

Understanding Land Use Evolution for Vacant Residential and Vacant Commercial Parcels in Miami, Florida

ABSTRACT

In this study, we develop quantitative models to identify land use changes to individual parcels in Miami, FL. We focus on indicators for changes in population and economic activity. In our analysis, we identify the factors that promote this activity by examining how residential and commercial parcels are changing over time. While significant efforts have been conducted in earlier literature, there is limited work on understanding how parcels of a particular land use type change over time. The main aim of the proposed research effort is to contribute to land use evolution models that are customized by land use type. These frameworks can allow for quantitative exploration mechanisms for policy makers to proactively encourage sustainable adaptation due to emerging challenges associated with global climate change. The frameworks were developed using high-resolution parcel level data from the Florida Department of Revenue for the time period 2011-2020. The framework has two components: (1) a binary logit model to analyze what factors affect a change from the current land use designation and (2) for parcels selected for a change, a multinomial logit model, to examine the factors contributing to the new land use type. We built a joint model system that allows for a simultaneous estimation of the two decision processes. The joint model was estimated using a comprehensive set of independent variables including socio-demographic variables, economic development variables, and transportation infrastructure variables. The models developed were validated using hold-out sample data to show the value of the proposed model system.

INTRODUCTION

The impending impacts of Global Climate Change are well documented and include warming and rising oceans, severe storms and hurricanes, hotter temperatures, droughts, loss of biodiversity, health risks and displacement (UN Climate Action). Miami, FL, lying in the southern-most and lowest-lying part of the Florida peninsula, is likely to be affected by many of these consequences over time. The Greater Miami region, composed of Miami-Dade and Broward Counties, is home to nearly 4.7 million residents and accounts for about 20% of Florida's population. Given the locational characteristics and the large population, Miami region offers a unique test bed to study and understand how the region responds over time to adapt to the impacts of climate change. While it can be argued that the major impacts of climate change are yet to be felt, there is evidence to indicate that the effects are being experienced since 2000s. Keenan et al. (2018) noted an increased incidence of flooding since 2000 with locations such as El Portal, Miami Shores, and North Miami Beach being affected. Earlier research has presented concerns with sea-level rise and ensuing issues such as stormwater pollution (Abdul-Aziz & Al-Amin, 2016) and saltwater intrusion to wells (Groves et al., 2018). The study of climate adaptation will encompass evolution of several facets of life in the region. In our research, we specifically focus our attention on contributing to high-fidelity modeling of land use patterns in the region.

In our research, we study land use patterns as signals for understanding changes of population, transportation and economic patterns in the region over time. To be sure, several earlier research efforts have recognized the intricate relationship between climate change and land use (Endo et al., 2017; Mulkey, 2007; Rifat & Liu, 2022). The changes occurring can possibly lead to climate gentrification – displacement of populations from neighborhoods due to climate change (Trone & Shedd, 2019). Keenan et al. (2018) attributed the population shifts from the Miami Beach

neighborhood to the Little Haiti neighborhood in Miami to climate gentrification. Of course, the evidence of climate gentrification is still ambiguous. Conyers et al. (2019) highlighted that some of the most vulnerable neighborhoods are affluent and are not considering the impacts of impending sea-level rise. These differing conclusions from earlier research highlight that the impact of emerging climate change on communities is far from established. Given the low probability associated with natural disasters for a specific location, it is possible that the risk isn't being carefully considered by property owners. While our study does not directly address the impact of climate change on land use evolution, our study contributes to climate change analysis by developing an analytical framework that addresses land use evolution using high fidelity data and models. We posit that advanced high-fidelity models developed for understanding land use patterns can identify changes to individual parcels in the urban region. Understanding these decisions while controlling for the impact of neighborhood, urban region and/or global factors will provide quantitative frameworks that can contribute to our understanding of land use adaptation in urban regions over time (Rifat & Liu, 2022). The quantitative framework can provide a mechanism to identify the levers available to policy makers to proactively encourage sustainable adaptation while also allowing for an estimate of the impact of the levers.

With these broad objectives, the current study is focused on developing quantitative models for indicators for population, transportation and economic activity by focusing on two specific land use types: (a) vacant residential parcels and (b) vacant commercial parcels. The designated vacant parcels for residential and commercial activity are likely to be picked for new residential and commercial developments with growing population and economic activity. In our analysis, we examine the factors that promote this activity by examining how these parcels are changing over time. It is important to note that all vacant residential (vacant commercial) parcels do not change

to residential (commercial) parcels. It is possible that some parcels are recognized as non-conducive to residential (commercial) development and their designation might be appropriately modified. Understanding these changes and determining the indicators of these changes will be helpful in understanding how land use patterns emerge over time. The proposed analysis dimensions are rarely examined in land use models. Specifically, there is very little work examining how a land use type of a particular parcel changes over time. The frameworks are developed using high-resolution parcel level data from the Florida Department of Revenue for the time period 2011-2020. The framework is composed of two components. First, we analyze what factors affect a change from the current vacant residential designation. Second, for vacant residential parcels tagged for a change, we examine the factors contributing to the new land use type. The first process is studied using a binary logit model while the second process is examined using a multinomial logit model system. Given the same parcels are transitioning through the two processes, we recognize that factors affecting the first process are also likely to influence the second process. For this reason, it is appropriate to build a joint model system – joint binary logit and multinomial logit model - that allows for a simultaneous estimation of the two processes. The joint model is estimated using a comprehensive set of independent variables including socio-demographic variables, economic development variables, and transportation infrastructure variables.

The remainder of the paper is organized as follows. The second section presents an overview of earlier literature relevant to land use modeling and positions the current study. The third section presents an overview of the data that was used in our research. The fourth section presents the methodological approach employed in our research. The fifth section presents a discussion of the

results for the models developed. The sixth and final section concludes the paper and provides future research directions.

LITERATURE REVIEW

Given the importance of land use inputs on transportation, there have been many research efforts analyzing land use pattern changes over time. The broad literature on land use modeling can be classified into two groups. The studies in the first group focus on understanding change patterns for a specific land use type. For example, understanding the conversion of vacant land use types to a single-family development. The second group of studies develop a model system for analyzing the evolution of all land use types in an urban region. The two approaches have different motivations. The first approach provides conceptual understanding of how change happens for a land use type. The second approach is more geared towards generating future estimates for the entire region and less focused on specific type of land use. Our current study contributes to the first category of studies – we focus on specific components of land use evolution – how vacant single family and commercial land use parcel change over time. We emphasize that land use change pattern is unique for each land use category, thus it is important to develop individual model components for various categories. Given this focus, in our literature review, we limit ourselves to studies on land use models from the first category (for a review of integrated models please see (Golias et al., 2014)).

In this literature, as opposed to providing a study-by-study discussion, we organize our review by important dimensions of analysis including (a) dependent variables of interest, (b) spatial resolution of analysis, (c) modeling approaches employed and (d) important factors identified in earlier literature. The different *dependent variables* considered in earlier literature include future land use type such as urban, agricultural, water, forest, barren lands, and roads for rural areas, and

commercial, residential, industrial, vacant, and other for urban areas (Aljoufie et al., 2013; Arsanjani et al., 2013; Gharaibeh et al., 2020; Guan et al., 2011; Guzman et al., 2020; Iacono & Levinson, 2009; Islam et al., 2018; Kim & Newman, 2019; Ku, 2016; Liang et al., 2021; Liu et al., 2017; Lu et al., 2017; Ralha et al., 2013; Rifat & Liu, 2022; Rimal et al., 2020; Subedi et al., 2013; Turk & Zwick, 2019; Wang et al., 2020; Zheng et al., 2015), binary dependent variables (such as decision to proceed (or not) with development, construction, and vacancy) (Lake Sumter MPO; Newman et al., 2016; Pijanowski et al., 2009) or urban land distribution (Hu & Lo, 2007; Liang et al., 2018; Pijanowski et al., 2002).

The most common *spatial resolution* considered in earlier work was a grid level resolution of varying sizes (100 square meters (Aljoufie et al., 2013; Liang et al., 2018; Pijanowski et al., 2002; Turk & Zwick, 2019), 75 square meters (Iacono & Levinson, 2009), 60 square meters (Guzman et al., 2020), 30 square meters (Arsanjani et al., 2013; Islam et al., 2018; Liang et al., 2021; Liu et al., 2017; Lu et al., 2017; Rifat & Liu, 2022; Rimal et al., 2020; Subedi et al., 2013; Wang et al., 2020), 28.5 square meters (Pijanowski et al., 2009), 10 square meters (Ku, 2016), and one hectare (Ralha et al., 2013)). Although the vast majority of studies used the grid level resolution, there were also studies that used a parcel level spatial resolution for land use type analysis (Lake Sumter MPO; Newman et al., 2016).

The most common *modeling methods* used for land use models were artificial neural networks (ANN) (Kim & Newman, 2019; Newman et al., 2016; Pijanowski et al., 2002; Pijanowski et al., 2009), multinomial logit (MNL) models or cellular automata (CA) models with MNL formulation (Aljoufie et al., 2013; Guzman et al., 2020; Hu & Lo, 2007; Iacono & Levinson, 2009; Ku, 2016; Liang et al., 2021), or a combination of Markov models with one or more of ANN, MNL, and/or CA (Arsanjani et al., 2013; Gharaibeh et al., 2020; Guan et al., 2011; Islam et al., 2018; Liang et

al., 2018; Liu et al., 2017; Lu et al., 2017; Rifat & Liu, 2022; Rimal et al., 2020; Subedi et al., 2013; Wang et al., 2020; Zheng et al., 2015).

A host of independent variables were considered in earlier research on land use modeling. These variables can be broadly classified into four categories: (a) socio-demographic variables, (b) economic development variables, (c) transportation infrastructure variables, and (d) observation record specific variables. Socio-demographic variables considered include population (Arsanjani et al., 2013; Lake Sumter MPO; Liang et al., 2021; Liang et al., 2018; Liu et al., 2017), population density (Arsanjani et al., 2013; Gharaibeh et al., 2020; Guan et al., 2011; Hu & Lo, 2007; Kim & Newman, 2019; Ku, 2016; Rifat & Liu, 2022; Zheng et al., 2015), race (Kim & Newman, 2019; Newman et al., 2016), and education (Lake Sumter MPO; Newman et al., 2016). Economic development variables that impacted land use models include income (Newman et al., 2016), employment (Lake Sumter MPO), and proximity to special generators/city center/shopping (Arsanjani et al., 2013; Gharaibeh et al., 2020; Hu & Lo, 2007; Islam et al., 2018; Kim & Newman, 2019; Ku, 2016; Liang et al., 2018; Pijanowski et al., 2002; Pijanowski et al., 2009; Rifat & Liu, 2022; Rimal et al., 2020; Zheng et al., 2015). Two common transportation infrastructure variables considered were roadway density (Liu et al., 2017) and proximity to major roadways (Aljoufie et al., 2013; Arsanjani et al., 2013; Gharaibeh et al., 2020; Guan et al., 2011; Hu & Lo, 2007; Iacono & Levinson, 2009; Islam et al., 2018; Kim & Newman, 2019; Ku, 2016; Liang et al., 2021; Liang et al., 2018; Lu et al., 2017; Newman et al., 2016; Pijanowski et al., 2002; Pijanowski et al., 2009; Rifat & Liu, 2022; Rimal et al., 2020; Wang et al., 2020; Zheng et al., 2015). The observation record specific variables considered include property value (Guan et al., 2011; Newman et al., 2016; Rifat & Liu, 2022; Zheng et al., 2015), distance to river/coast/lake (Arsanjani et al., 2013; Islam et al., 2018; Liang et al., 2021; Pijanowski et al., 2002; Rifat & Liu, 2022; Rimal et al., 2020;

Zheng et al., 2015), flood risk (Guzman et al., 2020; Lu et al., 2017), surrounding land uses (Hu & Lo, 2007; Iacono & Levinson, 2009; Lu et al., 2017; Pijanowski et al., 2002; Subedi et al., 2013), vacancy rate (Newman et al., 2016), elevation (Gharaibeh et al., 2020; Islam et al., 2018; Pijanowski et al., 2009; Rimal et al., 2020; Wang et al., 2020; Zheng et al., 2015), and slope (Aljoufie et al., 2013; Arsanjani et al., 2013; Gharaibeh et al., 2020; Guan et al., 2011; Islam et al., 2018; Liang et al., 2021; Liang et al., 2018; Liu et al., 2017; Lu et al., 2017; Pijanowski et al., 2009; Rifat & Liu, 2022; Rimal et al., 2020; Wang et al., 2020; Zheng et al., 2015). The analysis from earlier literature was also augmented by reviewing the land use variables used in Miami's transportation demand model (SERPM), which included variables listed above such as population, employment, education, and proximity to shopping (Shanmugam, 2022).

The reader would note that a majority of these study efforts are empirical analyses considering the influence of different variables across the four variable groups in a multivariate model system. While it would be elegant to suggest a unifying theoretical framework to represent the impact across the various interconnected dimensions influencing land use, it is not straight forward to develop one. Specifically, the assumptions necessary to build an elegant theoretical framework might not be justified given the complexity involved in modeling land use evolution. Thus, earlier studies posit that the different variables across the variable groups collectively influence land use evolution. Given the large number of interconnected dimensions, we believe that a data driven land use evolution as opposed to an elegant theoretical model system is a practical solution. To be sure, the data-driven approach employed is supported by rigorous statistical analysis and allows us to explain the potential impact of each variable (while controlling for other variables) on land use evolution.

While significant data driven efforts have been conducted in earlier literature, there is limited work on understanding how parcels of a particular land use type change over time. The main aim of the proposed research effort is to contribute to land use evolution models that are customized by current land use type. Towards this end, in our research, we develop model systems that can identify changes to individual parcels in the greater Miami region. Understanding the factors that lead to land use change can contribute to our understanding of land use adaptation in urban regions over time. This can provide a mechanism to identify the levers available to policy makers to proactively encourage sustainable adaptation while also allowing for an estimate of the impact of the levers. This is done using a joint modeling system. In the first step we identify factors that affect a change from the current land use designation using a binary logit model. After this, we examine the factors contributing to the new land use type using a MNL model. Since we are analyzing the same parcels in both processes, these two steps have been combined in a joint model.

DATASET DESCRIPTION

Dependent Variable

The data for our analysis is drawn from Miami-Dade and Broward counties from 2011 to 2020 from the Florida Department of Revenue (FDOR) (Florida Department of Revenue). We used the name-address-legal (NAL) files to obtain each parcel's land use and GIS files to get a map of each parcel's location and geometry. These files list 100 different land use codes that were condensed into 18 land uses: vacant residential, single family residential, multi-family residential, other residential, vacant commercial, mixed use, office, commercial, vacant industrial, industrial, agricultural, vacant institutional, institutional, vacant public, public, recreational, water, and other. We identified land use changes by using ArcMap to intersect the GIS files of subsequent years and identifying the areas in which the land use changed. For this paper, we focused on vacant

residential and vacant commercial land use change as they will be the best indicators for areas of population and economic growth respectively.

A summary of the vacant residential and vacant commercial land use change data is shown in FIGURE 1. Between 2011 and 2019 there were 278,815 parcels classified as vacant residential, with 75.8% repeated records for parcels classified as vacant residential for multiple years. Out of these parcels, 42,422 converted to another land use (overall conversion rate is 15%) between 2012 and 2020. Of the 42,422 vacant residential parcels that converted to another land use, about 53.3% of these parcels convert to single family residential, another 28.4% convert to other residential (including condominiums, retirement communities, and mobile homes) and 18.3% account for the remaining 15 land use types. As these categories on their own account for less the 5% of the overall conversions, we recategorized them into one category to develop our model for land use change.

Between 2011 and 2019 there were 58,383 parcels classified as vacant commercial, with 81.7% repeated records for parcels classified as vacant commercial for multiple years. Of these parcels, 3,236 converted to another land use (overall conversion rate is 6%) between 2012 and 2020. Of the 3,236 vacant commercial parcels that converted to another land use, about 34.3% of these parcels convert to commercial, 12.0% convert to vacant residential, 10.0% convert to other, 7.1% convert to office, 6.7% convert to vacant public, 6.6% convert to multi-family residential, 5.3% convert to industrial, and 17.8% convert to the remaining land use types with none of the categories exceeding 5% of vacant commercial conversions.

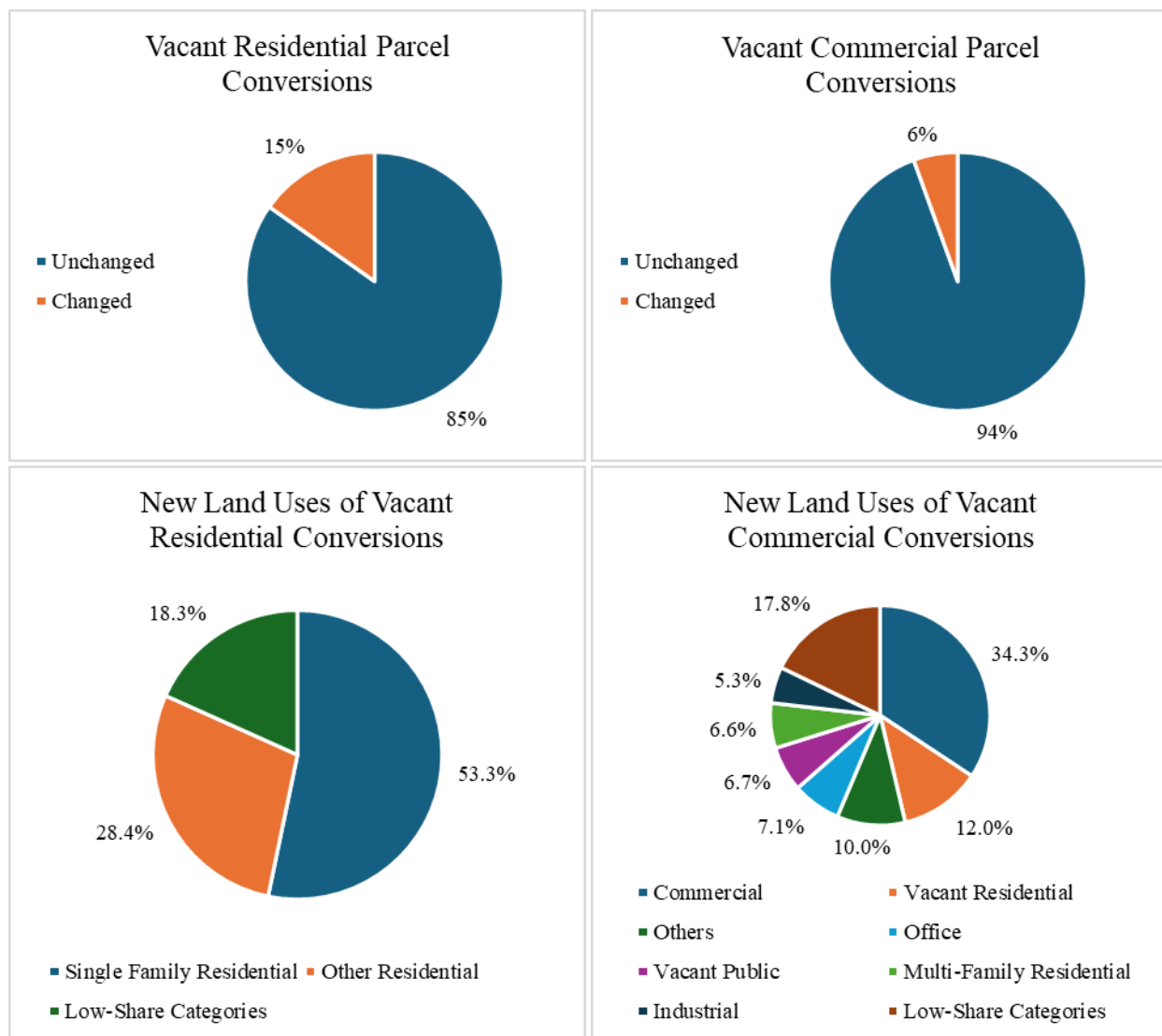


FIGURE 1 Summary of Vacant Residential and Commercial Land Use Changes

Independent Variables

We consider a comprehensive set of independent variables including socio-demographic characteristics, economic development indicators, transportation infrastructure variables, and site characteristics. Independent variables considered are sourced from Census’s American Community Survey (ACS), the Census’s TigerLine (TL) GIS files, Florida Department of Transportation (FDOT) roadway network GIS files, FDOT’s Florida Transit Information System (FTIS), and the Federal Emergency Management Agency’s (FEMA) GIS flood maps. It is

important to note that we generate the variables at the finest spatial resolution available. For example, population is identified at the block group (BG) resolution and number of households is identified at the census tract (CT) resolution. In order to associate these variables with individual parcels, we intersected the FDOR parcel GIS files with the Census block group (census tract) GIS file to identify the block group (census tract) that each parcel is located within. Among socio-demographic characteristics, we consider population density (BG), number of households (CT), household density (CT), gender (BG), age (BG), race (BG), and education (CT). Among economic development indicators, we consider median income (CT), household vehicle ownership (CT), unemployment rate (CT), and number of workers (CT). Among transportation infrastructure variables, we consider road density (CT), number of transit stops (BG), and proximity to a highway (BG). Among observation record characteristics, we consider parcel area (parcel), parcel value (parcel), proximity to coast (BG), flood risk (BG), surrounding land use distribution (BG), land mix (BG), vacancy rate (CT), urban/rural (BG), and county indicator (Broward or Dade).

We compared the averages of the independent variables for the datasets of vacant residential and vacant commercial parcels and found that vacant residential parcels tend to be located in areas with a lower population density (9.37 and 12.37 people per acre respectively), higher high school graduation rates (82.11% and 75.89% respectively), higher median income (\$58,141 and \$39,417 respectively), lower unemployment rates (10.48% and 13.13% respectively), lower road density (3.58 and 5.66 miles of road per square mile respectively), and farther from the coast (6.74 and 5.55 miles respectively). Additionally, while the majority of both land use types are located in Miami-Dade County, vacant residential parcels are more likely to be located in Broward County than vacant commercial parcels (37% and 25% respectively). A summary of the comparisons is presented in TABLE 1.

TABLE 1: Summary of Independent Variables

Group	Variable (Resolution)		Vacant Residential		Vacant Commercial	
			Mean	Std. Dev.	Mean	Std. Dev.
Socio-Demographic Characteristics	Pop. Density (per acre) (BG)		9.37	9.85	12.37	11.52
	LN(Number of households) (CT)		7.68	0.50	7.54	0.71
	Household Density (per acre) (CT)		3.73	4.67	5.15	5.03
	Gender (BG)	% Male	48.92	7.12	49.81	8.83
		% Female	50.52	7.18	49.47	8.82
	Age (BG)	% Young (0-14)	19.41	8.81	17.91	8.73
		% Middle Age (15-64)	66.55	9.91	68.12	11.76
		% Older (65+)	13.48	10.16	13.30	9.87
	Race (BG)	% Hispanic	43.61	28.17	44.93	30.60
		% White alone	26.97	25.07	16.95	21.13
		% Black or African American	25.30	30.25	34.88	33.57
		% Asian	2.07	3.41	1.29	2.82
		% Other Races	1.49	2.18	1.28	2.49
	% High School Grad Rate (CT)		82.11	12.02	75.89	13.28
Economic Development Indicators	LN(Median Income) (CT)		10.81	0.60	10.42	0.87
	Household Vehicle Availability (%) (CT)	0	9.86	10.06	16.79	12.20
		1	37.65	13.60	43.98	11.09
		2	36.79	12.40	28.45	11.28
		3+	15.65	10.31	10.28	7.73
	Unemployment Rate (%) (CT)		10.48	6.43	13.13	7.36
Transportation Infrastructure Variables	LN(Number of workers) (CT)		7.82	0.62	7.58	0.80
	Transit stops (BG)		6.18	7.21	10.32	8.45
	Road density category (CT)	High (>5 mi/sq mi)	0.21	0.41	0.46	0.50
		Medium (3-5 mi/sq mi)	0.33	0.47	0.35	0.48
		Low (<3 mi/sq mi)	0.46	0.50	0.19	0.39
	Near highway (highway in BG)		0.26	0.44	0.32	0.47
Site Characteristics	Parcel Area (in acres) (parcel)		7.85	40.06	7.12	30.55
	LN(Just Value of parcel) (parcel)		8.79	4.03	11.91	1.66
	Near coast (coast within 5 mi of BG)		0.38	0.49	0.52	0.50
	% Flood risk (BG)	High	46.68	32.34	34.71	31.63
		Moderate	18.38	26.51	18.58	26.94
		Minimum	33.45	33.05	45.70	36.61
	% Surrounding Land Use (BG)	Agriculture	6.29	15.37	1.41	6.90
		Commercial	6.97	10.11	12.58	12.82
		Industrial	3.80	9.05	6.38	11.63
		Institutional	2.51	4.70	3.64	6.01
		Mixed Use	0.42	1.09	1.01	1.53
		Multi-Family Residential	7.04	10.86	11.60	12.39
		Office	1.29	3.10	3.11	5.52
		Other Residential	3.88	8.15	1.53	5.03
		Other	5.89	8.86	4.11	7.77
		Public	5.85	10.52	8.74	12.02
		Recreational	3.64	7.71	1.33	4.38
		Single Family Residential	31.62	24.02	25.64	23.15
		Vacant	18.34	17.21	17.95	15.07
		Water	2.47	5.63	0.95	3.89
	Land use mix (BG)		0.67	0.15	0.70	0.13
	Vacant Residences (BG)		14.35	9.73	16.17	10.14
	Vacant land uses (BG)	Unoccupied	47.94	26.04	51.62	25.45
		Seasonally occupied	24.79	25.94	21.93	24.61
		Other	26.39	21.49	25.85	20.30
	Urban (>50% of BG)		0.94	0.25	0.98	0.15
Broward (County)		0.37	0.48	0.25	0.44	

ECONOMETRIC METHODOLOGY

In this section, we discuss mathematical formulation and estimation procedure of the joint binary logit-multinomial logit model framework.

Binary Logit Component

Let i ($i = 1, 2, \dots, I$) be an index to represent a parcel, and y represents a binary dependent variable where 1 indicates a change and 0 indicates no change.

The propensity component for land use decision takes the following form:

$$y_i^* = \{(\alpha + \gamma_i)z_i + \varepsilon_i\}, \quad u_i = 1 \text{ if } y_i^* > 0, u_i = 0 \text{ otherwise} \quad (1)$$

where, y_i^* represents the propensity for land use change decision for parcel i ; If u_i is 1, parcel i is predicted to change otherwise it remains unchanged. z_i is a vector of attributes associated with parcel i . α is the vector of corresponding mean effects. γ_i is a vector of common unobserved factors of change probability and new land use type for parcel i and its associated characteristics assumed to be realization from standard normal distribution: $\gamma_i \sim N(0, \varsigma_i^2)$. ε_i is an idiosyncratic error term assumed to be identically and independently standard logistic distributed. The reader will note that γ_i can also be specified to incorporate random parameters separately for the two decisions.

Multinomial Logit Component

Let i ($i = 1, 2, \dots, I$), and k ($k = 1, 2, \dots, K$) be the indices to represent a parcel and the corresponding new land use type, respectively. In the joint framework, the modeling of incident type follows an MNL model structure. Following the random utility theory, the propensity of a parcel i being land use type k takes the following form:

$$v_{ik}^* = (\beta_k + \gamma_i)x_{ik} + \xi_{ik} \quad (2)$$

Where, x_{ik} is a vector of independent variables and β_k is a vector of unknown parameters specific to land use type k . ξ_{ik} is an idiosyncratic error term (assumed to be identically and independently standard logistic distributed) capturing the effect of common unobserved factors on the propensity

associated with land use change and new land use type k . A parcel i is identified as land use type k if and only if the following condition holds:

$$v_{ik}^* > \max_{l=1,2,\dots,K, l \neq k} \mu_{il}^* \quad (3)$$

Estimation Procedure

In examining the model structure of change decision and new land use type, it is necessary to specify the structure for the unobserved vectors γ which is assumed to be realization from standard normal distribution: $\gamma_i \sim N(0, \varsigma_i^2)$. Thus, the equation system for modeling the probability of land use change takes the following form (conditional on γ_i):

$$P_i = P(y_i = 1) | \gamma_i = \frac{\exp\{(\alpha + \gamma_i)z_i\}}{1 + \exp\{(\alpha + \gamma_i)z_i\}} \quad \forall i \quad (4)$$

The corresponding probability for no change is computed as:

$$Q_i = 1 - P_i \quad (5)$$

Similarly, the probability for the new land use type component takes the form (conditional on γ_i):

$$R_{ik} = P_{ik}(k) | \gamma_i = \frac{\exp\{(\beta_k + \gamma_i)x_{ik}\}}{\sum_{m=1}^K \exp\{(\beta_m + \gamma_i)x_{im}\}} \quad \forall i, k \quad (6)$$

Further, conditional on $\mathbf{\gamma}$, the quasi-likelihood function for the joint probability can be expressed as:

$$\mathcal{L}_i = \int_{\mathbf{\gamma}} \prod_{k=1}^K \{ (P_i * R_{ik})^{w_{ik}y_i} * (Q_i)^{(1-y_i)/K} \} f(\mathbf{\gamma}) \mathbf{\gamma} \quad \forall i \quad (7)$$

y_i is 1 if land use of a parcel i changes and 0 otherwise. w_{ik} is 1 if new land use type for a parcel i is k and 0 otherwise. Finally, the quasi-log-likelihood function is:

$$\mathcal{LL} = \sum_{i=1}^I \ln (\mathcal{L}_i) \quad (8)$$

All the parameters in the model are estimated by maximizing $\mathcal{LL}$ in Equation 8. The parameters to be estimated in the joint model are: α , ς , and β . To estimate the proposed joint model, we apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated quasi-likelihood function across individuals (see (Bhat, 2001; Eluru et al., 2008) for more details of Quasi-Monte Carlo approaches).

ANALYSIS AND RESULTS

Model Selection

We first estimated an independent binary logit – multinomial logit model system and a joint binary logit – multinomial logit model system. This independent model system is considered as a benchmark to evaluate the performance of the proposed joint model system. Log-likelihood (Bayesian Information Criteria) for independent models for vacant residential and vacant commercial land uses are -20023.90 (40566) and -7026.05 (14537), respectively. Log-likelihood (Bayesian Information Criteria) for the joint models for vacant residential and vacant commercial land uses are -20012.56 (40554) and -6981.06 (14457), respectively. From the comparison, it is evident that the inclusion of common unobserved factors improves the model performance for both land use types. Therefore, we selected the joint model system over the independent model and discussed the results by land use type from the joint model.

Estimation Results

Vacant Residential

The results of the joint model for the vacant residential land use type parcels are presented in

TABLE 2.

TABLE 2: Vacant Residential Joint Land Use Change Model

Model	BL	MNL (base Single Family Residential)	
<i>Alternatives</i>	<i>Change =1</i>	<i>Other Residential</i>	<i>Other Category</i>
Parameters	Est. (t stat)	Est. (t stat)	Est. (t stat)
Constant	-3.0484 (-14.65)	-4.2319 (-9.72)	-1.7027 (-7.28)
Socio-demographic Characteristics			
Population Density	-0.0235 (-8.009)	0.1352 (13.733)	0.1839 (17.006)
<i>Gender (Base: % Male)</i>			
% Female	0.0224 (8.983)	--	--
<i>Race (Base: % Hispanic, Asian, Other)</i>			
% Black or African American	-0.0130 (-13.54)	-0.0162 (-6.592)	-0.015 (-5.68)
% White alone	-0.0166 (-14.53)	0.0074 (2.95)	0.0123 (4.571)
% High School Graduation Rate	0.0204 (10.512)	0.0324 (7.356)	--
Economic Development Indicators			
<i>Household Vehicle Availability (Base: % 2 or fewer vehicles available)</i>			
% 3+ vehicles available	--	-0.0081 (-1.863)	0.017 (3.481)
% Unemployment Rate	--	0.0504 (5.459)	0.0664 (6.945)
Transportation Infrastructure Variables			
<i>Road density (Base: Low and high density)</i>			
Medium road density	-0.3214 (-8.194)	--	--
Near highway	--	0.465 (5.922)	0.2964 (3.106)
Transit stops	-0.0183 (-6.492)	--	--
Site Characteristics			
LN(Parcel Area)	-0.3532 (-23.87)	--	--
Near coast	-0.3217 (-7.21)	-1.0264 (-10.609)	--
<i>Flood Risk (Base: % Low and moderate risk)</i>			
% High flood risk	-0.0046 (-7.554)	--	--
<i>Surrounding Land Use (Base: % Agricultural, Commercial, Mixed-use, Office, Others)</i>			
% Industrial	--	0.0099 (2.261)	0.0114 (2.592)
% Institutional	-0.0088 (-2.061)	--	--
% Multi-Family Residential	-0.0176 (-7.148)	--	--
% Other Residential	--	-0.0789 (-16.471)	-0.0754 (-11.901)
% Public	-0.0138 (-7.456)	0.0084 (1.822)	0.0249 (6.044)
% Recreational	0.0142 (6.798)	0.0422 (9.799)	-0.0396 (-5.815)
% Single Family Residential	-0.0105 (-4.516)	-0.0292 (-11.448)	-0.0614 (-8.553)
% Vacant	--	0.0112 (4.337)	0.0081 (2.846)
% Water	0.0326 (11.117)	0.0365 (8.234)	--
Broward County	0.8816 (16.131)	0.6681 (5.727)	-0.5191 (-4.175)
Effect of Random Parameters			
% Single Family Residential	0.0207 (6.549)	--	0.0207 (6.549)
* N = 38968; LL = -20012.56			

Binary Logit Results

We found several demographic characteristics, transportation infrastructure variables, and site characteristics influencing vacant residential parcels propensity to convert. Among *socio-demographic characteristics*, we can see that the parcels that are most likely to change tend to be in areas with any of the following characteristics: lower population density (Hu & Lo, 2007), higher female proportion, lower proportions of African American and Caucasian populations, and/or higher high school graduation rates. While several *economic development variables* were considered in our model estimation, no statistically significant parameter was found. Among *transportation infrastructure variables*, we can see that the parcels that are most likely to change tend to be in areas that do not have medium road density and/or have fewer transit stops. Among *site characteristics*, we can see that the parcels that are most likely to change tend to have any of the following characteristics: smaller area, not located within 5 miles of the coast, in an area with a lower proportion of high flood risk, in an area with a lower proportion of institutional, multi-family residential, public, and single-family residential parcels and a higher proportion of recreational and water parcels, in an area with a lower proportion of vacant housing units, and/or located within Broward County.

Multinomial Logit Results

We found several socio-demographic characteristics, economic development indicators, transportation infrastructure variables, and site characteristics influencing the new land use category of a vacant residential parcel. We considered a single-family residential conversion to be the base and then evaluated a conversion to either other residential or other category (encompasses all low share categories).

The base probabilities of other residential and other category are lower than single-family residential. Among *socio-demographic characteristics*, we can see that areas with a higher population density are more likely to convert to other residential or other category. The results highlight that increasing population density is less conducive to single family homes. Areas with a higher proportion of Caucasians are more likely to convert to other residential or other category. Areas with a higher proportion of African Americans are less likely to convert to other residential or other category. Areas with a higher high school graduation rate are more likely to convert to other residential. Among *economic development indicators*, we can see that areas with a higher proportion of households with three or more vehicles available are less likely to convert to other residential and more likely to convert to other category. Areas with a higher unemployment rate are more likely to convert to other residential or other category.

Among *transportation infrastructure variables*, we can see that parcels located near a highway are more likely to convert to other residential or other category. Among *site characteristics*, we can see that parcels within 5 miles of the coast are less likely to convert to other residential. Parcels with a higher proportion of industrial land nearby are more likely to convert to other residential or other category. Parcels with a higher proportion of other residential land nearby are less likely to convert to other residential or other category. Parcels with a higher proportion of public land nearby are more likely to convert to other residential or other category. Parcels with a higher proportion of recreational land nearby are more likely to convert to other residential and less likely to convert to other category. Parcels with a higher proportion of single-family residential land nearby are less likely to convert to other residential or other category. Parcels with a higher proportion of vacant land nearby are more likely to convert to other residential or other category. Parcels with a higher proportion of water nearby are more likely to convert to other residential.

Finally, parcels located in Broward County are more likely to convert to other residential and less likely to convert to other category.

Common Unobserved Factors

We added parameters to account for the impact of common unobserved factors affecting the two decisions. One variable was found to have a significant parameter jointly affecting the two decisions - proportion of surrounding single family residential land use. Proportion of surrounding single family residential land use presented a common random effect for change alternative in the binary logit and the other category alternative of the MNL model. The result indicated while the coefficient for the binary logit change alternative was found to be -0.0105, it could reasonably fluctuate between -0.0312 and 0.0102. Similarly, for the MNL other category alternative the coefficient was found to be -0.0614, but from parcel to parcel these values can fluctuate between -0.0821 and -0.0407.

Vacant Commercial

The results of the joint model for the vacant commercial land use type parcels are presented in TABLE 3.

TABLE 3: Vacant Commercial Joint Land Use Change Model

Model	BL	MNL (base Commercial)						
<i>Alternative</i>	<i>Change = 1</i>	<i>Vacant Residential</i>	<i>Others</i>	<i>Office</i>	<i>Vacant Public</i>	<i>MF Residential</i>	<i>Industrial</i>	<i>Other Category</i>
Parameters	Est. (t stat)	Est. (t stat)	Est. (t stat)	Est. (t stat)	Est. (t stat)	Est. (t stat)	Est. (t stat)	Est. (t stat)
Constant	-3.5825 (-29.29)	-1.3163 (-5.7)	-3.4996 (-5.007)	-3.6263 (-4.41)	-3.3953 (-12.22)	-6.1454 (-5.00)	-2.9022 (-11.8)	-2.6538 (-7.905)
Socio-demographic Characteristics								
Population Density	-0.0064 (-1.748)	--	-0.0656 (-2.384)	--	--	0.0316 (3.532)	--	-0.0231 (-2.086)
<i>Race (Base: % Hispanic, Asian, Other Race)</i>								
% White alone	--	--	-0.0206 (-3.84)	--	--	-0.0278 (-3.42)	--	--
% Black/African American	-0.0061 (-4.882)	--	--	--	0.016 (4.347)	--	0.0093 (2.377)	--
% High School Graduation Rate	--	--	--	0.0313 (3.293)	--	0.0362 (2.529)	--	--
Economic Development Indicators								
<i>Household Vehicle Availability (Base: % 1 or 2 vehicles available)</i>								
% 0 vehicles	--	--	-0.0358 (-2.165)	--	0.0333 (3.354)	0.06 (4.34)	--	0.0387 (4.536)
% 3+ vehicles	--	-0.0405 (-3.22)	--	--	--	--	--	0.0449 (4.109)
% Unemployment Rate	-0.02 (-3.447)	--	--	--	--	--	--	--
Transportation Infrastructure Variables								
<i>Road Density (Base: High and Medium Density)</i>								
Low Density	0.1131 (1.349)	--	--	--	--	--	--	--
Site Characteristics								
LN(Parcel Area)	-0.0737 (-1.85)	--	-0.8778 (-10.2)	--	--	-0.3262 (-3.11)	--	--
Near Coast	-0.1999 (-2.562)	--	--	--	--	--	--	--
<i>Surrounding Land Use (Base: % Agricultural, Commercial, Institutional, Mixed Use, Office, Other Residential, Other, Public, SF Residential, Water)</i>								
% Industrial	0.0088 (3.294)	--	--	--	--	--	0.0414 (5.55)	0.0264 (4.497)
% MF Residential	0.0088 (2.782)	--	--	--	--	--	--	--
% Recreational	-0.0171 (-2.414)	--	--	--	--	--	--	--
% Vacant	0.0073 (2.989)	0.0288 (4.894)	0.0232 (1.892)	-0.0356 (-3.36)	0.0329 (4.592)	--	--	0.0323 (5.717)
% Vacant Residences	0.0225 (7.251)	--	--	--	--	--	--	--
Broward County	1.1882 (14.517)	0.5226 (2.566)	4.2424 (7.777)	--	--	--	0.7655 (2.879)	0.8267 (4.369)
Effect of Random Parameters								
LN(Parcel Area)	0.6033 (12.1)	N/A	0.6033 (12.1)	N/A	N/A	0.6033 (12.1)	N/A	N/A
* N = 24369; LL = -6981.06								

Binary Logit Results

We found several socio-demographic characteristics, economic development indicators, transportation infrastructure variables, and site characteristics influencing the decision of converting vacant commercial parcels. Among *socio-demographic characteristics*, we can see that the parcels that are most likely to change tend to be in areas with lower population density and/or lower proportions of African American populations. Among *economic development indicators*, we can see that the parcels that are most likely to change tend to be in areas with a lower unemployment rate. Among *transportation infrastructure variables*, we can see that the parcels that are most likely to change tend to be in areas with low road density (Hu & Lo, 2007). Among *site characteristics*, we can see that the parcels that are most likely to change tend to have any of the following characteristics: larger size, not located within 5 miles of the coast, in an area with a lower proportion of recreational parcels and a higher proportion of industrial (Zhao et al., 2017), multi-family residential (Zhao et al., 2017), and vacant parcels, in an area with a higher proportion of vacant residences, and/or located within Broward County.

Multinomial Logit Results

We observed several socio-demographic characteristics, economic development indicators, transportation infrastructure variables, and site characteristics influencing the new land use of a vacant commercial parcel that converts. We considered conversion to commercial land use type as the base, and then evaluated a conversion to vacant residential, others, office, vacant public, multi-family residential, industrial, or other category (encompassing all low share categories). The base probabilities of vacant residential, others, office, vacant public, multi-family residential, industrial, or other category are lower than commercial.

Among *socio-demographic characteristics*, we can see that parcels in areas with a higher population density are more likely to convert to multi-family residential, and less likely to convert to others and other category. Parcels in areas with a higher Caucasian population are less likely to convert to others and multi-family residential. Parcels in areas with a higher African American population are more likely to convert to vacant public and industrial. Parcels in areas with a higher high school graduation rate are more likely to convert to office and multi-family residential. Among *economic development indicators*, we can see that parcels in areas with a higher proportion of households with no vehicles are more likely to convert to vacant public, multi-family residential, and other category, and less likely to convert to others. Parcels in areas with a higher proportion of households with three or more vehicles are more likely to convert to other category and less likely to convert to vacant residential. While several *transportation infrastructure variables* were considered in our model estimation, no statistically significant parameter was found. Among *site characteristics*, we can see that larger parcels are less likely to convert to others and multi-family residential. Parcels with a higher proportion of industrial land nearby are more likely to convert to industrial and other category. Parcels with a higher proportion of vacant land nearby are more likely to convert to vacant residential, others, vacant public, and other category, and less likely to convert to office. Finally, parcels located in Broward County are more likely to convert to vacant residential, others, industrial, and other category.

Common Unobserved Factors

We added a parameter to estimate the common random effects on both dependent variables. One variable was found to have statistically significant impact: the natural log of parcel area. The natural log of parcel area had a random effect of 0.6033 specifically for the binary logit change alternative, and the others and multi-family residential alternatives of the MNL model. This means

that while the coefficient for the binary logit change alternative was found to be -0.0737, it could reasonably fluctuate between -0.6770 and 0.5296. Similarly, for the MNL others and multi-family residential alternatives, the coefficients were found to be -0.8778 and -0.3262 respectively, but from parcel to parcel these values can fluctuate between -1.4811 and -0.2745 for others and -0.9665 and 0.2771 for multi-family residential.

Model Validation

To evaluate the predictive performance of the proposed models, we undertake a validation exercise using holdout samples (records not included in model estimation). In this analysis, we compare predicted log-likelihood (LL) values for the independent model and the joint model. Validation datasets for vacant residential and vacant commercial consist of approximately 239,847 and 34,014 records, respectively. From these holdout samples, we create 20 subsamples for each land use type by randomly drawing approximately 10% records. For these subsamples, we employ both independent model and joint model to compute mean LL at the observation level. The results of the analysis are presented in Figure 2. From the model validation results, it is evident that the joint model system offers significant data fit improvements on holdout samples for both land use types.

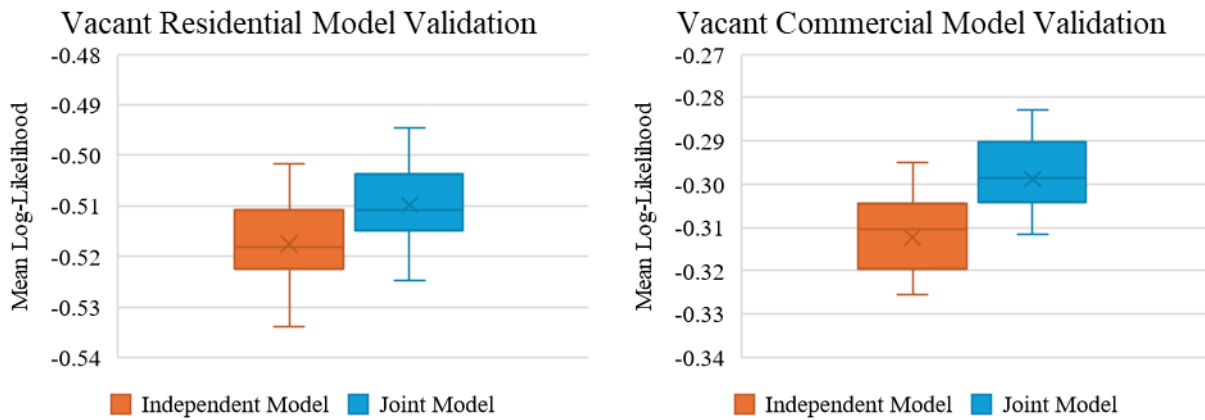


FIGURE 2 Comparison of Log-Likelihood for Independent and Joint Models

DISCUSSION AND IMPLICATIONS

The preceding section presented the estimates of the parameters for the joint models for vacant residential and commercial parcels. In this section, we provide a discussion of these findings across the two land use types and present how these findings can contribute to agency level land use planning exercises.

From the parcel level change models, we observe that BG population density exhibits a similar impact across residential and commercial parcels. Further, we observe that a higher presence of minority residents is likely to slow down land use transformations (when all else is the same). The impact of transportation infrastructure varies across the two land use types. Interestingly we observe that across the two land use types, near coast parcels are less likely to change from their vacant status, potentially highlighting the inherent risk in developing these parcels (relative to the parcels away from the coast).

From the land use type change models, we observe that increasing BG population density and high school graduation shares contribute to reduced possibility of SF residential conversions. It is interesting to note that transportation infrastructure variable - road density - has no impact on the conversion of land use across the two land use types. While the surrounding land use types have significant impact on land use conversion outcomes, it is not possible to infer a simple relationship of conversion across the two land use types. Overall, the results highlight the complexity of land use conversion highlighting the multivariate impact of a host of independent variables.

In addition to these qualitative insights, the proposed model can be employed by various municipalities and agencies to proactively understand how land use conversion is likely to occur over time. The main benefit of the proposed model system is to predict potential changes in the region in response to major residential development investments, transportation roadway and

transit projects while considering evolving sociodemographic and economic changes in the region. Specific jurisdictions can build a host of different initiatives to guide the evolution in a proactive manner to ensure high quality of life in the jurisdiction. The findings will also allow municipalities and transportation agencies to work together in planning for and providing necessary infrastructure as land use patterns evolve over time – an important consideration in a fast-growing state like Florida.

CONCLUSION

The research effort is geared toward contributing to our understanding of land use evolution models by developing change models customized by current land use type. We focused on indicators for changes in population and economic activity: (a) vacant residential parcels and (b) vacant commercial parcels. The designated vacant parcels for residential and commercial activity are likely to be picked for new residential and commercial developments with growing population and economic activity. In our analysis, we examine the factors that promote this activity by examining how these parcels are changing over time. The frameworks were developed using high-resolution parcel level data from the Florida Department of Revenue.

The framework has two components: (1) a binary logit model to analyze what factors affect a change from the current land use designation and (2) a multinomial logit model where, for parcels tagged for a change, we examine the factors contributing to the new land use type. Since the same parcels are transitioning through the two processes, factors affecting the first process are also likely to influence the second process. Therefore, we built a joint model system that allows for a simultaneous estimation of the two processes. This joint model also allows us to accommodate for potential common unobserved factors affecting the two decisions. The joint model was estimated

using a comprehensive set of independent variables including socio-demographic variables, economic development variables, and transportation infrastructure variables.

In the models we found that all four categories of variables have a significant impact on decisions to change/update vacant residential and vacant commercial parcels. For vacant residential parcels we found that population density, gender proportion, race proportion, high school graduation rate, household vehicle availability, unemployment rate, road density, proximity to highway, number of transit stops, parcel area, proximity to coast, flood risk, surrounding land use, and county were significant predictors. For vacant commercial parcels we found that population density, race proportion, high school graduation rate, household vehicle availability, unemployment rate, road density, parcel area, proximity to coast, surrounding land use, housing unit vacancy, and county were found to be significant predictors. The models results for the two land use types also showed the presence of common unobserved factors affecting the two decisions.

This paper is not without limitations. In our modeling approach we did not consider parcels that split to create multiple new parcels or combine multiple parcels to create one parcel. While this is an infrequent occurrence, it does happen and may have an impact. Future studies may consider this in their modeling approaches. Additionally, future studies may want to consider additional land uses in their modeling. In this paper we only focused on vacant residential and vacant commercial parcels, but it would be interesting to examine how other land uses change over time occur for other land use types. The current research effort does not consider the municipality specific variations across Miami-Dade and Broward counties in developing our frameworks. Given the large number of municipalities in the region, the consideration of these variations would offer a fruitful area of future research.

Finally, the current research effort examined how land use evolution occurs – it is observing current patterns to allow us to see what variables influence and how they interact with other variables. The effort forms the first step in an effort to understand how land use evolution affects land use efficiency goals. The current study is not designed to answer this question. However, using the land use evolution patterns from our analysis, future research efforts can conduct a scenario analysis of how land use efficiency goals defined by stakeholders vary across scenarios. The outputs from our study will serve as important data inputs for such an analysis.

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