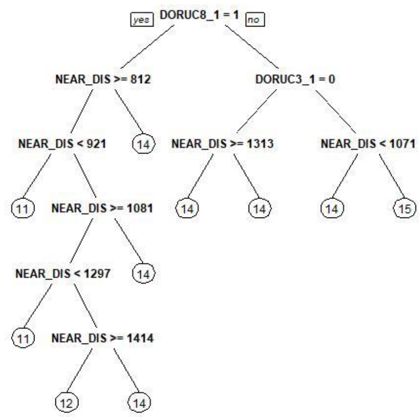
Table D-4. Assessment of Variable Performance (1-Mile Buffer)

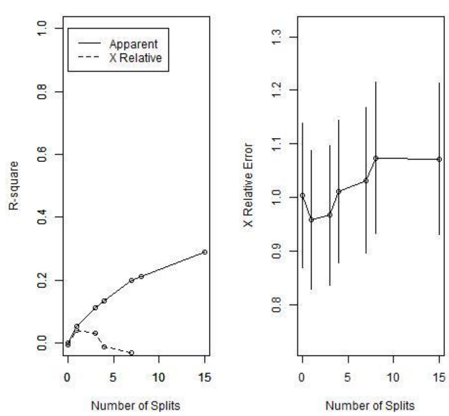
	Relative Variable Strength Standardized Beta	Variables' Contributions to the Model Adjusted R^2
ACTYRBLT	0.242771342	0.1012
TOTLVGAREA	0.111657088	0.0208
DIFDOR	-0.149117982	0.0082
JVCNG	0.062345407	0.0122
NEAR_DIST	-0.095661691	0.0256
SETYR	-0.050915137	0.0019
DORUC1_1	-0.026030982	0.0142*
DORUC3_1	0.111616604	0.0088*
DORUC4_1	0.055285557	0.0024*
DORUC6_1	0.055831854	0.00175*
DORUC8_1	0.001354328	8.106e-05*
SRCOYR	0.236672562	0.09127

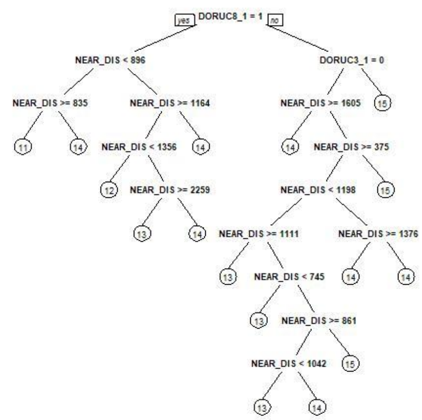
APPENDIX E
RECURSIVE PARTITIONING SUPPLEMENT

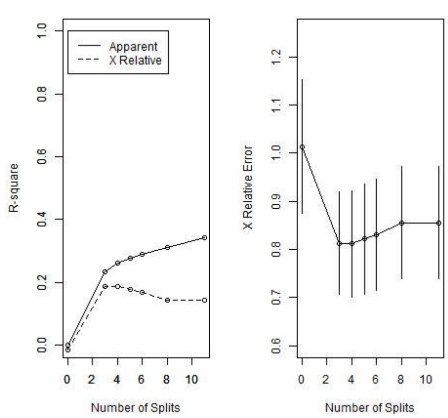
R2 Plots	Trees

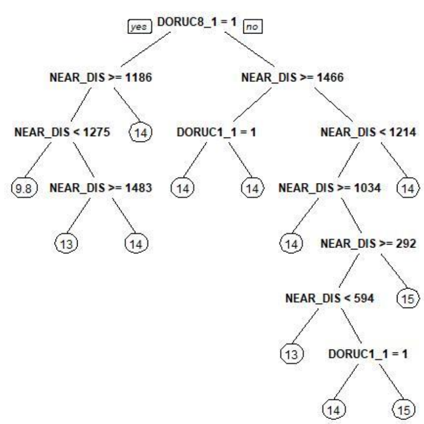


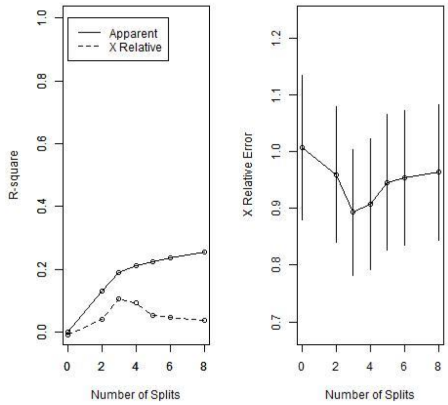


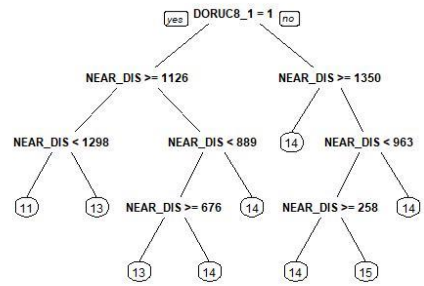


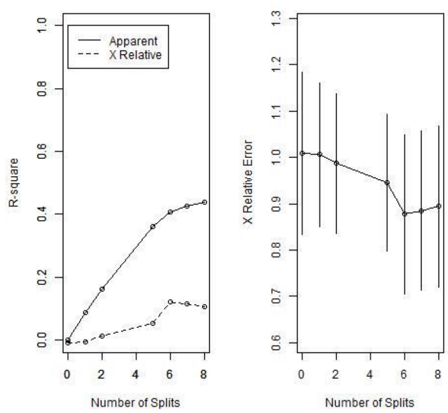


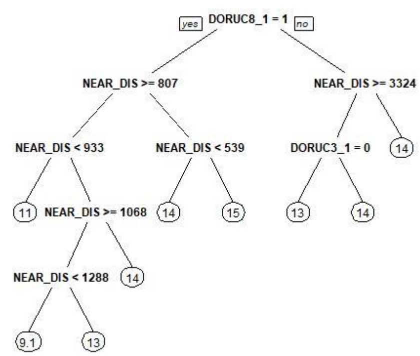


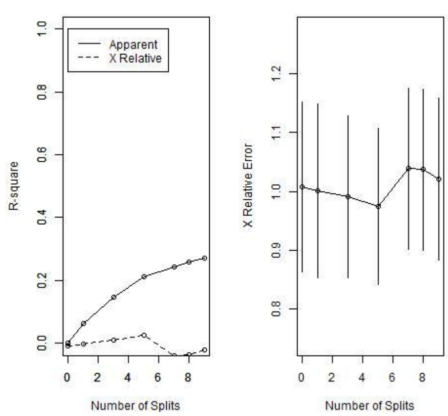


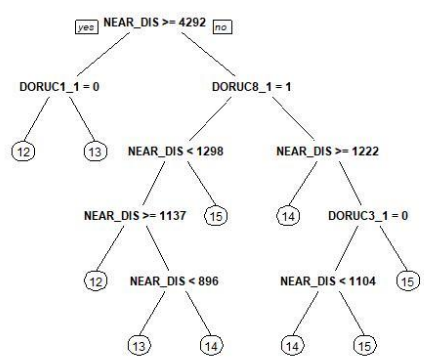

Apparent
X Relative
R-square
X Relative Error
Number of Splits
Number of Splits

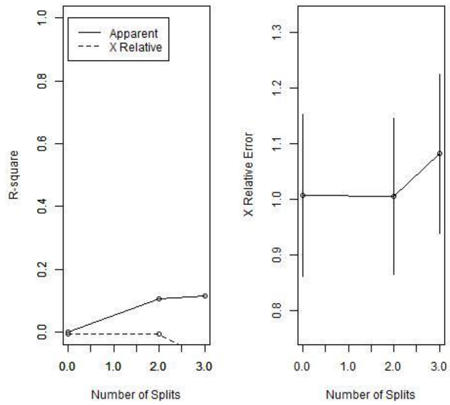

yes
DORUC8_1 = 1
no
NEAR_DIS >= 1126
NEAR_DIS >= 1350
NEAR_DIS < 1298
NEAR_DIS < 889
14
NEAR_DIS < 963
11
13
NEAR_DIS >= 676
14
NEAR_DIS >= 258
14
13
14
14
15


Apparent
X Relative
R-square
X Relative Error
Number of Splits
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 807
NEAR_DIS >= 3324
NEAR_DIS < 933
NEAR_DIS < 539
DORUC3_1 = 0
14
11
NEAR_DIS >= 1068
14
15
13
14
NEAR_DIS < 1288
14
9.1
13


Apparent
X Relative
R-square
X Relative Error
Number of Splits
Number of Splits


yes
NEAR_DIS >= 4292
no
DORUC1_1 = 0
DORUC8_1 = 1
12
13
NEAR_DIS < 1298
NEAR_DIS >= 1222
NEAR_DIS >= 1137
15
14
DORUC3_1 = 0
12
NEAR_DIS < 896
NEAR_DIS < 1104
15
13
14
14
15


Apparent
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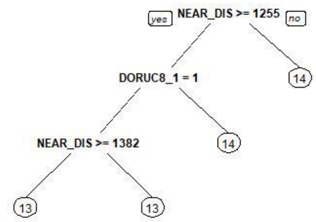
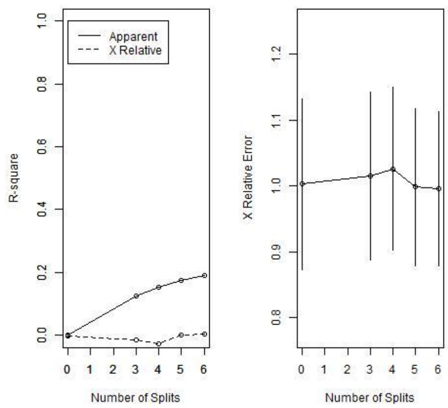
R-square
Number of Splits
X Relative Error
Number of Splits


yes
NEAR_DIS >= 1255
no
DORUC8_1 = 1
14
NEAR_DIS >= 1382
14
13
13


Apparent
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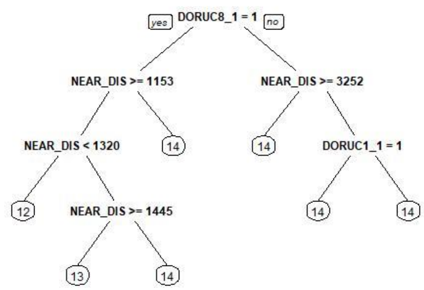
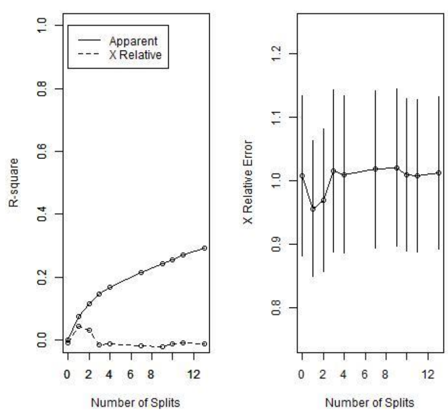
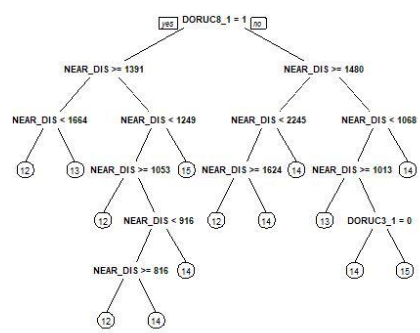
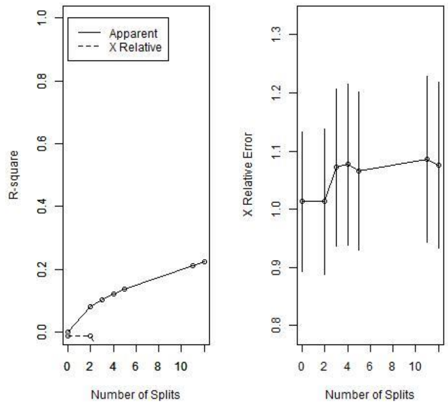
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 1153
NEAR_DIS >= 3252
NEAR_DIS < 1320
14
14
DORUC1_1 = 1
12
NEAR_DIS >= 1445
14
14
13
14


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 1391
NEAR_DIS >= 1480
NEAR_DIS < 1664
NEAR_DIS < 1249
NEAR_DIS < 2245
NEAR_DIS < 1068
12
13
NEAR_DIS >= 1053
15
NEAR_DIS >= 1624
14
NEAR_DIS >= 1013
14
12
NEAR_DIS < 916
12
14
13
DORUC3_1 = 0
NEAR_DIS >= 816
14
14
15
12
14


Apparent
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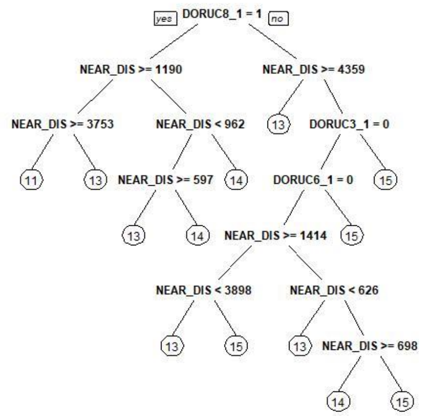
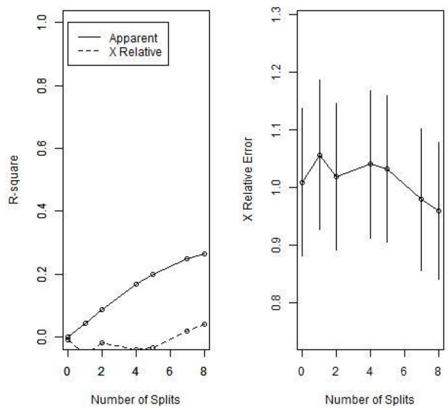
R-square
X Relative Error
Number of Splits
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 1190
NEAR_DIS >= 4359
NEAR_DIS >= 3753
NEAR_DIS < 962
13
DORUC3_1 = 0
11
13
NEAR_DIS >= 597
14
DORUC6_1 = 0
15
13
14
NEAR_DIS >= 1414
15
NEAR_DIS < 3898
NEAR_DIS < 626
13
15
13
NEAR_DIS >= 698
14
15


Apparent
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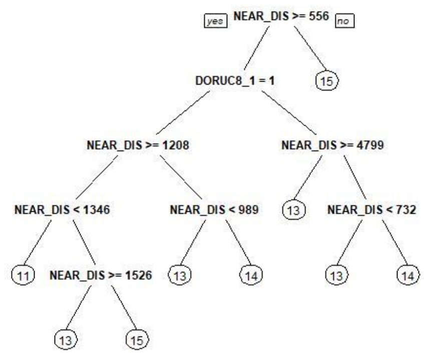
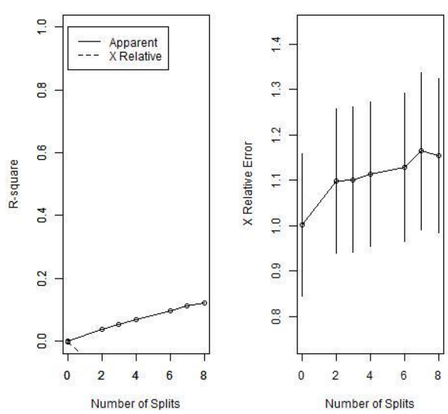
R-square
X Relative Error
Number of Splits
Number of Splits


yes
NEAR_DIS >= 556
no
DORUC8_1 = 1
15
NEAR_DIS >= 1208
NEAR_DIS >= 4799
NEAR_DIS < 1346
NEAR_DIS < 989
13
NEAR_DIS < 732
11
NEAR_DIS >= 1526
13
14
13
14
13
15


Apparent
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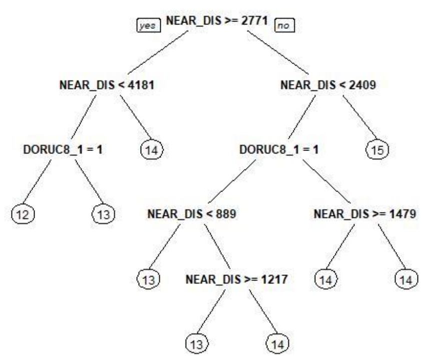
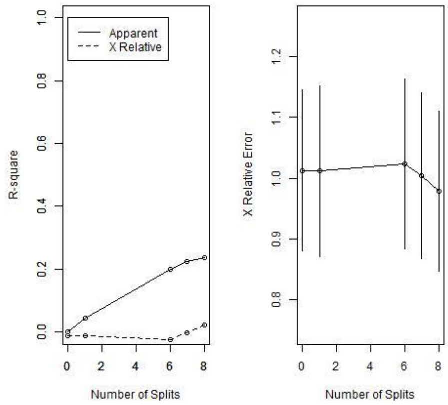
R-square
X Relative Error
Number of Splits
Number of Splits


yes
NEAR_DIS >= 2771
no
NEAR_DIS < 4181
NEAR_DIS < 2409
DORUC8_1 = 1
14
DORUC8_1 = 1
15
12
13
NEAR_DIS < 889
NEAR_DIS >= 1479
13
NEAR_DIS >= 1217
14
14
13
14



Apparent
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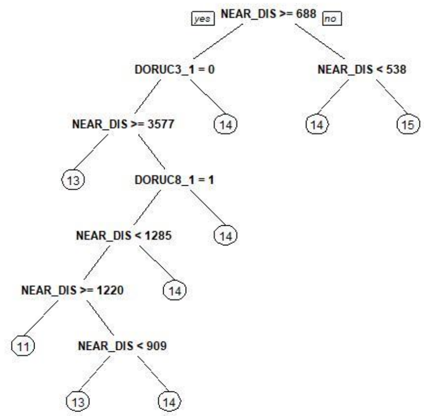
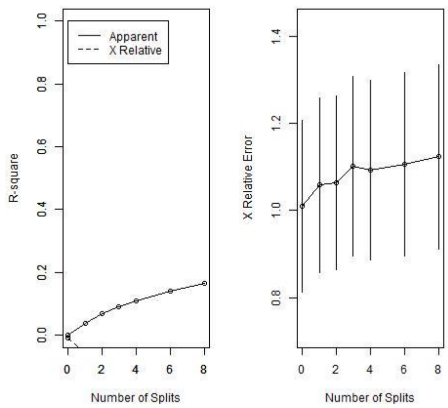
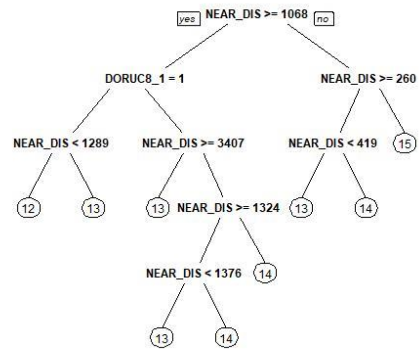
R-square
Number of Splits
X Relative Error
Number of Splits



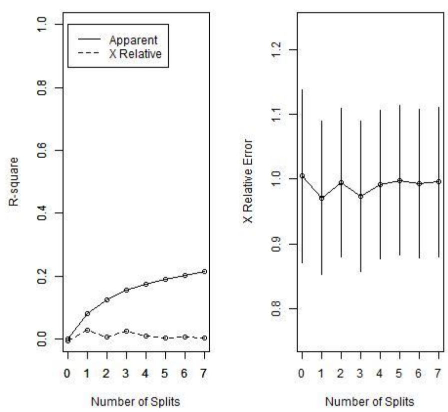
yes
NEAR_DIS >= 688
no
DORUC3_1 = 0
NEAR_DIS < 538
NEAR_DIS >= 3577
14
14
15
13
DORUC8_1 = 1
NEAR_DIS < 1285
14
NEAR_DIS >= 1220
14
11
NEAR_DIS < 909
13
14



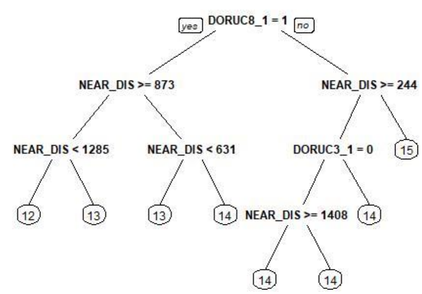
Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits



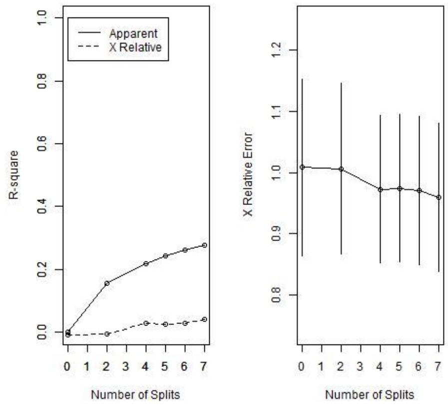
yes
NEAR_DIS >= 1068
no
DORUC8_1 = 1
NEAR_DIS >= 260
NEAR_DIS < 1289
NEAR_DIS >= 3407
NEAR_DIS < 419
15
12
13
13
NEAR_DIS >= 1324
13
14
NEAR_DIS < 1376
14
13
14

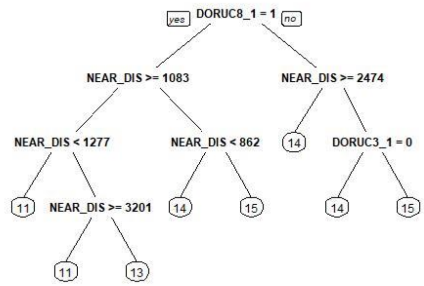


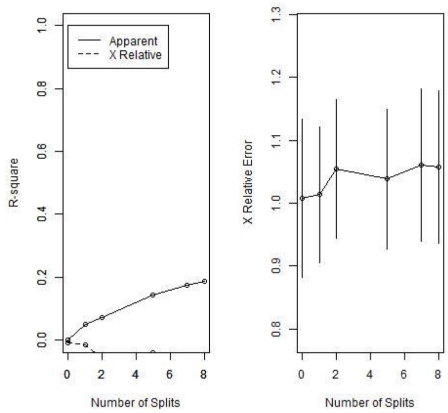
Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits



yes
DORUC8_1 = 1
no
NEAR_DIS >= 873
NEAR_DIS >= 244
NEAR_DIS < 1285
NEAR_DIS < 631
DORUC3_1 = 0
15
12
13
13
14
NEAR_DIS >= 1408
14
14
14


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 1083
NEAR_DIS >= 2474
NEAR_DIS < 1277
NEAR_DIS < 862
14
DORUC3_1 = 0
11
NEAR_DIS >= 3201
14
15
14
15
11
13


Apparent
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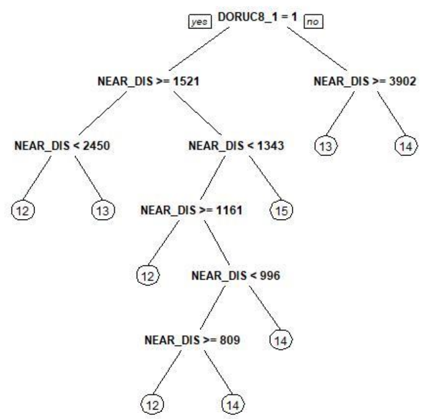
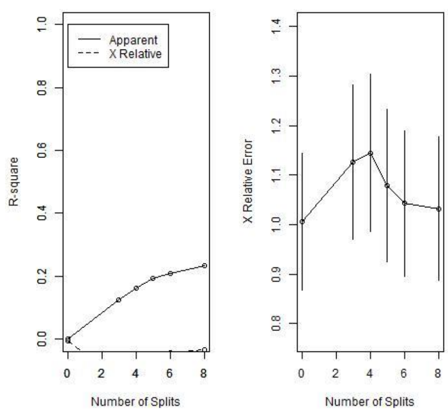
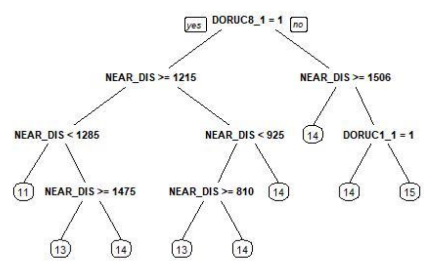
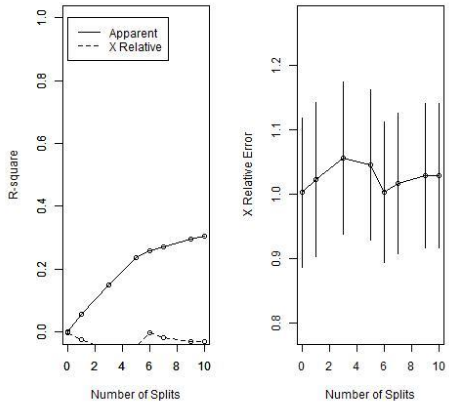
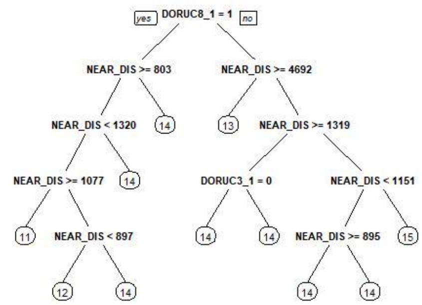
R-square
Number of Splits
X Relative Error
Number of Splits

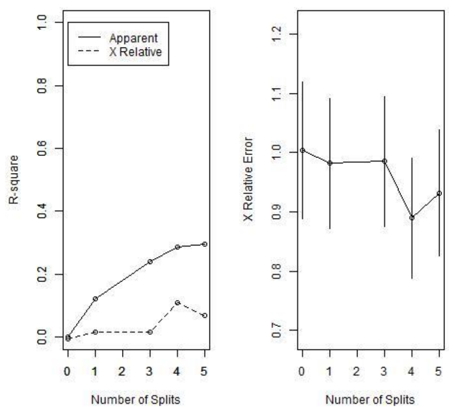

yes
DORUC8_1 = 1
no
NEAR_DIS >= 1521
NEAR_DIS >= 3902
NEAR_DIS < 2450
NEAR_DIS < 1343
13
14
12
13
NEAR_DIS >= 1161
15
12
NEAR_DIS < 996
NEAR_DIS >= 809
14
12
14

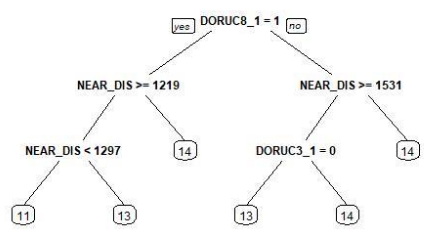

Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits

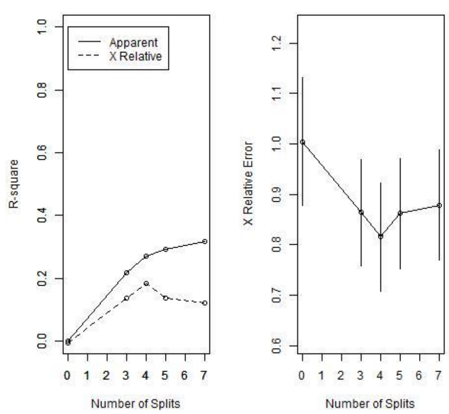

yes
DORUC8_1 = 1
no
NEAR_DIS >= 1215
NEAR_DIS >= 1506
NEAR_DIS < 1285
NEAR_DIS < 925
14
DORUC1_1 = 1
11
NEAR_DIS >= 1475
NEAR_DIS >= 810
14
14
15
13
14
13
14

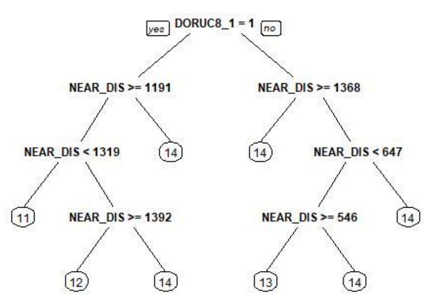

Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits

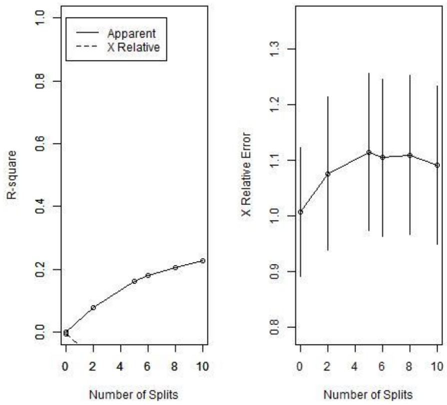

yes
DORUC8_1 = 1
no
NEAR_DIS >= 803
NEAR_DIS >= 4692
NEAR_DIS < 1320
NEAR_DIS >= 1319
NEAR_DIS >= 1077
DORUC3_1 = 0
NEAR_DIS < 1151
NEAR_DIS < 897
NEAR_DIS >= 895
11
12
13
14
15


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits

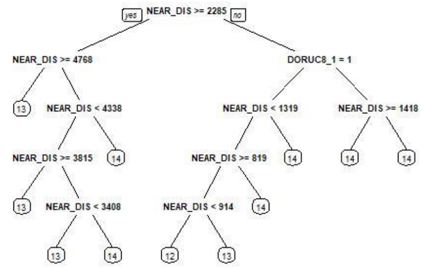

yes
DORUC8_1 = 1
no
NEAR_DIS >= 1219
NEAR_DIS >= 1531
NEAR_DIS < 1297
DORUC3_1 = 0
11
13
14


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits

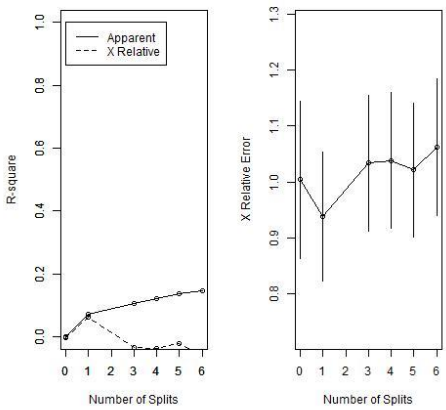

yes
DORUC8_1 = 1
no
NEAR_DIS >= 1191
NEAR_DIS >= 1368
NEAR_DIS < 1319
NEAR_DIS < 647
NEAR_DIS >= 1392
NEAR_DIS >= 546
11
12
13
14



Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits



yes
NEAR_DIS >= 2285
no
NEAR_DIS >= 4768
DORUC8_1 = 1
13
NEAR_DIS < 4338
NEAR_DIS < 1319
NEAR_DIS >= 1418
NEAR_DIS >= 3815
14
NEAR_DIS >= 819
14
14
14
13
NEAR_DIS < 3408
NEAR_DIS < 914
14
13
14
12
13



Apparent
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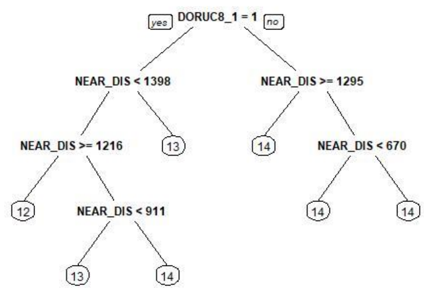
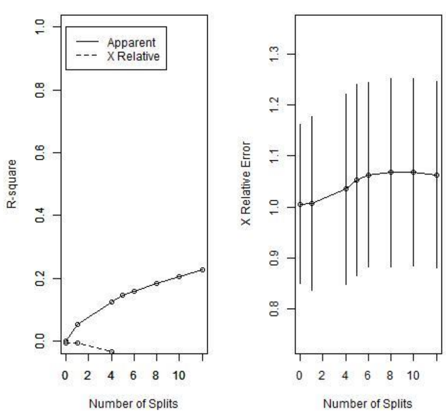
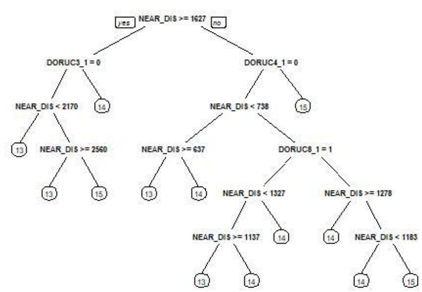
R-square
Number of Splits
X Relative Error
Number of Splits



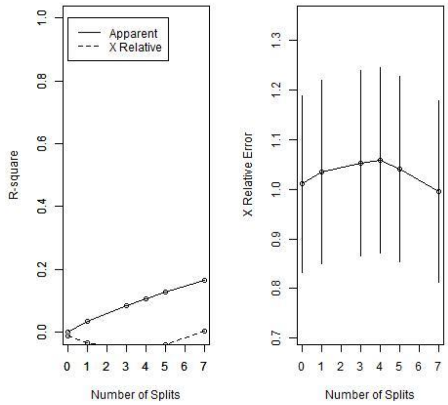
yes
DORUC8_1 = 1
no
NEAR_DIS < 1398
NEAR_DIS >= 1295
NEAR_DIS >= 1216
13
14
NEAR_DIS < 670
12
NEAR_DIS < 911
14
14
13
14



Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits



yes
NEAR_DIS >= 1627
no
DORUC3_1 = 0
DORUC4_1 = 0
NEAR_DIS < 2170
14
NEAR_DIS < 738
15
13
NEAR_DIS >= 2560
NEAR_DIS >= 637
DORUC8_1 = 1
13
15
13
14
NEAR_DIS < 1327
NEAR_DIS >= 1278
NEAR_DIS >= 1137
14
14
NEAR_DIS < 1183
13
14
14
15


Apparent
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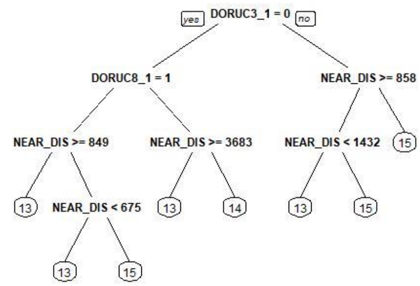
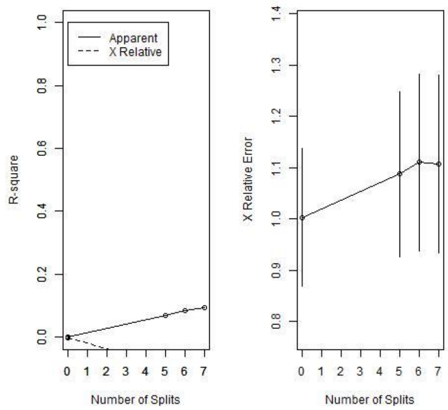
R-square
Number of Splits
X Relative Error
Number of Splits


DORUC3_1 = 0
yes
no
DORUC8_1 = 1
NEAR_DIS >= 858
NEAR_DIS >= 849
NEAR_DIS >= 3683
NEAR_DIS < 1432
15
13
NEAR_DIS < 675
13
14
13
15
13
15


Apparent
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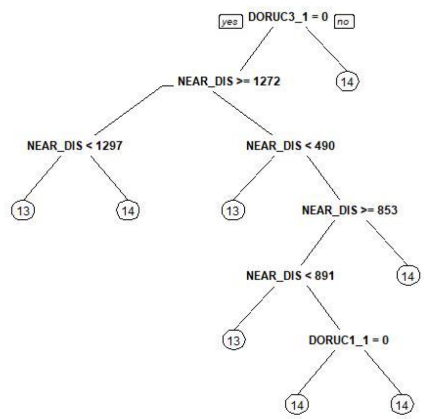
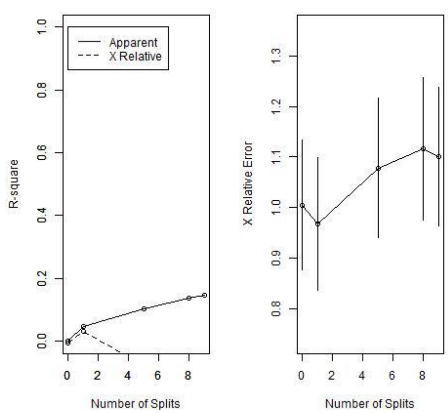
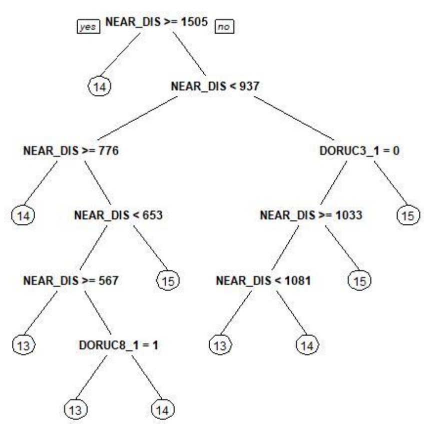
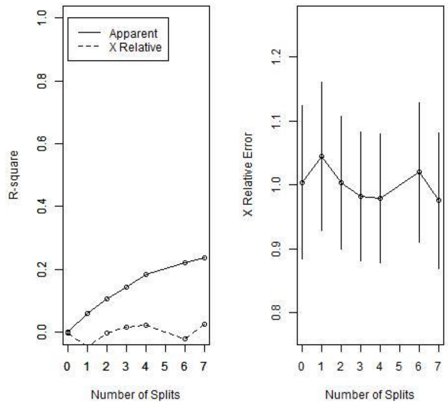
R-square
Number of Splits
X Relative Error
Number of Splits


DORUC3_1 = 0
yes
no
NEAR_DIS >= 1272
14
NEAR_DIS < 1297
NEAR_DIS < 490
13
14
13
NEAR_DIS >= 853
NEAR_DIS < 891
14
13
DORUC1_1 = 0
14
14


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits


NEAR_DIS >= 1505
yes
no
14
NEAR_DIS < 937
NEAR_DIS >= 776
DORUC3_1 = 0
14
NEAR_DIS < 653
NEAR_DIS >= 1033
15
NEAR_DIS >= 567
15
NEAR_DIS < 1081
15
13
DORUC8_1 = 1
13
14
13
14


Apparent
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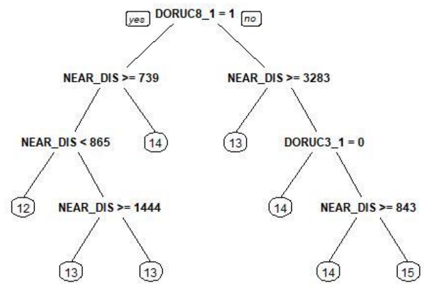
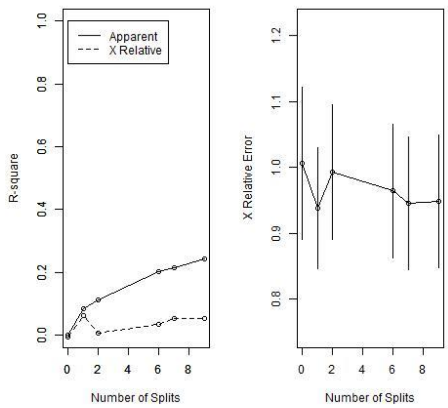
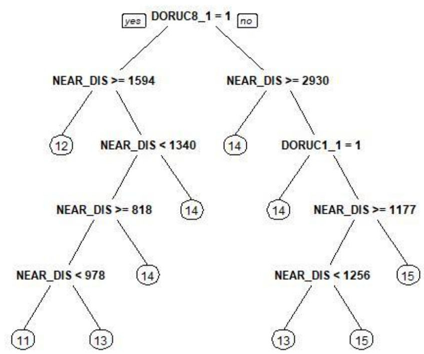
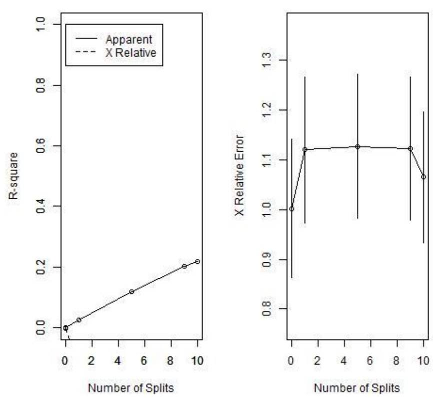
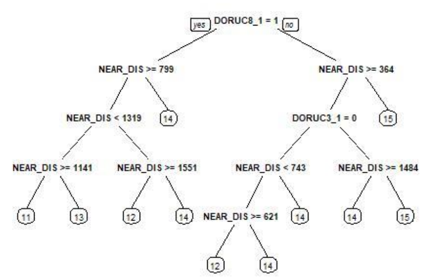
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 739
NEAR_DIS >= 3283
NEAR_DIS < 865
DORUC3_1 = 0
NEAR_DIS >= 1444
NEAR_DIS >= 843


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 1594
NEAR_DIS >= 2930
NEAR_DIS < 1340
DORUC1_1 = 1
NEAR_DIS >= 818
NEAR_DIS >= 1177
NEAR_DIS < 978
NEAR_DIS < 1256


Apparent
X Relative
R-square
Number of Splits
X Relative Error
Number of Splits


yes
DORUC8_1 = 1
no
NEAR_DIS >= 799
NEAR_DIS >= 364
NEAR_DIS < 1319
DORUC3_1 = 0
NEAR_DIS >= 1141
NEAR_DIS >= 1551
NEAR_DIS < 743
NEAR_DIS >= 1484
NEAR_DIS >= 621

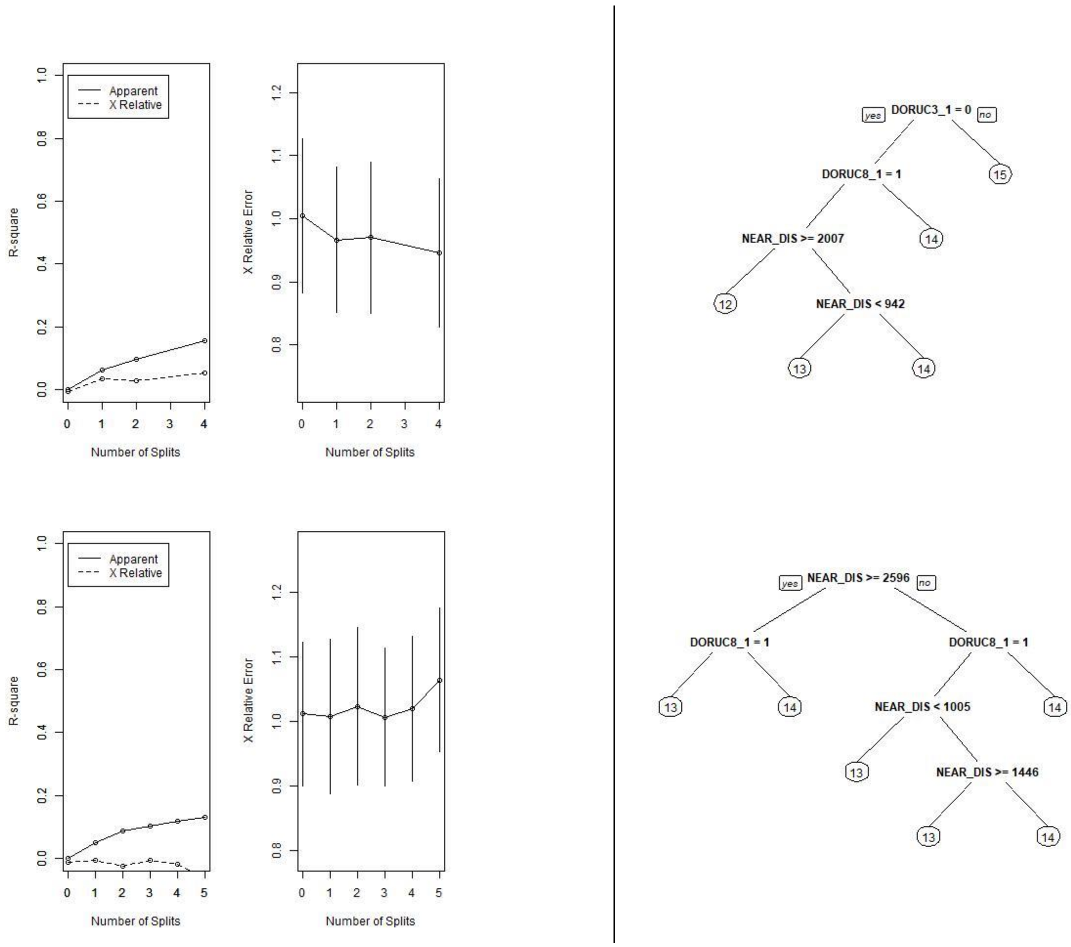


Figure E-1. Sample of Model Results (1-mile buffer)

APPENDIX F

CENSUS AND AMERICAN COMMUNITY SURVEY DATA SUMMARY

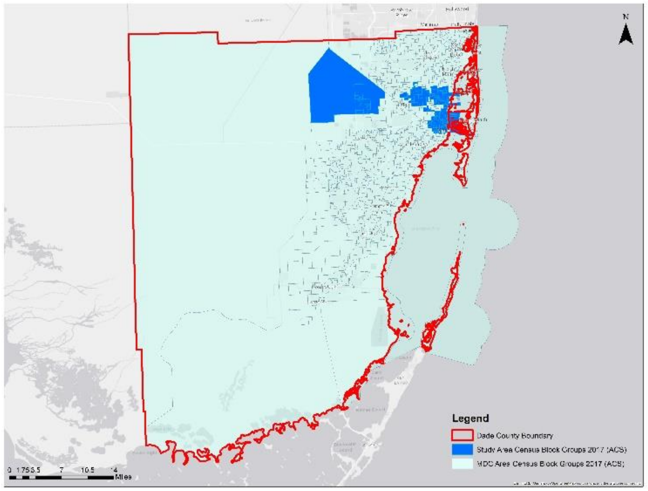


Figure F-1. 2017 ACS Census Block Groups (study area and Miami-Dade County)

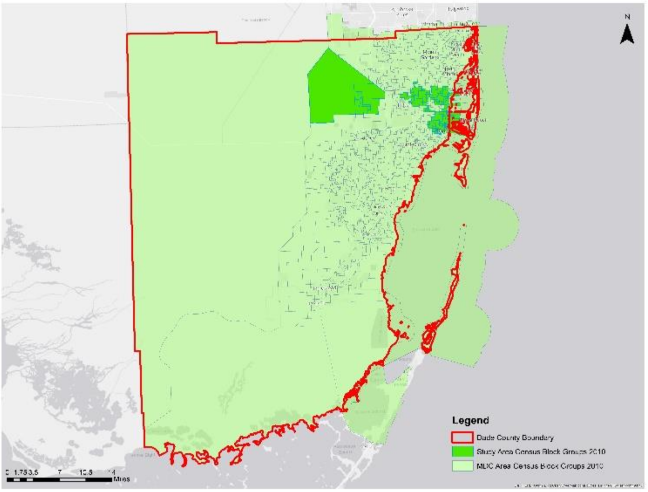


Figure F-2. 2010 ACS Census Block Groups (study area and Miami-Dade County)

Table F-1. 2010 and 2017 Census Data Summaries

Variable Name	Study Area 2010	Study Area 2017	Miami-Dade County 2010	Miami-Dade County 2017
FREQUENCY	168	168	1621	1594
SUM_ACRES	58690.24	58694.35	1603186	1555945
SUM_TOTALPOP	223136	245850	2573219	2702602
POPULATION DENSITY	3.801927	4.188648	1.605066	1.736953
SUM_WHITE	127177	149169	1882541	2043272
% WHITE*	0.569953	0.606748	0.73159	0.756039
SUM_BLACK	75905	81199	500224	485602
% BLACK*	0.340174	0.330279	0.194396	0.179679
SUM_AMERI_ES	792	174	5183	4040

Table F-1. Continued

Variable Name	Study Area 2010	Study Area 2017	Miami-Dade County 2010	Miami-Dade County 2017
% AMERI_ES*	0.003549	0.000708	0.002014	0.001495
SUM_HAWN_PI	47	78	706	724
% HAWAIIAN/PACIFIC ISLANDER*	0.000211	0.000317	0.000274	0.000268
SUM_ASIAN	2632	2764	40774	42770
% ASIAN*	0.011795	0.011243	0.015846	0.015825
SUM_OTHER	10060	8716	82296	84892
% OTHER*	0.045085	0.035453	0.031982	0.031411
SUM_MULT_RACE	6523	3750	61495	41302
% MULTI-RACE*	0.029233	0.015253	0.023898	0.015282
SUM_NOT_HISP	95399	N/A	919671	N/A
% NOT HISPANIC*	0.427537	N/A	0.357401	N/A
SUM_HSE_UNITS	92967	N/A	1023008	N/A
SUM_BELOW_POV	61069	66224	418410	505182
% BELOW POVERTY*	0.273685	0.269368	0.162602	0.186924
SUM_AGE_5_17	35007	37079	410604	397099
% AGE 5-17*	0.156886	0.15082	0.159568	0.146932
SUM_AGE_18_21	12398	11122	145970	136640
SUM_AGE_18_21	12398	11122	145970	136640
% AGE 18-21*	0.055563	0.045239	0.056727	0.050559
SUM_AGE_22-29	28392	28540	284598	302842
% AGE 22-29*	0.127241	0.116087	0.1106	0.112056
SUM_AGE_30_39	34817	39515	364375	375425
% AGE 30-39*	0.156035	0.160728	0.141603	0.138912
SUM_AGE_40_49	33366	36832	398174	396640
SUM_AGE_50_64	36662	44581	452920	523434
SUM_AGE_40-49	33366	36832	398174	396640
SUM_AGE_50_64	36662	44581	452920	523434
% AGE 50-64*	0.164303	0.181334	0.176013	0.193678

Table F-1. Continued

Variable Name	Study Area 2010	Study Area 2017	Miami-Dade County 2010	Miami-Dade County 2017
SUM_AGE_65_UP	27141	31526	361283	414322
% AGE 65+	0.121634	0.128233	0.140401	0.153305
SUM_OWNER	26106	24579	502542	448011
% HOMEOWNER*	0.116996	0.099976	0.195297	0.16577
SUM_RENTER	54398	59537	391238	410278
	0.243789	0.242168	0.152042	0.151809
SUM_BACHELORS	18153	28376	286109	339002
% OF TOTAL ED W/ BACHELORS*	0.127549	0.166353	0.168013	0.177833
SUM_HSGRAD	94766	129807	1315351	1543966
% OF TOTAL ED GRADUATED HS*	0.665856	0.760988	0.772421	0.809929
SUM_ED_TOTAL	142322	170577	1702894	1906299
SUM_HOUSEHOLDS	80504	84116	893780	858289
SUM_WHITE_NH	N/A	21145	N/A	371233
% WHITE NON-HISPANIC*	N/A	0.086008	N/A	0.137361

*Field calculated from base data
See metadata for CENACS_2017 hosted by the Florida Geographic Data Library for variable descriptions

APPENDIX G
DATA SOURCES

Table G-1. Data Source Tables

File Name	Year(s)	Originator	Description
NAL_2011_23Dade_F NAL_2013_23Dade_F NAL_2015_23Dade_F NAL_2016_23Dade_F	2011, 2013, 2015, 2016	Florida Department of Revenue	2011, 2013, 2015, and 2016 parcel datasets
Contaminated_Site	2018	Miami-Dade County (OpenData)	A point feature class of open DERM Contaminated sites within Miami-Dade County. See phase code for the status of the site. Contaminated Sites, identifies properties where environmental contamination has been documented in the soil or around water. Facilities get listed as a contaminated site by a DERM inspector who finds a violation on the property. Facilities that store potentially contaminated materials are permitted and/or tracked by DERM. A site is removed from the active contaminated sites layer/list when the site is found by DERM to be cleaned up.
Environmental_Permits	2018	Miami-Dade County (OpenData)	List of open and closed permits issued or tracked by DERM

Table G-2. GIS Shapefiles Data Sources

File Name	Year(s)	Originator	Description
CNTBND_SEP15	2016	University of Florida GeoPlan Center (Hosted on the Florida Geographic Data Library website)	2015 county boundaries for the State of Florida with generalized shorelines
Brownfield_Areas	2019	Florida Department of Environmental Protection (OpenData)	Designated Brownfield Areas throughout the State of Florida
countyshore_areas_sep15	2016	University of Florida GeoPlan Center	2015 county boundaries for the State of Florida with detailed shorelines
MAJRDS_JUL19	2019	University of Florida GeoPlan Center (Hosted on the Florida Geographic Data Library website)	2019 major roads for the State of Florida

Table G-2. Continued

File Name	Year(s)	Originator	Description
CENACS_2017	2019	United States Census Bureau (Hosted on the Florida Geographic Data Library website)	2013-2017 American Community Survey statistics by 2015 Census Block Group
CENBLKGRP2010_SF_MAR11	2019	United States Census Bureau (Hosted on the Florida Geographic Data Library website)	2013-2017 American Community Survey statistics by 2015 Census Block Group
parcels_2010, parcels_2012, parcels_2014, parcels_2017, and parcels_2018	2019, 2013, 2014, 2016, 2018, and 2019	University of Florida GeoPlan Center (Hosted on the Florida Geographic Data Library website)	2010, 2012, 2014, 2017, and 2018 parcel datasets from the Florida Department of Revenue's NAL tables
parcels_2004	2004	Provided by the University of Florida GeoPlan Center	2004 parcel datasets from the Florida Department of Revenue's NAL tables
Opportunity20Zones=8764.%209-10-2019	2019	United States Department of the Treasury Community Development Financial Institutions Fund	Shapefile containing designated Opportunity Zones throughout the United States as of 2019

APPENDIX H
MODEL SCRIPTS

Model 1 Script

```
###LIBRARIES/PACKAGES###
install.packages("ggcorrplot")
library(ggcorrplot)
install.packages("dplyr")
library(dplyr)
install.packages("lm.beta")
library(lm.beta)

##setwd("INPUT FOLDER”)
dadesource <- read.csv("INPUT FILE", na.strings="0", stringsAsFactors=FALSE)
View(dadesource)

##Replace na with 0##
head(dadesource)
dadesource <- as.data.frame(dadesource)
dadesource[is.na(dadesource)] <- 0
head(dadesource)

##More information about the master dataset##
write.csv(summary(dadesource),'summary-dadesource.csv')
write.csv(cor(dadesource,method="pearson"),file="cor-dadesource.csv")

##Review dataset variable names for model inputs##
names(dadesource)

##LM Test##
dadelm<-
lm(ADJV2~ACTYRBLT+TOTLVGAREA+DIFDOR+JVCNG+NEAR_DIST+SETYR+DORUC1_1+DORUC3_1+DORUC4_1+DORUC6_1+DORU
C8_1+SRCO_YR,data=dadesource)
summary(dadelm)

##Individual Variable Summaries##
summary(lm(ADJV2~ACTYRBLT,data=dadesource))
summary(lm(ADJV2~TOTLVGAREA,data=dadesource))
summary(lm(ADJV2~DIFDOR,data=dadesource))
summary(lm(ADJV2~JVCNG,data=dadesource))
summary(lm(ADJV2~NEAR_DIST,data=dadesource))
summary(lm(ADJV2~SETYR,data=dadesource))
summary(lm(ADJV2~DORUC1_1,data=dadesource))
summary(lm(ADJV2~DORUC3_1,data=dadesource))
summary(lm(ADJV2~DORUC4_1,data=dadesource))
summary(lm(ADJV2~DORUC6_1,data=dadesource))
summary(lm(ADJV2~DORUC8_1,data=dadesource))
summary(lm(ADJV2~SRCO_YR,data=dadesource))

##Standardized betas for the LM##
lm.beta(dadelm)

#Predictions#
pdadelm2<-data.frame(predict(dadelm,dadesource,se.fit=TRUE))
plot(pdadelm$fit[sample(pdadelm$fit,100,replace=TRUE)])

#Analysis/Plot of residuals#
dadelmres<-c(dadesource$ADJV2-pdadelm2$fit)

##Test for normal distribution of residuals##
shapiro.test(sample(dadelmres,5000,replace=TRUE))

##Plot of Residuals versus Actual Values for Model 1##
jpeg(filename='residvact.jpg')
plot(dadesource$ADJV2,dadelm.res,xlab='Actual Adjusted Just Value (ADJV2)',ylab='Residuals from Model 1')
```

```
title('Plot of Actual Values vs. Residuals for Model 1')
dev.off()
summary(pdadelm)
```

Model 2 Script

```
install.packages("rpart")
library(rpart)
install.packages("rpart.plot")
library(rpart.plot)

##setwd("INPUT FOLDER")
##dadesource <- read.csv("INPUT FILE", na.strings="0", stringsAsFactors=FALSE)
 dadesource <- as.data.frame(dadesource)
 dadesource[is.na(dadesource)] <- 0
 # Call dataframe #
 dadeneed<-
data.frame(dadesource$ADJV2,dadesource$ACTYRBLT,dadesource$TOTLVGAREA,dadesource$DIFDOR,dadesource$JVCNG,dadesource$
NEAR_DIST,dadesource$SETYR,dadesource$DORUC1_1,dadesource$DORUC3_1,dadesource$DORUC4_1,dadesource$DORUC6_1,dadesou
rce$DORUC8_1,dadesource$SRCO_YR, stringsAsFactors=FALSE)
 #Fix the variable names#
 names(dadeneed)<-c('ADJV2','ACTYRBLT', 'TOTLVGAREA', 'DIFDOR', 'JVCNG', 'NEAR_DIST','SETYR', 'DORUC1_1', 'DORUC3_1',
'DORUC4_1', 'DORUC5_1', 'DORUC6_1','DORUC8_1', 'SRCO_YR')


##Run function which will generate a random sample of n=300 of the dataset with replacement, then apply the rpart function##

rpartmodel<-function(x) {

  # Call dataframe #
  dadeneed<-
data.frame(dadesource$ADJV2,dadesource$ACTYRBLT,dadesource$TOTLVGAREA,dadesource$DIFDOR,dadesource$JVCNG,dadesource$
NEAR_DIST,dadesource$SETYR,dadesource$DORUC1_1,dadesource$DORUC3_1,dadesource$DORUC4_1,dadesource$DORUC5_1,dadesou
rce$DORUC6_1,dadesource$DORUC8_1,dadesource$SRCO_YR, stringsAsFactors=FALSE)

  #Fix the variable names#
 names(dadeneed)<-c('ADJV2','ACTYRBLT', 'TOTLVGAREA', 'DIFDOR', 'JVCNG', 'NEAR_DIST','SETYR', 'DORUC1_1', 'DORUC3_1',
'DORUC4_1', 'DORUC5_1', 'DORUC6_1','DORUC8_1', 'SRCO_YR')

 #Generate a random sample of 300 rows from the master dataset#
 singlesample<-dadeneed[sample(nrow(dadeneed),300,replace=TRUE),]

 #Fix the variable names again#
 names(singlesample)<-c('ADJV2','ACTYRBLT', 'TOTLVGAREA', 'DIFDOR', 'JVCNG', 'NEAR_DIST','SETYR', 'DORUC1_1', 'DORUC3_1',
'DORUC4_1', 'DORUC5_1', 'DORUC6_1','DORUC8_1', 'SRCO_YR')

  #Run recursive partitioning function#
dtreetest<-rpart(ADJV2~DORUC1_1+DORUC3_1+NEAR_DIST+DORUC4_1+DORUC5_1+DORUC6_1+DORUC8_1,data=singlesample)

#Write outputs to files#
jpeg(filename=paste('rpartprp',x,'.jpg',sep=''))
prp(dtreetest)
dev.off()
jpeg(filename=paste('rsquared',x,'.jpg',sep=''))
par(mfrow=c(1,2))
rsq.rpart(dtreetest)
dev.off()
capture.output(summary(dtreetest), file = paste('rpartred_',x,'.txt',sep=''))
write.csv(cbind(predict(dtreetest,dadeneed),x), file = paste('model',x,'.csv',sep=''))
assign(paste('model',x,sep=''),data.frame(cbind(predict(dtreetest,dadeneed)),x),envir = .GlobalEnv)
}

output<-sapply(1:32,rpartmodel)

IDkeeper<-function(x){
  ID<-c(1:nrow(dadesource))
  assign(paste('model',x,sep=''),data.frame(cbind(get(paste0('model',x,sep='')),ID)),envir = .GlobalEnv)
```

```
}

output1<-sapply(1:32,IDkeeper)

GCIDCON<-function(x){
  GCID<-dadesource$GCID[1:nrow(dadesource)]
  assign(paste('model',x,sep=''),data.frame(cbind(get(paste0('model',x,sep='')),GCID)),envir = .GlobalEnv)
}

output2<-sapply(1:32,GCIDCON)

predictedval<-
data.frame(rbind(model1,model2,model3,model3,model4,model5,model6,model7,model8,model9,model10,model11,model12,model13,
model14,model15,model16,model17,model18,model19,model20,model21,model22,model23,model24,model25,model26,model27,mode
l28,model29,model30,model31,model32))

names(predictedval)<-c('PRED','SET','ROWID')

write.csv(predictedval,file='predicted.csv')

###FAST RESULTS  IN LIEU OF MULTITHREAD PROCESSING###
averages<-function(x){
  subpredictedval<-subset(predictedval,ROWID==as.integer(x))
  mean(c(subpredictedval$PRED))
}

Model2results<-data.frame(c(sapply(sample(predictedval$ROWID,500),averages)))
list<-function(x){
  x*400
}
Model2sample<-sapply(1:500,list)
Model2results<-data.frame(c(sapply(Model2sample,averages)))
Model2results<-cbind(Model2results,dadesource$ADJV2[c(1:500)])
R2<-cor(Model2results,method="pearson")

###END FAST RESULTS###

###SLOW RESULTS (FULL DATASET)###

Model2fullresults<-data.frame(c(sapply(1:nrow(dadesource),averages)))
Model2results<-data.frame(c(sapply(Model2fullresults,averages)))
Model2results<-cbind(Model2results,dadesource$ADJV2[c(1:length(Model2fullresults))])
Model2results<-cbind(Model2fullresults,Model2results)
write.csv(Model2fullresults,file='Model2results25.csv')
r2fullresults<-cbind(Model2fullresults,c(1:nrow(dadesource)),dadesource$ADJV2)
names(r2fullresults)<-c('PRED','ROWID','ORIGADJV2')
r2fullresults<-cbind(r2fullresults,c(r2fullresults$ORIGADJV2-r2fullresults$PRED))
names(r2fullresults)<-c('PRED','ROWID','ORIGADJV2','RESID')
jpeg(filename='residvact2.jpg')
plot(r2fullresults$PRED,r2fullresults$RESID,xlab='Actual Adjusted Just Value (ADJV2)',ylab='Residuals from Model 2')
title('Plot of Actual Values vs. Residuals for Model 2 (0.25 miles)')
dev.off()
R2<-cor(r2fullresults,method="pearson")

###END SLOW RESULTS###
```

LIST OF REFERENCES

Aktas, C. B., Bartholomew, P., & Church, S. (2017). Application of GIS to Prioritize Brownfield Sites for Green Building Construction Based on LEED Criteria. *Journal of Urban Planning and Development*, 143(3), 04017004.

Allen, B. L. (2003). *Uneasy alchemy: citizens and experts in Louisianas chemical corridor disputes*. Cambridge, MA: MIT Press.

Bacot, H., & O'Dell, C. (2006). Establishing Indicators to Evaluate Brownfield Redevelopment. *Economic Development Quarterly*, 20(2), 142–161. doi: 10.1177/0891242405285749

Bäing, A. S., & Wong, C. (2018). The impact of brownfield regeneration on neighbourhood dynamics: The case of Salford Quays in England. *Town Planning Review*, 89(5), 513-534.

Bay, J.H., & Lehmann, S. (2017). Growing Compact : Urban Form, Density and Sustainability. New York: Routledge.

Blackwell, V. (2017, October 20). Toxic tensions in the heart of 'Cancer Alley'. Retrieved October 17, 2019, from https://www.cnn.com/2017/10/20/health/louisiana-toxic-town/index.html.

Davis, T. S. (2002). Brownfields: a comprehensive guide to redeveloping contaminated property. Chicago, IL: American Bar Association, Section of Environment, Energy, and Resources.

De Sousa, C. A., Wu, C., & Westphal, L. M. (2009). Assessing the Effect of Publicly Assisted Brownfield Redevelopment on Surrounding Property Values. *Economic Development Quarterly*, 23(2), 95-110.

DiPasquale, D., & Wheaton, W. C. (1996). *Urban economics and real estate markets*. Englewood Cliffs, NJ: Prentice-Hall.

Donahue, M., & Mitchell, S. (2019, April 23). Dollar Stores Are Targeting Struggling Urban Neighborhoods and Small Towns. One Community Is Showing How to Fight Back. Retrieved from https://ilsr.org/dollar-stores-target-cities-towns-one-fights-back/

Dubé, J., & Legros, D. (2014). Spatial econometrics and the hedonic pricing model: what about the temporal dimension? *Journal of Property Research*, 31(4), 333–359.

Draper, N. R., & Smith, H. (1998). *Applied regression analysis* (Vol. 326). John Wiley & Sons.

Dubin, R. A. (1998). Spatial Autocorrelation: A Primer. Journal of Housing Economics, 7(4), 304–327. doi: 10.1006/jhec.1998.0236

Dubin, R., Pace, K., & Thibodeau, T. (1999). Spatial Autoregression Techniques for Real Estate Data. *Journal of Real Estate Literature*, 7(1), 79–95.

Environmental Protection Agency (EPA). (2019a, April 15). Overview of EPA's Brownfields Program. Retrieved April 27, 2019, from https://www.epa.gov/brownfields/overview-brownfields-program

Environmental Protection Agency, United States (EPA). (2019b). [Table]. Cleanups in Your Community. Retrieved from

Esri Canada. (2018, Oct, 19). r-arcgis-tutorials [GitHub Repository]. Retrieved from https://github.com/EsriCanada-CE/r-arcgis-tutorials

Esri. (n.d.). How Spatial Autocorrelation (Global Moran's I) works—ArcGIS Pro | ArcGIS Desktop, from https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm

Florida Department of Environmental Protection (FDEP) & Environmental Protection Agency, United States (EPA). (2005). *Memorandum of Agreement Between the Florida Department of Environmental Protection and the United States Environmental Protection Agency Region 4.* Retrieved from https://floridadep.gov/sites/default/files/Brownfields%20MOA%20with%20EPA%2011-28-05_0.pdf

Florida Department of Environmental Protection (FDEP). (2019a, September 27). Brownfields Program. Retrieved October 12, 2019, from https://floridadep.gov/waste/waste-cleanup/content/brownfields-program.

Florida Department of Environmental Protection (FDEP). (2019b, October 1). Florida Brownfields Area and Site Documentation. Retrieved October 15, 2019, from https://floridadep.gov/waste/waste-cleanup/content/florida-brownfields-area-and-site-documentation.

Florida Department of Environmental Protection (FDEP). (n.d.a). Contamination Locator Map. Retrieved April 27, 2019, from http://prodenv.dep.state.fl.us/DepClnup/welcome.do

Florida Department of Environmental Protection (FDEP). (n.d.b). Florida Brownfields Area and Site Documentation. Retrieved April 27, 2019, from https://floridadep.gov/waste/waste-cleanup/content/florida-brownfields-area-and-site-documentation

Florida Department of Revenue (FDOR). (2018, August 10). 2018 User’s Guide Department Property Tax Data Files [Code book]. Retrieved from ftp://sdrftp03.dor.state.fl.us/Tax%20Roll%20Data%20Files/2018_NAL_SDF_NAP_Users_Guide/

Florida Department of State, State Library and Archives of Florida (FDOS). Brownfields Redevelopment Act. (n.d.). Retrieved October 12, 2019, from http://laws.flrules.org/node/562.

Gibbs, L. M. (2011). *Love Canal and the birth of the environmental health movement.* Washington: Island Press.

Haninger, K., Ma, L., & Timmins, C. (2014). The Value of Brownfield Remediation. National Bureau of Economic Research.

Hedonic Price Method. (n.d.). Retrieved September 30, 2018, from http://www.cbabuilder.co.uk/Quant5.html

Hernan, R. E. (2010). *This borrowed earth: lessons from the fifteen worst environmental disasters around the world*. New York: St. Martins Griffin.

Kent State. (2019, October 28). SPSS Tutorials: Pearson Correlation. Retrieved November 7, 2019, from https://libguides.library.kent.edu/SPSS/PearsonCorr.

Kernel Regression. (2014, February 2). Retrieved September 30, 2018, from http://mccormickml.com/2014/02/26/kernel-regression/

Mashayekh, Y., Hendrickson, C., & Matthews, H. S. (2012). Role of Brownfield Developments in Reducing Household Vehicle Travel. *Journal of Urban Planning and Development*, 138(3), 206-214.

McNichol, E., & Johnson, N. (2010). *Recession Continues to Batter State Budgets; State Responses Could Slow Recovery.* Center on Budget and Policy Priorities. Retrieved from https://www.researchgate.net/profile/Elizabeth_Mcnichol/publication/265082535_Recession_Continues_to_Batter_State_Budgets_State_Responses_could_Slow_Recovery/links/55ba34c908ae092e965da1a9.pdf

Miami-Dade County. (2014). Contaminated Site [Contaminated sites in Miami-Dade County maintained by DERM]. Retrieved December 5, 2018, from https://gis-mdc.opendata.arcgis.com/datasets/contaminated-site?geometry=-82.547,25.26,-80.402,26.126

Miami-Dade County. (2018, December 5). Environmental Permits [Comprehensive list of all DERM permits in Miami-Dade County]. Retrieved December 5, 2018, from https://opendata.miamidade.gov/Environment/Environmental-Permits/6r7z-v6nm

Miami-Dade County, Department of Regulatory and Economic Resources (RER). (2019, June 1). *Miami-Dade County's Brownfields Program 2019 Annual Report*. Retrieved October 12, 2019 from https://floridadep.gov/sites/default/files/2019-MDC-BF-Annual-Report_0.pdf

Miami-Dade County Property Appraiser. (n.d.). Retrieved December 5, 2018, from http://www.miamidade.gov/pa/

1-4.3(c) — Reorganization of County Administrative Departments, FL Miami-Dade County Code of Ordinances, § 1-4.3(c) (2011).

Moser, E., & Rittenberg, J. (2015). Leveraging Brownfields transformations: 5 proven finance tools for revitalization results. *Public Management*, (4), 6. Retrieved from http://lp.hscl.ufl.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,uid&db=edsgao&AN=edsgcl.426444295&site=eds-live

Mueller G.R. (2005). Brownfields Capital—Unlocking Value in Environmental Redevelopment. *The Journal of Real Estate Portfolio Management*, (1), 81.

National League of Cities (NLC). (2017, March 7). Urban Infill & Brownfields Redevelopment. Retrieved December 5, 2018, from https://www.nlc.org/resource/urban-infill-brownfields-redevelopment

Oliff, P., Mai, C., & Palacios, V. (2012). *States Continue to Feel Recession's Impact. States Continue to Feel Recession's Impact. Center on Budget and Policy Priorities*. Retrieved from https://www.cbpp.org/sites/default/files/atoms/files/2-8-08sfp.pdf

Palmquist, R. B. (2005). Chapter 16 Property Value Models. Handbook of Environmental Economics Valuing Environmental Changes, 2, 763-819.

Pizzol, L., Zabeo, A., Klusáček, P., Giubilato, E., Critto, A., Frantál, B., … Bartke, S. (2016). Timbre Brownfield Prioritization Tool to support effective brownfield regeneration. *Journal of Environmental Management*, 166, 178–192.

Polk County Property Appraiser. (n.d.). Department of Revenue Property Classification. Retrieved December 5, 2018, from http://www.polkpa.org/DORUseCodes.aspx

Practical Law Real Estate. (2018, April 2). BUILD Act Alters CERCLA Liability Considerations and Funds Brownfield Redevelopment. Retrieved, October 17, 2019, from https://content.next.westlaw.com/Document/I0c1d6ffd34cf11e89bf099c0ee06c731/View/FullText. html?contextData=(sc.Default)&transitionType=Default&firstPage=true&bhcp=1

R Foundation. (n.d.). What is R? Retrieved from https://www.r-project.org/about.html

Rosenbaum, W. A. (2002). *Environmental politics and policy* (5th ed.). Washington, D.C.: CQ Press.

Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America.* New York: Liveright Publishing Corporation, a division of W.W. Norton & Company.

Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological methods*, 14(4), 323-348. doi:10.1037/a0016973

Sun, W., & Jones, B. (2013). Using Multi-Scale Spatial and Statistical Analysis to Assess the Effects of Brownfield Redevelopment on Surrounding Residential Property Values in Milwaukee County, USA. *Moravian Geographical Reports*, 21(2), 56–64.

BIOGRAPHICAL SKETCH

Lian Plass is a master's student studying Urban and Regional Planning at the University of Florida. Prior to beginning her studies at the University, she worked for several years at the City of North Miami's Community Planning and Development Department. Lian served in the capacity of Sustainability Administrator for the city where she functioned as an entry level planner and sustainability specialist. During her time at the city she was a successful grant writer, facilitator for a wide array of capital improvement projects pertaining to sustainability, and coordinator for much of the City's "green" activities.

Prior to joining the City of North Miami, Lian obtained her bachelor's degree in Sustainable Development from Columbia University in the city of New York in 2016. There, she discovered an interest in environmental justice, infill development, and, specifically, brownfield development. Lian will complete her degree requirements and graduate in December of 2019. She hopes to use the knowledge gathered from her graduate studies and thesis paper to improve the quality of life in the communities of Miami-Dade county and other municipal areas with high concentrations of low-income individuals and ethnic minorities.