land

MDPI

Article

Green Infrastructure and Urban Vacancies: Land Cover and Natural Environment as Predictors of Vacant Land in Austin, Texas

Young-Jae Kim [1], Ryun Jung Lee [2], Taehwa Lee [3] and Yongchul Shin [3,*]

[1] Department of Landscape Architecture, Yeungnam University, Gyeongsan 38541, Republic of Korea; youngjae_kim@yu.ac.kr
[2] School of Architecture and Planning, University of Texas at San Antonio, San Antonio, TX 78207, USA; ryunjung.lee@utsa.edu
[3] Department of Agricultural Civil Engineering, Kyungpook National University, Daegu 41566, Republic of Korea; leethy28@knu.ac.kr
* Correspondence: ycshin@knu.ac.kr

Abstract: Urban vacancies have been a concern for neighborhood distress and economic decline and have gained more recent attention as potential green infrastructure is known to benefit communities in diverse ways. To investigate this, this study looked into the relationship between land cover, natural environment, and urban vacancies in Austin, Texas. Additionally, we investigated the spatial patterns of green infrastructure and urban vacancies by different income groups to see if low income communities would potentially lack the benefits of green infrastructure. To measure green infrastructure, we used different land covers such as forests and shrublands, as well as natural environments such as tree canopies and vegetation richness, using remote sensing data. Urban vacancy information was retrieved from the USPS vacant addresses and parcel land uses. Through a series of multivariate analyses examining green infrastructure variables one by one, the study results indicate that green infrastructure interacts with residential and business vacancies differently. Additionally, low-income communities lack green infrastructure compared with the rest of the city and are exposed to more urban vacancies in their neighborhoods. Further study is required to understand the dynamics of vacancies in underserved communities and examine how existing vacant land can benefit the communities as ecological resources.

Keywords: urban forestry; vacant land; vacant parcel; land cover; natural environment; environmental inequity

check for updates

Citation: Kim, Y.-J.; Lee, R.J.; Lee, T.; Shin, Y. Green Infrastructure and Urban Vacancies: Land Cover and Natural Environment as Predictors of Vacant Land in Austin, Texas. *Land* **2023**, *12*, 2031. https://doi.org/10.3390/land12112031

Academic Editor: Muhammad Shafique

Received: 22 September 2023
Revised: 3 November 2023
Accepted: 6 November 2023
Published: 8 November 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Urban vacancies are both a symptom and a result of urban changes caused by population and industrial shifts. Economic downturn and urban decline have been a concern, especially in the Rust Belt region, which used to heavily rely on the manufacturing industry [1,2]. As industrial trends shifted from manufacturing in the past decades, cities started experiencing a loss of jobs and tax bases, which led to disinvestments and depopulation, increasing vacant and abandoned properties in urbanized areas. Urban vacancies can spread and increase the number of empty housing units in the areas people have left for better job opportunities and a better living environment. As urban vacancies show patterns and are typically caused by large-scale urban change, a parcel-based cure may not be enough to manage and reuse vacant properties [3].

Addressing the concerns of urban vacancies requires an understanding of the city-wide social and economic contexts. Urban vacancies could be a problem for the city, reducing tax bases and increasing exposure to on-site hazards and debris, further raising concerns for neighboring residents from an environmental justice viewpoint [4] and public health concerns [5]. Additionally, abandoned properties not properly managed over

time can become public eyesores subject to potential crimes and additional neighborhood disorders [6,7] (confirmed by empirical studies [8]). The broken windows theory describes how a lack of management of a property would potentially make the property a target for a crime [9]. At the same time, it is also notable that the vacancy itself may not be the problem, rather it is the level of maintenance [10].

Typical views on urban vacancies tend to be negative, as vacant and abandoned land is highly associated with urban decline and neighborhood disorders, as stated above. However, in the past decades, views on urban vacancies have shifted rather to addressing the potential of vacant properties in urban areas. Deborah Popper and Frank Popper have coined the term 'Smart Decline' as a way to view urban shrinkage positively and see urban vacancies as an opportunity rather than a threat to the city [11]. Traditionally, city planners have considered urban growth as a way to prosper, which could create concerns when vacant and abandoned land increases. However, not all municipalities are subject to foreseeable growth, and not all vacant properties in urban areas are subject to development in the short term. Thus, planners and policymakers have revisited the potential of vacant properties as an instrument for right-sizing the city rather than urban expansion [4,11,12].

A prominent view on repurposing urban vacancies is to utilize vacant properties as green infrastructure in urban areas. With the concept of smart decline (or smart shrinkage), reusing vacant properties as green space has been discussed [4,11,12]. Turning vacant properties into green infrastructure can bring diverse benefits economically, socially, and environmentally [12]. This does not require pressure to invest in long-term solutions to fill the empty properties [4]. A study conducted by Deng and Ma in 2015 looked at three cities—Binghamton, Johnson City, and Endicott—in the State of New York and found that vacant land can be a proxy for the greenness of the city [13]. To examine the relationship between vacant land and green infrastructure, different types of vacancies can be further examined through land cover [14]. For example, forests, shrublands, grass, or wetlands would function differently in urban areas.

Green infrastructure brings multiple benefits to the city. The term green infrastructure refers to the ecological resources that not only function as ecosystems but also can promote environmental, social, and economic benefits [15]. Green infrastructure can promote outdoor activities [16] and promote public health benefits [17]. Additionally, it can be an instrument to mitigate floods, heat islands, and air pollution [18]. Green infrastructure is a critical element in urban areas to promote sustainable growth, not limiting its role to ecological restoration or the preservation of nature [19]. Existing vacant properties can potentially function as green infrastructure and bring more benefits than concerns to the community.

It is probably worthwhile to note that the socioeconomic characteristics of the community should be taken into account when examining the relationship between urban vacancies and green infrastructure. First of all, the benefits of green infrastructure tend not to be the same across communities. Even with a higher level of green space, the health benefits could be low or minimal for areas with low socioeconomic status [20,21]. Additionally, the distribution of vacant properties across the city may not be homogeneous due to the types of vacancy associated with investment activities, land uses, and ownerships [22,23]. Due to the unequal level of resources and capital available to communities with low socioeconomic status, some communities might have more greenery available through ecological resources provided from vacant properties while may not have those resources even with a massive vacant land.

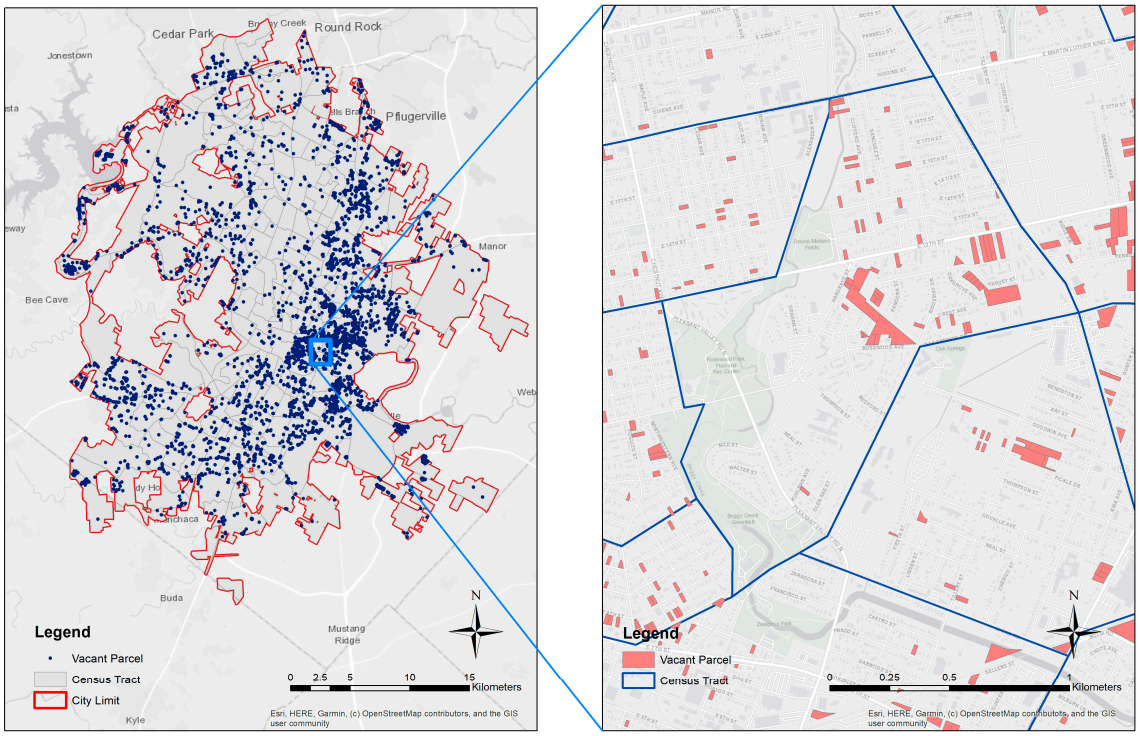
Despite the profound literature that addresses the importance of green infrastructure, particularly in socially vulnerable communities, and that outlines potential opportunities that urban vacancies can bring, not much is known about their relationship together. Vacant land might serve as green infrastructure in more affluent areas, while low-income areas continue to experience economic downturns or stagnant markets. As an attempt to address the relationship between green infrastructure, urban vacancies, and socioeconomic characteristics, this study examines (1) if the levels of green infrastructure and urban

vacancies differ by income group and (2) if certain types of green infrastructure would predict the level of urban vacancies. Green infrastructure can be measured with indicators such as land cover and natural environment. Identifying which indicators would predict existing vacancies in urban areas would help understand the types of green infrastructure expected around vacant properties and whether urban vacancies are contributing to green infrastructure in the community. Additionally, examining urban vacancies with diverse measures would help understand what kind of vacant land is in fact associated with green infrastructure.

2. Materials and Methods

2.1. Study Area and Samples

The study area is Austin, the capital city of the U.S. state of Texas. As of July 2022, Austin had an estimated population of 974,447 in the U.S. census and was ranked as the 2nd fastest growing U.S. city [24]. Even though the city does not show a pattern of urban decline or depopulation, vacant land still exists. As of 2021, a total of 4983 vacant addresses, including both residential and business vacancies, existed in Austin according to the USPS vacant address information available at the tract level, while the total vacant areas in Austin were 52,274,068 m^2. As shown in Figure 1, urban vacancies are more heavily observed in the eastern part of Austin. This unique pattern could be related to the locations of vacant addresses, and vacant land areas are related to land environmental characteristics such as land covers and natural environment as well as socioeconomic status in Austin areas.



(**a**) (**b**)

Figure 1. (**a**) Study area (Austin, TX); (**b**) Inset map showing the vacant parcels within census tracts.

To examine the relationship, the spatial unit of analysis for this study was set to census tracts. Out of a total of 221 census tracts in Austin, 210 census tracts were included for this study after excluding 11 census tracts. Those excluded tracts had missing information about median household incomes and property values that were used as confounding variables in this study.

2.2. Measures

2.2.1. Urban Vacancies (Dependent Variables)

Measuring urban vacancies is not straightforward due to the limited data available for vacant and abandoned land, especially at the city level. One of the most straightforward ways to capture vacancies is to identify vacant parcels from the citywide parcel data. The state of Texas has a unified land-use code for vacant parcels. The city of Austin open data portal makes the parcel data publicly available [25], and we were able to retrieve the 2021 parcel data and calculate the percentage of vacant land by census tract. While this would capture vacant and open spaces, it was limited to capturing vacancies by property level, whether the parcel had any structures or not. To capture urban vacancies more at the unit level, we also used the U.S. Postal Service vacant address dataset for 2021 [26]. This dataset captures units that have remained vacant for more than three months and separates vacant housing units from vacant business units. Using this dataset, we calculated the percentage of vacant residential and business addresses by census tract. With the diverse measures of urban vacancies, we examined the factors associated with different types of vacancies. We first examined residential and business vacancies separately using the vacant address information. Then, we examined the overall vacancies, including vacant addresses and vacant land areas. Finally, we linked this vacant dataset collected at the census tract level to the US Census Bureau data for statistical analyses.

2.2.2. Green Infrastructure as Land Cover and Natural Environments (Independent Variables)

Data for land cover and natural environment characteristics were all measured objectively at the census tract level using the geographic information system (GIS). We used the 2019 National Land Cover Database developed by the U.S. Geological Survey (USGS) and retrieved from the Multi-Resolution Land Characteristics Consortium [27]. The reason we selected the 2019 NLCD data was because they needed to be matched with the data period for the socioeconomic variables obtained from the 2019 U.S. census data platform. A total of seven representative land covers, including developed areas, barren land, forest, shrublands, herbaceous, planted or cultivated areas, and wetlands, were identified for this study, and the percentage of each land cover was captured within the census tracts. Additionally, to capture the natural environment, impervious surface and water information was also obtained from the USGS land cover data. Tree canopy digitized from aerial images in 2018 and park boundaries within the city of Austin were obtained from the city of Austin's open data portal. In addition to the tree canopy and park variables, the normalized difference vegetation index (NDVI) obtained from the USGS was also used for identifying the natural environment. The NDVI variable, which quantifies the vegetation richness in an area, was generated utilizing Landsat 8 operational land imager (OLI) images. NDVI with a 30 m $\times$ 30 m resolution was calculated as a ratio between bands 4 and 5 [28,29], and the mean of NDVI values was measured at the census tract level. Land surface temperature was also calculated using the Landsat 8 OLI thermal band image [28,29], and the mean values at the census tract level were generated. We also included information about slope conditions utilizing the digital elevation model data obtained from the Texas Natural Resources Information System. Two slope variables, indicating slopes greater than 5% and 8.33%, were generated for this study.

2.2.3. Socioeconomic Characteristics (Confounding Variables)

We also included variables representing the socioeconomic characteristics of the census tracts that could be associated with urban vacancies. Urban vacancies are known to be associated with neighborhood distress in marginalized areas [23]. Studies have indicated that there are different levels of land vacancies based on the neighborhood's socioeconomic characteristics [4,23,30,31]. To address this, we included household income, property values, poverty, and minority status to capture the socioeconomic status using the 2019 American Community Survey (2015–2019 5-year estimates) from the Census Bureau [32], which had small missing values compared with the 2021 census data. Minority status was

captured using the proportion of non-Hispanic White populations by census tracts. We also included population density to control the different land areas and population levels of each census tract. Finally, we measured the distance to downtown to account for the different environment that downtown could have.

2.3. Statistical Analyses

Two analytical approaches, including bivariate and multivariate analyses, were used in this study. First, a series of t-tests for bivariate analysis were conducted to examine the differences by income level in the mean of study variables, including socioeconomic status, land cover, and natural environment. The median household income in Austin (USD 72,797) was used as a threshold to categorize two income groups (0: low income, 1: high income). This also helped control some outliers that had too high or too low income values.

An ordinary least squares (OLS) regression model was used for multivariate analysis to examine the relationships between the independent variables and the dependent variables, controlling for the confounding variables. The OLS regression modeling involved two steps. First, four base models, including socioeconomic status and distance to downtown variables, were generated for four outcome variables: (1) residential addresses, (2) business addresses, (3) all vacant addresses, and (4) vacant-parcel land areas. Second, a series of one-by-one models were generated by adding each land cover and natural environment variable to the base model one at a time, including all the confounding variables. This method was chosen over adding all the land cover and natural environment variables together due to potential multicollinearity concerns between these variables. One-by-one models have the advantage of allowing for the examination of diverse aspects of green infrastructure without restricting the number of variables that represent the land cover and natural environment. The one-by-one tests examined the relationships of land cover and natural environment characteristics with four urban vacancy outcomes while controlling for socioeconomic status and distance to downtown. The bivariate and multivariate analyses were undertaken using STATA version 18 [33].

3. Results

3.1. Bivariate Tests

3.1.1. Socioeconomic Status and Vacancy Characteristics

Table 1 shows sample characteristics and bivariate test results identifying the differences in means of socioeconomic status and vacancy characteristics between low- and high-income areas. With a median household income of USD 83,034, the income level in low-income areas was USD 55,586, roughly half that of the average income in higher-income areas (USD 109,455). The mean property value was USD 365,301 for the whole city, and there was a significant difference in the mean property value between two income groups. The percentage of minority populations was significantly higher in low-income areas (60.55%) compared with high-income areas (36.62%). The average population density per square mile in low- and high-income areas was 5461 and 3408, respectively. The percentage of poverty in low-income areas was 18.05%, which was three times higher than in high-income areas. The average distance to downtown was 9060 m for the city, with high-income areas having a greater distance (10,374 m) than low-income areas (7696 m). The average percentages of vacant residential and business addresses were 1.32% and 5.49% for the whole city, with low-income areas having a significantly higher percentage for both residential and business vacant addresses than high-income areas.

Table 1. Sample characteristics and bivariate test results between low- and high-income areas for the study variables.

Variables	All (N = 210)	Low Income (N = 103)	High Income (N = 107)	Difference in Mean
	Mean (SD)	Mean (SD)	Mean (SD)	
Socioeconomic Characteristics				
Household income (USD)	83,034.12 (37,801.41)	55,586.84 (12,465.22)	109,455.30 (35,088.96)	−53,868.49 ***
Property value (USD)	365,301.40 (196,836.00)	269,079.60 (109,497.30)	457,926.20 (217,251.40)	−188,846.60 ***
Minority (%)	48.35 (21.72)	60.55 (19.63)	36.62 (16.61)	23.93 ***
Population density (no. per sq.mi.)	4415.46 (3601.28)	5461.75 (4394.25)	3408.28 (2214.24)	2053.47 ***
Poverty (%)	12.03 (10.75)	18.05 (12.18)	6.25 (3.99)	11.80 ***
Distance to downtown (m)	9060.78 (6177.01)	7696.13 (5509.50)	10,374.42 (6516.94)	−2678.29 ***
USPS Vacant Addresses				
Residential vacant address (%)	1.32 (1.30)	1.60 (1.40)	1.06 (1.14)	0.54 ***
Business vacant address (%)	5.49 (5.64)	6.51 (5.83)	4.50 (5.29)	2.01 ***
All vacant address (%)	1.61 (1.39)	1.95 (1.42)	1.28 (1.27)	0.67 ***
Vacant Parcel				
Vacant-parcel land area (%)	4.86 (8.81)	4.58 (6.31)	5.13 (10.72)	−0.55

*** $p < 0.01$; SD—standard deviation.

3.1.2. Land Cover and Natural Environment

Table 2 presents the mean differences in land cover and natural environmental characteristics between low- and high-income areas. The average percentage of developed area was 13.65% higher for low-income areas, while the percentage of forest was 10.10% higher in high-income areas. Impervious surface and land surface temperatures were 11.90% and 0.95 °C higher in low-income areas compared with high-income areas, respectively. High-income areas had higher tree canopy (34.46% vs. 21.01%), higher levels of greenery measured by NDVI (0.23 vs. 0.21), more water features (2.79% vs. 0.45%), and greater steep slopes over 8.33% (20.18% vs. 12.01%). Figures 2 and 3 show the spatial pattern of income levels, urban vacancies, and green infrastructure measured within the census tracts. The patterns indicate that low-income areas were heavily observed in the eastern part of Austin, with less green vegetation and higher percentages of vacancies.

Table 2. Bivariate test results identifying the differences in the mean of the land cover and natural environment variables between low- and high-income areas.

Variables	All (N = 210)	Low Income (N = 103)	High Income (N = 107)	Difference in Mean
	Mean (SD)	Mean (SD)	Mean (SD)	
Land covers				
Developed areas (%)	78.59 (27.53)	85.55 (22.42)	71.90 (30.29)	13.65 ***
Barren (%)	0.22 (1.03)	0.14 (0.33)	0.29 (1.40)	−0.15
Forest (%)	13.13 (16.96)	7.99 (9.98)	18.09 (20.52)	−10.10 ***
Shrubland (%)	3.05 (7.25)	2.28 (6.06)	3.80 (8.19)	−1.52
Herbaceous (%)	3.41 (9.14)	2.99 (9.75)	3.81 (8.54)	−0.82
Planted (%)	1.43 (4.88)	1.67 (5.65)	1.21 (4.01)	0.46
Wetlands (%)	1.74 (3.65)	2.19 (4.44)	1.30 (2.61)	0.89
Natural environment				
Impervious surface (%)	39.68 (18.04)	45.74 (16.78)	33.84 (17.34)	11.90 ***
Tree canopy (%)	27.86 (15.68)	21.01 (10.76)	34.46 (16.84)	−13.45 ***
NDVI (−1 to 1)	0.22 (0.04)	0.21 (0.03)	0.23 (0.04)	−0.02 ***
Park (%)	6.25 (9.40)	6.77 (10.17)	5.75 (8.61)	1.02
Water features (%)	1.64 (6.25)	0.45 (1.82)	2.79 (8.43)	−2.34 ***
Land surface temperature (°C)	33.22 (1.41)	33.70 (1.10)	32.75 (1.53)	0.95 ***
Slope > 5% (%)	29.82 (21.29)	26.32 (16.95)	33.19 (24.35)	−6.88 **
Slope > 8.33% (%)	16.17 (17.93)	12.01 (11.83)	20.18 (21.59)	−8.17 ***

** $0.01 \leq p < 0.05$; *** $p < 0.01$; SD—standard deviation.

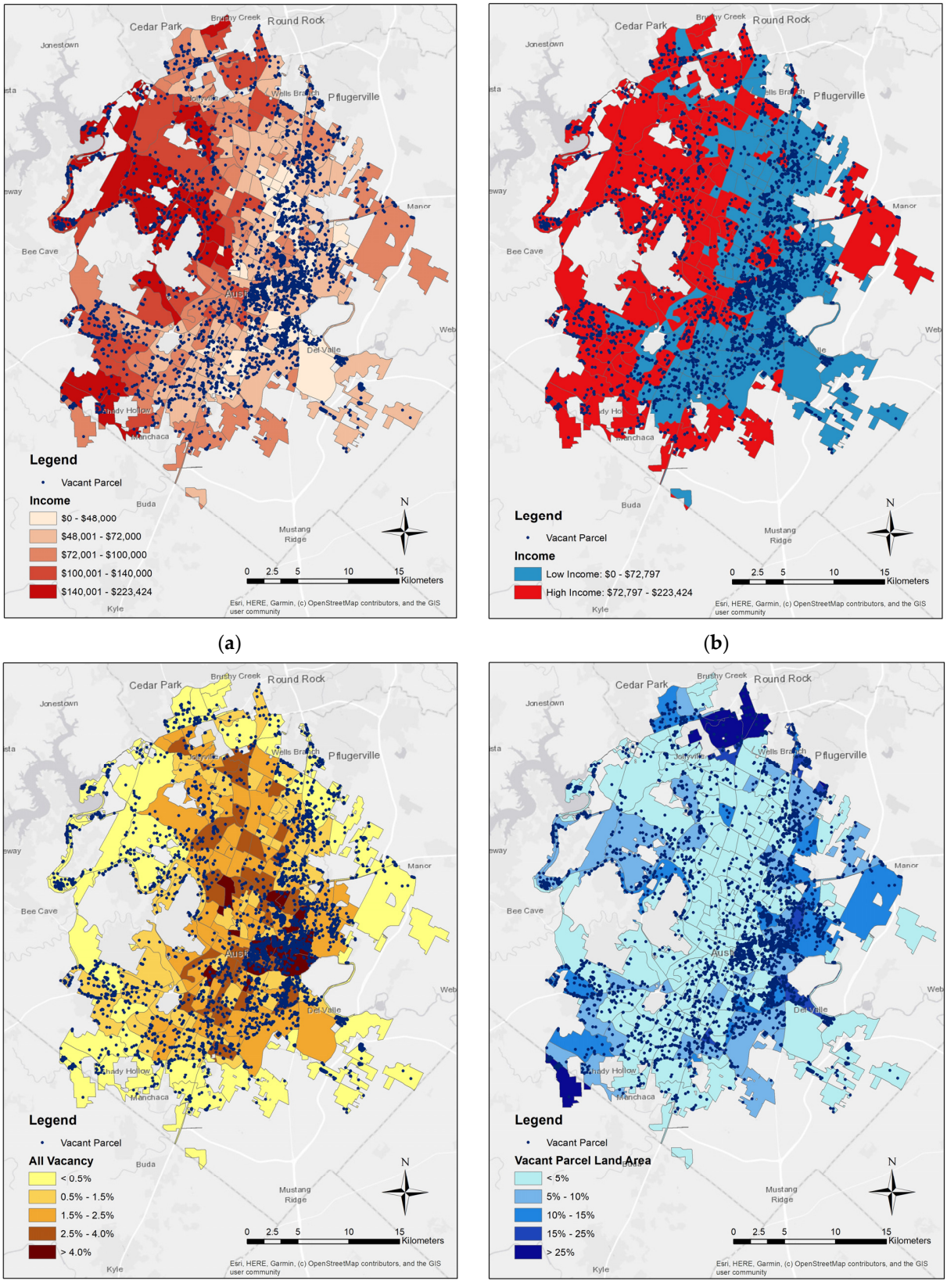
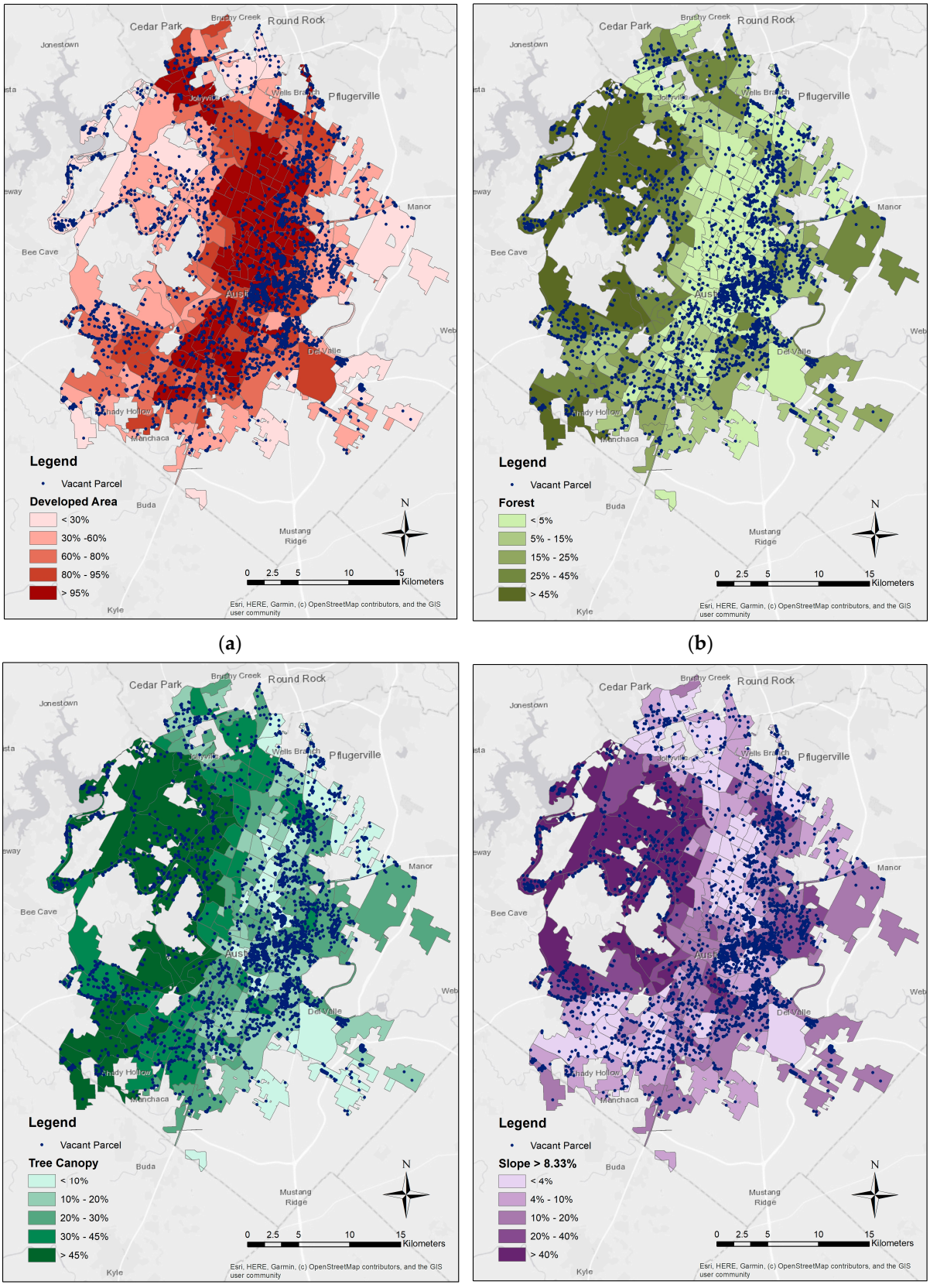


Figure 2. Spatial distributions of urban vacant parcels and income levels. (**a**) All income; (**b**) Low and high income; (**c**) All vacancy; (**d**) Vacant parcel land area.



(**a**) (**b**)

(**c**) (**d**)

Figure 3. Uneven distribution of green infrastructure. (**a**) Developed area; (**b**) Forest; (**c**) Tree canopy; (**d**) Slope > 8.33%.

3.2. Multivariate Analyses

3.2.1. Base Models (Control Variables)

Table 3 presents the results of OLS regressions, estimating the associations between socioeconomic status and urban vacancies and vacant-parcel land area. The median household income was negatively associated with residential, business, and all vacancies, indicating that urban vacancies are less likely to be observed when the median income percentage increases. Every additional increase in the minority percentage was negatively associated with the business vacant percentage. On the other hand, the population density measured by the number of residents per square mile was positively associated with the residential vacant percentage. The distance to downtown had a negative relationship with residential vacancy, all vacancy, and vacant-parcel land area, which means that areas closer to downtown would have a higher level of residential and all vacancies and a higher percentage of vacant-parcel land area.

Table 3. Base models estimating the associations between the control variables and urban vacancies and vacant land areas.

Control Variables	Residential Vacancy		Business Vacancy		All Vacancy		Vacant-Parcel Land Area	
	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$
Socioeconomic Status								
Median income (USD 1000)	−0.008 **	0.038	−0.055 **	0.004	−0.013 **	0.002	0.006	0.854
Property value (USD 1000)	0.001	0.186	0.002	0.692	0.001	0.257	−0.002	0.705
Minority (%)	0.000	0.981	−0.071 **	0.010	−0.010 †	0.095	0.057	0.187
Population density (per sq. miles)	0.066 **	0.020	0.116	0.413	0.043	0.149	−0.336	0.137
Poverty (%)	−0.008	0.474	0.002	0.978	0.006	0.623	0.013	0.886
Distance to downtown (1000 m)	−0.094 ***	0.000	−0.137 †	0.087	−0.098 ***	0.000	0.344 ***	0.007
No. of observations	210		210		210		210	
LR Chi	19.75		6.26		20.51		4.99	
Pro > Chi-Sq	<0.0000		<0.0000		<0.0000		0.0001	
Pseudo R^2	0.3686		0.1562		0.3774		0.1284	

† $0.05 \leq p < 0.1$; ** $0.01 \leq p < 0.05$; *** $p < 0.01$; Coef.—coefficient; Sq.—square; No.—number.

3.2.2. One-by-One Models

Table 4 presents the results of one-by-one OLS regression models, estimating the associations of land cover and natural environment with (1) the percentage of urban vacancies (three outcomes: residential vacancy, business vacancy, and all vacancy) calculated with vacant addresses and (2) the percentage of vacant land (one outcome) measured with vacant parcels. Among the land-cover variables, developed-area cover was positively associated with the percentage of residential vacancy and negatively associated with the percentage of vacant-parcel land area. Shrubland and planted covers showed a negative relationship with residential, business, and all vacancies. While every additional percentage of forest cover led to a decrease in the residential vacant percentage, it would increase the vacant-land percentage. Vacant-parcel land was more likely to be increased by an increase in the percentage of barren, herbaceous, and wetland covers.

Additionally, a greater amount of tree canopy was associated with a higher percentage of business vacancies. The surface temperature variable showed a positive relationship with the percentage of residential vacancy and all vacancies, indicating that every additional increase in surface temperature resulted in a greater percentage of residential and all vacancies. Greater impervious surfaces resulted in an increase in all vacancies but a decrease in vacant-parcel land areas. A steeper slope was more likely to decrease the percentage of residential vacancy and of all vacancies. Water features were marginally associated with decreased business and all vacancy percentages.

Table 4. One-by-one models estimating the associations of land cover and natural environment with the percentage of urban vacancies and vacant-parcel land area.

Green Infrastructure	Residential Vacancy		Business Vacancy		All Vacancy		Vacant-Parcel Land Area	
	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$	Coef.	$p > \|t\|$
Land Covers								
Developed areas (%)	0.012 ***	0.001	0.024	0.190	0.015 ***	0.000	−0.123 ***	0.000
Barren (%)	0.038	0.600	0.412	0.258	0.048	0.533	2.287 ***	0.000
Forest (%)	−0.013 **	0.018	0.030	0.277	−0.013 **	0.031	0.093 **	0.034
Shrubland (%)	−0.035 ***	0.003	−0.177 ***	0.002	−0.046 ***	0.000	−0.160 †	0.088
Herbaceous (%)	−0.002	0.855	−0.049	0.277	−0.006	0.506	0.490 ***	0.000
Planted (%)	−0.040 **	0.018	−0.170 **	0.045	−0.049 ***	0.006	0.058	0.668
Wetlands (%)	−0.016	0.469	0.160	0.149	0.005	0.842	0.449 **	0.010
Natural Environment								
Impervious surface (%)	0.007	0.186	0.019	0.475	0.014 **	0.008	−0.122 ***	0.003
Tree canopy (%)	−0.006	0.338	0.075 **	0.013	−0.003	0.601	0.014	0.779
NDVI (−1 to 1)	−0.090	0.967	17.101	0.118	−1.117	0.630	12.617	0.470
Park (%)	−0.004	0.648	0.019	0.639	0.002	0.791	0.019	0.778
Water features (%)	−0.012	0.304	−0.111 †	0.065	−0.021 †	0.093	−0.008	0.937
Surface temperature (°C)	0.150 **	0.025	0.262	0.436	0.219 ***	0.002	−0.447	0.402
Slope > 5% (%)	−0.009 **	0.021	0.003	0.885	−0.010 **	0.019	−0.011	0.730
Slope > 8.33% (%)	−0.008	0.103	0.044 †	0.090	−0.005	0.326	−0.011	0.783

Note: all the variables listed above were added into the base model one at a time, controlling for the control variables. † $0.05 \leq p < 0.1$; ** $0.01 \leq p < 0.05$; *** $p < 0.01$.

4. Discussion

This study looked into potential links between socioeconomic characteristics, green infrastructure, and urban vacancies to identify whether unique characteristics are observed by income level and whether land cover and the natural environment would predict the level of vacancies in Austin, Texas. When analyzing urban vacancies with different measures, we found that there was no consistency in the socioeconomic characteristics of the surroundings. For example, residential vacancies were more prevalent with higher density, while other vacancy types were not. Business vacancies were found with a higher minority level, while all vacancies measured with vacant addresses would be observed in lower income areas. None of the socioeconomic variables would predict vacant land areas. This suggests the importance of classifying vacancies based on the study purpose when measuring urban vacancies at a large scale.

The OLS regression results demonstrated that the role of the natural environment in predicting urban vacancies varied by vacancy type. For instance, a greater amount of tree canopy cover was associated with a higher business vacancy only and not with other vacancy types in our study area, Austin, TX. This could indicate that increased urban vacancies would not necessarily mean a higher level of green infrastructure, and perhaps areas with active businesses would not have enough tree canopy coverage compared with less active areas typically located a long distance from downtown. In contrast, higher land surface temperatures and a lower level of slope were associated with increased residential vacancy. High land surface temperatures lead to thermally uncomfortable conditions for residents, providing an undesirable living environment [34–37], and thus higher residential vacancy rates may be observed in areas with higher land surface temperatures. Steep slopes, on the other hand, are associated with a decreased residential vacancy percentage but a marginally increased business vacancy percentage. Those varying relationships might be because steep slopes in Austin are generally distributed in forest land in hilly areas that have a great amount of green vegetation but are a long distance from downtown, which will a provide pleasant living environment for residents but undesirable conditions for businesses.

In addition, land covers were shown to be differently associated with residential and business vacant types. Developed land covers were positively associated with residential vacancy rates but negatively associated with vacant land areas. This could be because more developed areas have a more impervious surface and a higher surface

temperature [34,38,39], leading to a thermally uncomfortable living environment for residents. Our study results support this relationship, emphasizing the importance of the microclimate environment, especially in urbanized areas. Our analysis also supports this by showing that forest and planted covers were positively associated with decreased residential vacant rates. This finding is quite obvious in that forests and planted land covers with a greater amount of greenery can provide residents with beautiful scenery and healthy environmental conditions [34,40–45]. Another interesting pattern was that water features were marginally associated with decreased business vacancy rates. Austin has many reservoirs and lakes, and the Colorado River flowing through downtown and the inner city, where business districts are located. These water features can provide a beautiful natural landscape for high-rise business and residential buildings and could attract waterfront development [46], which would eventually help reduce urban vacancies.

As more areas of the globe become urbanized, green infrastructure has become more crucial than ever. In fact, green infrastructure is known to bring physical and mental health benefits and increase social capital, leading to a healthy living environment [34,40–45]. This study sheds light on the potential link between the lack of green infrastructure and higher vacancy rates as, unfortunately, vacant addresses are observed in more urbanized areas with less greenery in Austin. Vacant addresses, identified through the USPS mailing service, represent either newly developed areas waiting for new residents to move in or declining areas with a higher level of housing vacancies. For newly developed residential areas, the lower level of green infrastructure makes these areas subject to heat exposure and flood risk. For areas experiencing economic decline, lower levels of green infrastructure could trigger further decline, contributing to an undesirable living environment. In either case, our study results lead to potential concern regarding the lack of green infrastructure in areas with higher vacancy rates.

In Austin, while urban vacancies measured with vacant addresses showed a lower level of green infrastructure, it is noteworthy that vacant land areas measured with vacant parcels showed a different pattern. Specifically, areas with more forest and herbaceous land covers tended to show a higher level of vacant land areas. Vacant land was also more prevalent in areas already covered in greenery but not associated with a tree canopy or rich vegetation. These findings can suggest that these vacant properties in Austin have been serving as ecological assets and green infrastructure. Several studies showed that vacant land that has a great quality of green infrastructure (i.e., number of trees, tree size, and tree species composition) can contribute to reducing air pollution and carbon dioxide [47,48], ameliorating urban heat island effects [48,49], and increasing habitat connectivity [48]. Furthermore, vacant land, if managed correctly as green infrastructure, can contribute to flood resilience by managing stormwater runoff in the community [50]. Thus, more consideration for repurposing vacant land with green infrastructure rather than chasing potential investment is necessary to contribute to both ecological and economic benefits.

This study also looked into potential inequity concerns in the relationship between green infrastructure and urban vacancies by conducting bivariate tests and analyzing spatial patterns through GIS mapping. A consistent pattern in the literature on green infrastructure is that more affluent communities tend to have better green infrastructure in the community [51,52]. Austin is no different when examining the level of greenery and land cover in high and low income groups. This is a devastating pattern that is never too dated to address repeatedly until this pattern no longer becomes the norm. When low-income communities have almost half of the forests and two thirds of the tree canopy with more impervious surfaces and higher surface temperatures compared with higher-income areas according to our study, the indirect impact on community health and even property values is concerning.

This study has several limitations. First, this study conducted a series of one-by-one models while controlling for socioeconomic status, thus not generating a fully adjusted statistical model. The reason for utilizing the one-by-one model method was because the multicollinearity problem existed among the green infrastructure variables. Many natural

variables, such as tree canopy, NDVI, impervious surface, and land surface temperature, were highly correlated with each other in this study. Thus, each variable was added to the base model one at a time, as controls for the confounding variables. Second, this study was a cross-sectional study that needed a careful interpretation of the relationship between green infrastructure and urban vacancies and should not be interpreted as a causal relationship. A future study may handle the sequencing possible relationship between the study variables by utilizing structural equation modeling. This study was also subject to spatial autocorrelation, as observations were not truly independent. While further studies can explore potential spillover effects in the model, we expected a modest spatial autocorrelation in our analyses, given that census tracts were a large unit to examine green infrastructure and vacancies that were not enough to influence neighboring tracts. An advantage of using OLS instead was that the results could be interpreted more intuitively. Third, correlations among the census tract level data generally reflected spatial patterns of land cover and natural environmental characteristics related to urban vacancies and could not capture more fine-grained details. We also wanted to address potential modifiable aerial unit problems, as the property level vacancy information was aggregated into census tracts. Aggregating data had the potential to dilute the distinctive characteristics of the vacant properties and, depending on the way tract boundaries were defined, to bias the results. Thus, future studies may need to explore more detailed environmental characteristics within and around urban vacancies at the vacant-parcel level, utilizing different units of analysis such as buffered areas around vacant parcels. Furthermore, it would be helpful if a future study used high spatial resolution imagery such as the National Agriculture Imagery Program that has a 0.6 to 1.0 m spatial resolution for identifying the land cover characteristics at the micro- or parcel level.

5. Conclusions

Green infrastructure is known to benefit communities, yet the relationship with urban vacancies, particularly in socially vulnerable communities, is unknown. This study investigated this relationship to identify potential spatial heterogeneity in green infrastructure and vacancies by income level in Austin. By analyzing the land covers and natural environment associated with vacant addresses and properties, we identified potential green infrastructure patterns associated with higher levels of vacancies. This study provides insight into future policies toward citywide vacancies in relation to existing green infrastructures that vary by income level. The study results indicate that the relationship between land cover, the natural environment, and urban vacancies may be complex, and green infrastructure can potentially interact with residential and business vacancies differently. Additionally, in Austin, vacancies measured with addresses tend to show a lower level of green infrastructure than vacant land areas. Potential inequity concerns are also addressed with heterogeneous patterns of green infrastructure and urban vacancies by income level. Further questions can be asked to address the long-term health concerns in marginalized communities with the role of green infrastructure and vacancies.

Author Contributions: Conceptualization, Y.-J.K., R.J.L. and Y.S.; methodology, Y.-J.K., R.J.L. and Y.S.; software, Y.-J.K., T.L. and Y.S.; validation, Y.-J.K., R.J.L. and Y.S.; formal analysis, Y.-J.K., R.J.L. and Y.S.; investigation, Y.-J.K., R.J.L. and Y.S.; resources, Y.-J.K. and Y.S.; data curation, Y.-J.K., R.J.L., T.L. and Y.S.; writing—original draft preparation, Y.-J.K., R.J.L., T.L. and Y.S.; writing—review and editing, Y.-J.K., R.J.L., T.L. and Y.S.; visualization, Y.-J.K. and T.L.; supervision, Y.-J.K. and Y.S.; project administration, Y.-J.K., R.J.L. and Y.S.; funding acquisition, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Korea Ministry of Environment as "the SS (Surface Soil conservation and management) projects; 2019002820002".

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: We are so grateful to the anonymous reviewers and editors for their suggestions.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Coleman, A. The death of the inner city: Cause and cure. *Lond. J.* **1980**, *6*, 3–22. [CrossRef]
2. Newman, G.D.; Bowman, A.O.M.; Jung Lee, R.; Kim, B. A current inventory of vacant urban land in America. *J. Urban Des.* **2016**, *21*, 302–319. [CrossRef]
3. Ryan, B.D. Toward Social Urbanism for Shrinking Cities. In *Design after Decline: How America Rebuilds Shrinking Cities*; University of Pennsylvania Press: Philadelphia, PA, USA, 2012.
4. Németh, J.; Langhorst, J. Rethinking urban transformation: Temporary uses for vacant land. *Cities* **2014**, *40*, 143–150. [CrossRef]
5. Garvin, E.; Branas, C.; Keddem, S.; Sellman, J.; Cannuscio, C. More than just an eyesore: Local insights and solutions on vacant land and urban health. *J. Urban Health* **2013**, *90*, 412–426. [CrossRef] [PubMed]
6. Perkins, D.D.; Meeks, J.W.; Taylor, R.B. The physical environment of street blocks and resident perceptions of crime and disorder: Implications for theory and measurement. *J. Environ. Psychol.* **1992**, *12*, 21–34. [CrossRef]
7. Immergluck, D.; Smith, G. The impact of single-family mortgage foreclosures on neighborhood crime. *Hous. Stud.* **2006**, *21*, 851–866. [CrossRef]
8. Ellen, I.G.; Lacoe, J.; Sharygin, C.A. Do foreclosures cause crime? *J. Urban Econ.* **2013**, *74*, 59–70. [CrossRef]
9. Kelling, G.L.; Wilson, J.Q. Broken windows. *Atl. Mon.* **1982**, *249*, 29–38.
10. Kondo, M.; Hohl, B.; Han, S.; Branas, C. Effects of greening and community reuse of vacant lots on crime. *Urban Stud.* **2016**, *53*, 3279–3295. [CrossRef]
11. Popper Deborah, E.; Popper Frank, J. Small Can Be Beautiful: Coming to Terms with Decline. *Planning* **2002**, *68*, 20–23.
12. Schilling, J.; Logan, J. Greening the rust belt: A green infrastructure model for right sizing America's shrinking cities. *J. Am. Plan. Assoc.* **2008**, *74*, 451–466. [CrossRef]
13. Deng, C.; Ma, J. Viewing urban decay from the sky: A multi-scale analysis of residential vacancy in a shrinking US city. *Landsc. Urban Plan.* **2015**, *141*, 88–99. [CrossRef]
14. Song, X.; Wen, M.; Shen, Y.; Feng, Q.; Xiang, J.; Zhang, W.; Zhao, G.; Wu, Z. Urban vacant land in growing urbanization: An international review. *J. Geogr. Sci.* **2020**, *30*, 669–687. [CrossRef]
15. Benedict, M.A.; McMahon, E.T. Green infrastructure: Smart conservation for the 21st century. *Renew. Resour. J.* **2002**, *20*, 12–17.
16. Coombes, E.; Jones, A.P.; Hillsdon, M. The relationship of physical activity and overweight to objectively measured green space accessibility and use. *Soc. Sci. Med.* **2010**, *70*, 816–822. [CrossRef]
17. Maas, J.; Verheij, R.A.; de Vries, S.; Spreeuwenberg, P.; Schellevis, F.G.; Groenewegen, P.P. Morbidity is related to a green living environment. *J. Epidemiol. Community Health* **2009**, *63*, 967–973. [CrossRef]
18. Nieuwenhuijsen, M.J. Green infrastructure and health. *Annu. Rev. Public Health* **2021**, *42*, 317–328. [CrossRef]
19. Wang, J.; Banzhaf, E. Towards a better understanding of Green Infrastructure: A critical review. *Ecol. Indic.* **2018**, *85*, 758–772. [CrossRef]
20. Hong, A.; Martinez, L.; Patino, J.E.; Duque, J.C.; Rahimi, K. Neighbourhood green space and health disparities in the global South: Evidence from Cali, Colombia. *Health Place* **2021**, *72*, 102690. [CrossRef]
21. Lee, S.; Lee, R.J.; Scherr, S. How tree canopy cover can reduce urban suicide attempts: A geospatial analysis of the moderating role of area deprivation. *Landsc. Urban Plan.* **2023**, *230*, 104606. [CrossRef]
22. Lee, R.J.; Newman, G. The relationship between vacant properties and neighborhood gentrification. *Land Use Policy* **2021**, *101*, 105185. [CrossRef]
23. Lee, R.J.; Newman, G.; Van Zandt, S. Using neighborhood characteristics to predict vacancy types: Comparing multi-scale conditions surrounding existing vacant lots. *Environ. Plan. B Urban Anal. City Sci.* **2023**, 23998083231160542. [CrossRef]
24. Project, A.G. *2022's Fastest-Growing Cities in the U.S., Ranked*; Kenan Institute of Private Enterprise: Chapel Hill, NC, USA, 2022.
25. City of Austin Open Data Portal Topics. Available online: https://data.austintexas.gov/ (accessed on 28 April 2023).
26. HUD. HUD Aggregated USPS Administrative Data on Address Vacancies. Available online: https://www.huduser.gov/portal/datasets/usps.html (accessed on 3 March 2023).
27. MRLC. NLCD Land Cover. Available online: https://www.mrlc.gov/data (accessed on 10 March 2023).
28. Kumar, B.P.; Babu, K.R.; Anusha, B.; Rajasekhar, M. Geo-environmental monitoring and assessment of land degradation and desertification in the semi-arid regions using Landsat 8 OLI/TIRS, LST, and NDVI approach. *Environ. Chall.* **2022**, *8*, 100578. [CrossRef]
29. Guha, S.; Govil, H.; Dey, A.; Gill, N. Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *Eur. J. Remote Sens.* **2018**, *51*, 667–678. [CrossRef]
30. Foo, K.; Martin, D.; Wool, C.; Polsky, C. Reprint of "The production of urban vacant land: Relational placemaking in Boston, MA neighborhoods". *Cities* **2014**, *40*, 175–182. [CrossRef]
31. Shlay, A.B.; Whitman, G. Research for democracy: Linking community organizing and research to leverage blight policy. *City Community* **2006**, *5*, 153–171. [CrossRef]

32. Bureau, C. American Community Survey 5-Year Data. Available online: https://www.census.gov/data/developers/data-sets/acs-5year.html (accessed on 10 May 2023).
33. STATA. Available online: https://www.stata.com/ (accessed on 10 May 2023).
34. Kim, Y.-J.; Lee, C.; Kim, J.-H. Sidewalk landscape structure and thermal conditions for child and adult pedestrians. *Int. J. Environ. Res. Public Health* **2018**, *15*, 148. [CrossRef]
35. Shashua-Bar, L.; Pearlmutter, D.; Erell, E. The influence of trees and grass on outdoor thermal comfort in a hot-arid environment. *Int. J. Climatol.* **2011**, *31*, 1498–1506. [CrossRef]
36. Liu, B.; Lian, Z.; Brown, R.D. Effect of landscape microclimates on thermal comfort and physiological wellbeing. *Sustainability* **2019**, *11*, 5387. [CrossRef]
37. Harlan, S.L.; Brazel, A.J.; Prashad, L.; Stefanov, W.L.; Larsen, L. Neighborhood microclimates and vulnerability to heat stress. *Soc. Sci. Med.* **2006**, *63*, 2847–2863. [CrossRef]
38. Jiang, Y.; Fu, P.; Weng, Q. Assessing the impacts of urbanization-associated land use/cover change on land surface temperature and surface moisture: A case study in the midwestern United States. *Remote Sens.* **2015**, *7*, 4880–4898. [CrossRef]
39. Dutta, D.; Rahman, A.; Paul, S.; Kundu, A. Impervious surface growth and its inter-relationship with vegetation cover and land surface temperature in peri-urban areas of Delhi. *Urban Clim.* **2021**, *37*, 100799. [CrossRef]
40. James, P.; Banay, R.F.; Hart, J.E.; Laden, F. A review of the health benefits of greenness. *Curr. Epidemiol. Rep.* **2015**, *2*, 131–142. [CrossRef] [PubMed]
41. De Vries, S.; Van Dillen, S.M.; Groenewegen, P.P.; Spreeuwenberg, P. Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. *Soc. Sci. Med.* **2013**, *94*, 26–33. [CrossRef] [PubMed]
42. Nutsford, D.; Pearson, A.L.; Kingham, S. An ecological study investigating the association between access to urban green space and mental health. *Public Health* **2013**, *127*, 1005–1011. [CrossRef] [PubMed]
43. Markevych, I.; Schoierer, J.; Hartig, T.; Chudnovsky, A.; Hystad, P.; Dzhambov, A.M.; De Vries, S.; Triguero-Mas, M.; Brauer, M.; Nieuwenhuijsen, M.J. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environ. Res.* **2017**, *158*, 301–317. [CrossRef]
44. Aram, F.; Solgi, E.; Holden, G. The role of green spaces in increasing social interactions in neighborhoods with periodic markets. *Habitat Int.* **2019**, *84*, 24–32. [CrossRef]
45. Jennings, V.; Bamkole, O. The relationship between social cohesion and urban green space: An avenue for health promotion. *Int. J. Environ. Res. Public Health* **2019**, *16*, 452. [CrossRef]
46. Hou, D. Urban Waterfront Landscape Planning. 2009. Available online: https://www.diva-portal.org/smash/get/diva2:828355/FULLTEXT01.pdf (accessed on 26 May 2023).
47. Kim, G.; Miller, P.; Nowak, D. The value of green infrastructure on vacant and residential land in Roanoke, Virginia. *Sustainability* **2016**, *8*, 296. [CrossRef]
48. Meerow, S.; Newell, J.P. Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit. *Landsc. Urban Plan.* **2017**, *159*, 62–75. [CrossRef]
49. Abdulateef, M.F.; Al-Alwan, H.A. The effectiveness of urban green infrastructure in reducing surface urban heat island. *Ain Shams Eng. J.* **2022**, *13*, 101526. [CrossRef]
50. Newman, G.; Dongying, L.; Rui, Z.; Dingding, R. Resilience through regeneration: The economics of repurposing vacant land with green infrastructure. *Landsc. Archit. Front.* **2019**, *6*, 10. [CrossRef] [PubMed]
51. Kim, Y.-J.; Woo, A. Estimating natural environmental characteristics of subsidized households: A case study of austin, texas. *Sustainability* **2015**, *7*, 13433–13453. [CrossRef]
52. Kim, Y.-J.; Kim, E.J. Neighborhood greenery as a predictor of outdoor crimes between low and high income neighborhoods. *Int. J. Environ. Res. Public Health* **2020**, *17*, 1470. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.