sustainability

MDPI

Article

Analysis of Residential Satisfaction Changes by the Land Bank Program Using Text Mining

Seongbeom Park [1], Jaekyung Lee [1,*] and Yunmi Park [2]

[1] Department of Urban Design & Planning, Hongik University, Seoul 04066, Korea
[2] Architectural and Urban Systems Engineering, College of Engineering, Ewha Womans University, Seoul 03760, Korea
* Correspondence: jklee1@hongik.ac.kr; Tel.: +82-2-320-1107

Abstract: Many American manufacturing cities have experienced depopulation and economic downturns over the past five decades, and various revitalization strategies have been suggested to overcome the decline issue—ranging from redevelopment to smart decline. However, while most land bank-related studies have focused on socioeconomic dynamics (income levels, unemployment rate, etc.) through the program, there is a lack of direct research on residential satisfaction changes. Additionally, surveys were frequently used in previous studies to evaluate residential satisfaction; however, this method has disadvantages, including constraints on time and cost, and the inability to take into account external factors that may affect residential satisfaction. Furthermore, most studies on urban decline have focused primarily on declining factors, and there have been few investigations into how cities change as urban regeneration strategies advance. Therefore, the primary purpose of this study is to identify the influence of the land bank program on residential satisfaction by using Twitter data. Approximately 300,000 Twitter posts containing location information generated within the city of Detroit were collected to determine the degree of sensitivity to each tweet and categorized into positive and negative emotions to determine the relationship between residential satisfaction and the land bank program. As a result, the increase in homeownership, built year, house value, and the number of land banking sold properties were found to have a negative effect on neighborhood satisfaction in Detroit. Although the research results indicated that while the land bank program did not significantly improve residential satisfaction in Detroit, it has made a partial contribution to improving living standards. These findings emphasize the importance of enhancing residential satisfaction and suggest the need for policy change. In response to the problem of urban contraction, it seems that indiscriminately distributing houses is not the only solution to prevent urban shrinkage. Furthermore, this study shows meaningful results on text mining and provides the possibility of developing research using social network services.

Keywords: twitter; text mining; urban revitalization; land bank program; Detroit Land Bank Authority; Detroit

check for updates

Citation: Park, S.; Lee, J.; Park, Y. Analysis of Residential Satisfaction Changes by the Land Bank Program Using Text Mining. *Sustainability* **2022**, *14*, 11707. https://doi.org/10.3390/su141811707

Academic Editors: Xiaoguang Zhou, Yijiang Zhao and Fei Chen

Received: 9 July 2022
Accepted: 15 September 2022
Published: 18 September 2022

1. Introduction

While many American cities are currently going through rapid urban growth, this trend is not evenly distributed. Many former manufacturing cities have experienced depopulation and economic downturn over three decades, and razing and redevelopment are the most common and direct strategies used to overcome the urban decline issue. However, the impact falls short of the planners' expectations. The lack of understanding of the sites' physical capabilities and the residents' socioeconomic features have worsened the situation, such as tenants' housing problems and the departure of existing residents. Furthermore, the ongoing maintenance costs were excessive, even after the raze and redevelopment were completed. Rybczynski and Linneman (1999) also mentioned that American cities with population loss continue to have more housing, transportation, and public infrastructure than they can use and maintain. As a result of these strategies, diminishing cities have become less attractive and productive places to work and live, resulting in a "self-destructive response" [1].

In the 2000s, low-income people had difficulty obtaining loans for housing due to a vicious cycle of low income and high-interest rates. Accordingly, the federal government tried to facilitate housing purchases through subsidies and overcome the crisis through various methods [2]. Local governments have set up land banks to deal with problems such as housing seizures. Instead of chasing massive economic development strategies and hefty incentives for companies, they began to provide development benefits to residents directly. Land banks play multiple roles in coping with crisis, especially by purchasing neglected and abandoned real estate, caused by an increase in the vacancy rate. They remodel the acquired properties and resupply them to solve real estate and community problems [3]. As interest in quality of life increases with these efforts, the government and local planners are developing urban policy indicators and using them in policies to handle them more efficiently [4]. Nevertheless, while most land bank-related studies have focused on socioeconomic dynamics (income levels, unemployment rate, etc.), it is difficult to evaluate residents' actual satisfaction due to the movement between classes caused by land banks' housing distribution.

Recently, diverse types of value (personal taste, tracking fashionable goods, voter orientation, etc.) have been created through mass-generated social network service (SNS) data. As data collection and utilization become possible, multi-faceted research is being conducted based on text resources [5]. In big data parsing, the comments of unstructured data (social media posts, mobile activity, etc.) extract people's behavior or sensibility and interpret the positive or negative meanings scattered in words. This is called sentiment analysis, and it can help identify the values or product ideas that individuals value. Using this method, we intend to measure the quality of life using comments on SNS.

This study aims to identify the influence of Detroit Land Bank using Twitter on SNS and to examine residential satisfaction. Twitter data were used to collect opinions from residents and investigate residential satisfaction to compare it before and after Detroit's Land Bank initiative (2011, 2017). Then, comparing the Detroit Land Bank program with Detroit's basic statistics provides implications for the policy of shrinking cities and empty houses.

2. Literature Review

2.1. Smart Decline and Land Bank

The term 'urban decline' is being actively discussed. Each area deals with the concept of urban shrinkage for different reasons, methods, and definitions. The well-known concept of urban decline is a phenomenon that occurs when a large population loss occurs in large cities [6–9]. Sixteen of the largest twenty U.S. cities by population have experienced depopulation over the past 50 years [10]. Various planning strategies have been suggested to overcome the depopulation issue. Multiple problems and risks accompany large-scale projects, such as redevelopment and reconstruction; these problems include tenants' housing problems and the departure of existing residents.

Along with the depopulation phenomenon, long-term industrial transformation, high unemployment, poverty, criminal activity, and increased vacancy and abandonment are features of many declining cities [11,12]. Due to the economic decline, the budget for maintaining infrastructure would be limited, and the situation leads the residential environment to a vicious cycle of repetition [13].Various urban regeneration projects have been implemented as an alternative to the phenomenon of shrinking cities; for example, smart decline has recently been gaining attention. Examples of successful smart decline include Cleveland and Leipzig, where smart decline focuses on improving residents' quality of life rather than pursuing employment and growth to development. Smart urban regeneration methods vary from country to country, and the United States is also implementing various policies, among which our focus is the land bank program. Land bank, one of the urban regeneration programs, was established in the United States to manage aged and abandoned land. Most land banks are operated to promote urban redevelopment and restore unmanaged real estate [14]. Negro (2012) explained the critical roles and directions of the land bank. He argued that the program could be used to stabilize the value of local real estate and dispose of abandoned real estate [15]. Furthermore, he emphasized that the tax seizure process must be rationalized for the success of land banks, and sufficient authority must be established [15]. These studies show the definition and roles of the land bank policy. In addition, many successful land bank programs have improved the conditions of the residential environment.

Whitaker and Fitzpatrick (2016) said that preserving the value of unsold houses is one of land bank's biggest influences; thus, reducing negative effects, such as preventing the value of real estate (acquired by the land bank) from falling [16]. In addition, they found that the demolition program increased the sales prices of nearby properties by 3.4%. Bozgo et al. (2006) evaluated estimates of the impact of land bank activities on land bank programs. The study revealed that the Side Lot Transfer Program had positive effects by selling vacant land to nearby residents [17]. It was confirmed that the real estate owner who purchased the vacant lot (from the Side Lot Program) used or invested in the land. In addition, it was possible to reduce the number of vacant lots that had a negative impact on the surrounding area. Among the smart decline methods, various land bank policy studies have proven the effects and benefits of land bank in solving urban problems.

2.2. Residential Satisfaction

As mentioned earlier, many studies judge urban decline based on population decline, and what matters is not the population itself but who stays and who leaves and how quality of life changes when policies are proposed. Therefore, are residents happy with where they live now, and is residential satisfaction low in areas where urban regeneration has not been carried out? As a result, many studies have been conducted to measure residents' satisfaction with their lives.

2.2.1. Studies Using Surveys

Surveys were used in many studies to assess residential satisfaction. Knoechelmann et al. (2020) argued that improving the basic quality of individual life improves life satisfaction and residential satisfaction. Additionally, Knoechelmann et al. (2020) emphasized the importance of factors that judge quality of life, such as income or satisfaction with the neighborhood. Therefore, previous studies were scrutinized to identify factors that can improve the basic quality of life. Among them is a similar study on income, one of the factors mentioned by Knoechelmann et al. (2020) [18]. Gerdtham and Johannesson (2001) investigated the relationship between happiness and socio-economic variables. They found that happiness increased with income, health, and education. It decreased with unemployment, urbanization, unmarried, and male gender, and the lowest level of happiness was discovered in the 45–64 age group [19]. Through this, the factors affecting happiness were evaluated.

Elsinga and Hoekstra (2005) identified the relationship between homeownership and residential satisfaction, which was conducted on homeowners and tenants using European Community Household Panel data [20]. As a result of the analysis, it was confirmed that people who owned houses had higher residential satisfaction than tenants in most of the target countries. The difference in residential satisfaction felt by homeowners and tenants was identified, and there were cases of analyzing residential satisfaction with surrounding environment. Ibem and Aduwo (2013) surveyed 452 households living in public housing. They evaluated the most significant indicators that predict residential satisfaction as temperature, security, housing size, housing complexes' management, and evaluated residential satisfaction [21]. As a result of analyzing 452 households, the overall satisfaction level dropped significantly due to poor access to nearby facilities and poor electricity and drinking water supply. Through this, the provision of basic social amenities and infrastructure and the implementation of participatory housing policies were emphasized.

Li and Wu (2013) conducted a household survey by selecting 20 random villages to investigate the housing satisfaction of informal settlements in Beijing, Shanghai, and Guangzhou [22]. The residential satisfaction of immigrants and low-income earners was not lower than that of middle-income earners, and the most critical determinant was social attachment in the community. Through this survey, it was discovered that the removal of informal settlements is not the only solution, and it was emphasized that removing barriers to migrant integration is a way to increase housing satisfaction. According to the findings of the previous studies, homeownership, income, education, and employment impacted on residential satisfaction. Furthermore, the studies that used surveys had the advantage of receiving more accurate answers, but they also had the disadvantage of having fewer samples.

2.2.2. Studies Using SNS

As mentioned above, various surveys have been conducted to determine residential satisfaction. However, there are limitations such as the diversity problem of samples, difficulty in collecting answers, and time and cost limits. In that vein, a Twitter-based tool, along with traditional survey-based analysis, has emerged as an analysis method for analyzing people's psychological mechanisms in urban spaces. Twitter was established in 2006, and over 400 million tweets are created each day [23]. In addition, around one in five U.S. adults use Twitter and there are 288 million monthly active users with mobile phones accounting for 80% of active users. Under the circumstance, both the private and public sectors can benefit from the wealth of free information available on Twitter [24,25]. Users can use Twitter to voice their thoughts on a variety of topics and to discuss current events. It has been widely used in various fields, such as health research, marketing, and job satisfaction surveys. Even so, Luhmann (2017) had a different opinion. Using SNS profiles and mobile usage pattern, he found that big data approaches can be used to analyze language patterns on SNS and measured subjective well-being, which is highly accurate in terms of emotion. However, he argued they are not enough to measure life satisfaction [26].

Nguyen et al. (2016) collected tweets based on Salt Lake, San Francisco, and New York and set indicators for happiness, eating, and physical activity [27]. Of the 2.8 million tweets, 3.1–6.6% were food-related, and 1.7% were physical activity-related. The results of the calculation of happiness by region were as follows: Salt Lake was 46.2% positive, San Francisco was 37.9% positive, and New York was 52.3% positive. If tweets can be obtained consistently by region, this will increase the understanding of well-being and health. They suggested that more open neighborhood-level data could help establish policies related to well-being [27]. Zivanovic et al. (2020) approached the method of mixing manual coding, automatic classification, and spatial analysis and evaluated the quality of life on Twitter [28]. Through this, 50.4% of Twitter was related to transportation, and most traffic-related tweets contained expressions of emotion. Zivanovic et al. (2020) expected this study to improve residents' quality of life [28].

There have been studies, as mentioned above, and recently, research has also been conducted in the urban planning field. It is approaching SNS in various ways, such as regional and residential satisfaction changes. Park et al. (2020) measured neighborhood happiness based on Twitter and examined the factors that increase happiness [29]. As a result, factors such as young age, public transportation utilization, and bus stops increased happiness, and Twitter data were used to suggest directions for urban vitality and regeneration in declining cities. Additionally, Durahim and Coskun (2015) found a strong correlation between users' happiness levels and Twitter characteristics [30]. Unlike Luhmann (2017)'s argument, many studies have produced meaningful results, and it has been proved that residents' satisfaction can be measured using SNS.

3. Literature Gaps and Research Objective

The primary purpose of this research is to investigate what changes the land bank program has made to residents' residential satisfaction in Detroit. Previous research confirmed that there were various factors affecting urban decline, and various policies were also proposed to revitalize the city. Nevertheless, limitations existed. This study has distinguished three ways from the previous literature on residential satisfaction changes in shrinking cities.

First, most previous studies on urban decline have mostly been related to declining factors (with utilization strategies) and right-sizing strategies such as the land bank programs. However, there is a lack of research on urban change following the progress of urban regeneration strategies.

Second, the factors and their use focused on physical or socio-economic aspects such as population decline or an increase in empty houses, and there is a limit to seeing the change in the quality of life after the regeneration strategy. Therefore, this study is not about presenting a regeneration strategy; instead, it is about seeing changes after the regeneration strategy and what changes have been made in the residential satisfaction of residents. In addition, since existing studies focus only on presenting regeneration strategies, there is an aspect of overlooking how and how much residents' life satisfaction has actually changed. Even if the city declines, residential satisfaction will be high if the culture, projects, and policies are carried out appropriately.

Third, many studies have measured residential satisfaction through surveys when looking at past studies. However, this type of study has disadvantages, such as difficulty in collecting answers (sample collection difficulties) and limitations in terms of time and cost. In addition, other factors, such as a decrease in residential satisfaction due to changes in economic and social environments, cannot be considered. Previous research has shown that studies using SNS have a comparable impact as surveys. It was discovered that SNS research could be conducted contemporaneously with the survey, or that SNS research could yield meaningful results and implications on its own. Therefore, we approached using big data to solve the number of samples and were not limited in terms of time and cost. In addition, new values can be created by analyzing positive and negative meanings scattered in words.

Many shrinking cities in the United States have implemented various approaches to solve the depopulation issue. Among them, the land bank program has emerged as a great alternative to increase residents' quality of life. Therefore, to overcome the limitations mentioned above, we used Twitter data to determine how the land bank program affected residential satisfaction.

4. Materials and Methods

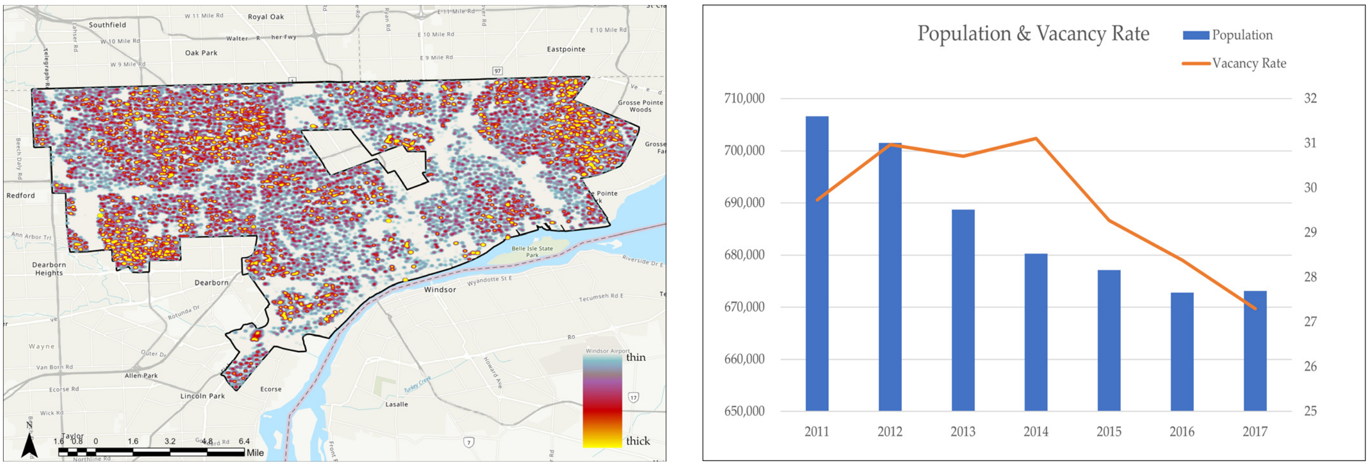
4.1. Study Area and Land Bank

As Detroit became known as the center of the world's automobile industry, its population began to rise in the 1910s, ranking fourth in the U.S. urban population until the 1920s and 1940s. However, as the oil crisis approached in the 1970s, the market share quickly decreased as fuel-efficient vehicles were imported from Asia. The housing market collapse in the United States in 2008 resulted in significant foreclosures and widespread property abandonment in several locations across the country [31]. This collapse affected many cities in the Rust Belt region particularly hard [32]. The real estate slump caused by the increase in vacant houses was a severe problem. About 80 million vacant houses were found in the Motor City Mapping Project survey among Detroit's regeneration projects, half of which were ruins. Detroit's economy and crime rates have improved significantly recently, but the problem caused by empty houses is still big.

The spatial scope of this study is Detroit, Michigan (U.S., Wayne County, State of Michigan). Detroit Land Bank began in 2008 but grew in size and extensively entered the business in 2014. Twitter has included location data from September 2010. The time span of analysis is six years, covering a time from 2011 to 2017 to compare the impact of the land bank program before and after the policy implementation. The Detroit Land Bank sold 236,746 properties between 2011 and 2017, in the time range. Data from 2018 onwards were excluded from the time range because Twitter location data was not provided.

Detroit has made a variety of efforts to cope with urban decline. In response, Detroit strived to revitalize the city by conducting a comprehensive investigation of vacant houses, diversifying and revitalizing commercial activity through changes in land use regulations, investment by large private companies, and revitalizing the land bank program. Typical investments by private companies include JP Morgan's investment cases, which has supported various fields such as residential development, small business support, infrastructure development, and recovery of local real estate. With this investment, Detroit tried to recover to a certain level of economy, such as job creation and GSP growth.

Land banks were established to manage vacant and abandoned properties that had been left unmanaged, promote urban redevelopment, and restore unmanaged real estate [14]. Figure 1 shows the distribution of land bank properties that were sold in Detroit (a) and Detroit's population and vacancy rate patterns between 2010 and 2016 (b).



(**a**) Distribution of Land Bank Properties Sold in Detroit (**b**) Population and Vacancy Rate

Figure 1. The study area of this study with a distribution of land bank properties sold in Detroit (Source: Detroit Land Bank Authority, U.S. Census Bureau).

Although the land bank has been in place for some time, the population decline has continued, so it is vital to assess actual residents' satisfaction. To investigate the relationship between residential satisfaction and land bank program, it is necessary to understand the programs being implemented by land banks. The land bank has different items and programs for each local government. The programs used in the study were Auction, Own it Now, Partner Sales, and Side Lots. Unused programs were deleted because of their small sample size and unsuitability for data usage (Table 1). In addition, it was difficult to obtain meaningful results, even though statistical analysis (multiple regression analysis) was conducted with each program as a separate dependent variable. Therefore, we focused on the total number of sales since the land bank's establishment. It is processed as a ratio of the number of land bank properties sold to the total number of vacant houses. Then, it is converted into an increased rate to observe the change in the number of land bank properties sold in 2011 and the number of land bank properties sold in 2017.

Table 1. Land Bank Programs (2017).

Program	Description	Number of Land Bank Program (%)
Auction	Real estate auction held by the land bank.	446 (10.14%)
Own it Now	Sell as it is acquired without additional intervention in the property.	808 (18.37%)
Partner Sale	Properties that are sold for housing rehabilitation projects, urban gardening, green space projects, or any purpose to improve the quality of life in the neighborhood.	355 (8.07%)
Side Lots	A program to sell vacant properties next to applicants' houses.	2789 (63.42%)
Total Number		4398

Data Used for Study: Auction, Own it Now, Partner Sale, Side Lots (Unused programs are scheduled to run or have fewer samples). Source: DLBA (Detroit Land Bank Authority).

4.2. Variables

To identify annual living standards and basic statistical data in Detroit, 13 variables were chosen. A description of the variables is shown in Table 2. All variables were converted into a rate of change between 2011 and 2017, and inflation, which may affect the economic growth rate, was adjusted for all variables.

As variable selection can significantly impact the outcome of predictions, a literature study was used to identify the causal mechanism that contributes to residential satisfaction. Many studies have indicated that occupying populations' educational attainment impacts urban decline [33–38]. Furthermore, increased vacant properties and crimes in urban areas can have negative impacts on residents' life satisfaction [39–41]. As a result, it was assumed that as the percentage of people with less than or equal to a high-school diploma increased, residential satisfaction would increase.

Historically, many depopulating urban areas have had a substantial percentage of urban secondary industries [36,42]. However, service employment increased in certain cities where secondary industry was concentrated, resulting in a massive population and economic decrease [34,43–45]. As a result, it is assumed that the rise in secondary industry and the unemployment rate have an impact on urban decline, lowering resident happiness.

Job availability is strongly connected to factors related to individual personal wealth. Property values and income may fall when employers and people leave cities, and poverty can be focused on specific areas [36,46–51]. As a result, since income and poverty rates are related to urban decline, it is assumed that residential satisfaction will also drop if income falls and the poverty rate rises.

From 2010 to 2016, the total number of vacant homes in the United States was 762,567. The housing crash in the United States in 2008 had a direct detrimental influence on housing values, mortgage markets, house constructions, and real estate markets. As a result, many cities experienced depopulation. Many municipalities have attempted to revitalize, but supply frequently outnumbers need. Furthermore, areas with non-owner tenants have a higher rate of aging, and wealthy homeowners are more likely to relocate [36,52–56]. As a result, it is assumed that the built year and homeownership ratio impact urban decline and that the older the built year and the lower the home-ownership ratio, the lower the residential satisfaction.

These include variables that can measure living standards and variables that can affect residential satisfaction. Six variables changed more than the average between 2011 and 2017. Homeownership, unemployment, and house value decreased in 2017. Homeownership, unemployment, and house value decreased in 2017 compared to 2011, while per capita income, poverty, and vacancy increased. Through this, it can be seen that the gap between the rich and the poor has widened, and the standard of living has generally declined. Figure 2 shows the region where all six variables have increased or decreased, based on the average.

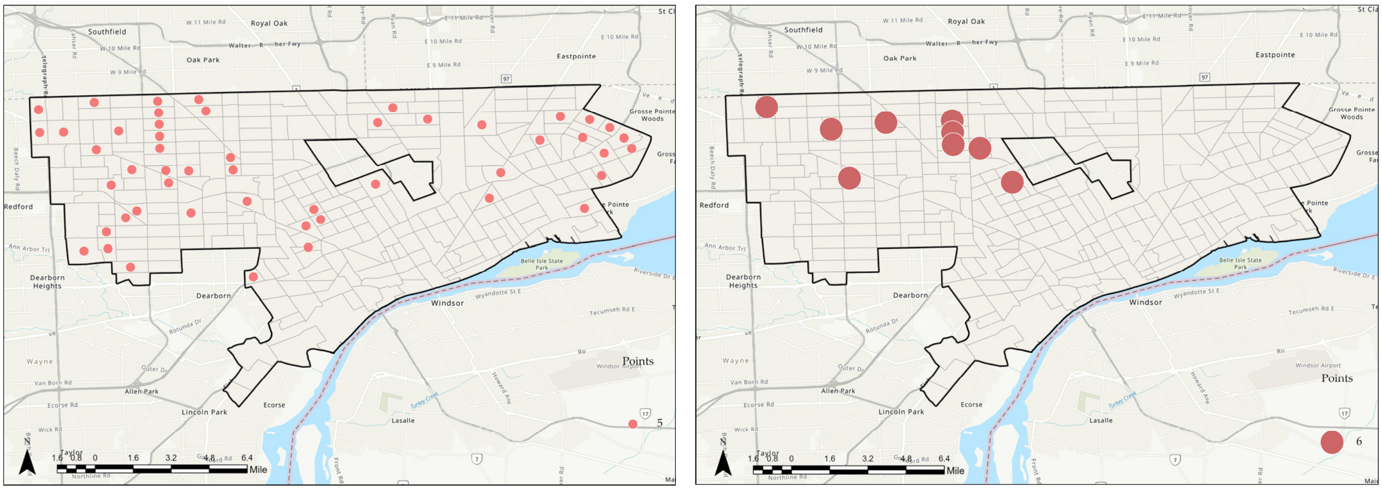


Figure 2. Six variables are given points to represent locations with lower or higher living standards than the national average.

4.3. Methods

4.3.1. Text Mining

Many parts of information are saved in text formats, such as online news articles, technical documents, books, e-mails, micro-blogs, social networking sites, and web pages. Text-mining techniques are used to extract data parts related to a specific topic from various text information that is publicly released and to derive high-quality information such as social phenomena and public opinion trends. It has the advantage of being able to understand people's overall opinions and create new values that meet the purpose. The text-mining technologies are natural language processing, language modeling, machine learning algorithms, and mining techniques. In addition, searching, extracting, organizing, and analyzing information are the steps in the text-mining process.

SNS data can be collected using open application programming interfaces (API) or through various coding programs. This study crawled Twitter data using Twitter developer API by Python. Twitter is a microblogging academic research resource as well as the most popular microblogging social media platform [57]. In the case of Twitter, as of 2016, there were about 318 million actual users, which is at the top of the SNS market share [58]. It is suitable for text mining because it can express free opinions and personal emotions in short sentences within 150 characters. In addition, Twitter was selected because it is easier to search for past data and is more accessible to collect data than Facebook, Instagram, and YELP. However, Twitter only supported location data for each tweet until 2017. The starting date was January 1 to December 31, 2011, and the last data collected was from January 1 to December 31, 2017. The latitude and longitude were set enough to cover the entire Detroit area, and data were collected with the approval of Twitter developers.

The crawled data include text, username, latitude, and longitude. In 2011, the number of tweets in Detroit was 156,119, and the number of users was 9159; in 2017, the number of tweets was 180,820, and the number of users was 20,764. Residential satisfaction was measured using Twitter data, but it was difficult to determine which tweets were uploaded by the residents. Since there are many accounts for various advertising and promotional purposes on SNS, it was necessary to distinguish people who actually live in Detroit among users.

Table 2. Variables and Related Literature for Data Collection.

Domain	Variable	Census Level	Description	References for Input Factors
Planning Policy	Land Bank	Census Tract	Percentage of Land Bank programs sold.	
Socio-economic status	%individuals below poverty	Census Tract	Individuals below poverty = "under 0.50" + ".50 to 0.74" + "0.75 to 0.99." Percent of persons below federally-defined poverty line, a threshold that varies by the size and age composition of the household. Denominator is total population where poverty status is checked.	Brian and Christopher (1996), Deaton (2006), Tate (2012). [36,48,49]
	Per capita income in 2011 & 2017	Census Tract	The mean income computed for every person in the census tract group.	Tate (2012), Holcombe and Lacombe (2004), Hasan (2010). [36,50,51]
	%persons with less than high school diploma	Census Tract	Percent of persons 25 years of age and older, with less than a 12th grade education (including individuals with 12 grades but no diploma).	Berke et al. (2015), Amos (2008), Tate (2012). [36–38]
	%civilian unemployed	Census Tract	Based on total population 16+. Civilian persons unemployed divided by total civilian population. Unemployed persons actively seeking work.	Armas and Gavriş (2016), Helpman et al. (2010), Yoon (2012). [44,45,59]
	%of secondary industry	Census Tract	Based on total industry. Second industry divided by total industry.	Tate (2012), Chen et al. (2013), Lee (2014). [36,42,60]
	Mortgage	Census Tract	Percentage of households with mortgage	Gonçalves (2016), Lee and Zandt (2014). [61,62]
	Minority	Census Tract	Total of the following: "black or African American alone" + "American Indian and Alaska Native alone" + "Asian alone" + "Native Hawaiian and other Pacific Islander alone" + "some other race alone" + "two or more races" + "Hispanic or Latino—white alone."	Fatemi et al. (2017), Karaye et al. (2020), Zahran et al. (2008). [55,63,64]
Housing	Homeownership	Census Tract	Percentage of homeowner	Dupuis and Thorns (1998), Zandt et al. (2012), Tate (2012). [36,53,54]
	Housing value	Census Tract	Median house value	Kain and Quigley (1970), Wood et al. (2010). [65,66]
	Built year	Census Tract	Median year structure built	Fatemi et al. (2017), Oulahen et al. (2015). [55,56]
	Vacancy	Census Tract	Percentage of vacant structures	Chuang and Gober (2015), Mortensen and Nagypál (2007), Rufat et al. (2019). [39–41]
	Householder type	Census Tract	Percentage of householders without a spouse	Tate (2012), Yoon (2012), Lee (2014). [36,59,60]

4.3.2. Resident Distribution

Tweets generated in Detroit were collected through the Twitter developer API, but there is insufficient evidence that users who posted tweets were Detroit residents or visitors. Accordingly, residents were distinguished in the collected data to identify users residing in Detroit. If users posted tweets in Detroit in different months of the year, they were selected as residents [67]. Table 3 presents the number of tweets per user in the corresponding month, and 'Count' is the number of months in which the tweets are uploaded. As such, users with a count of 2 or more for the year were selected as residents.

Table 3. Residential Distribution Example.

User	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Count
User1	36	9	11	12	8	14	13	10	15	8	2	0	5	12
User2	16	13	0	0	0	15	2	59	0	0	0	0	0	5
User3	111	77	84	40	45	32	14	31	61	80	76	76	81	13

4.3.3. Botometer (Complete Automation Probability)

Botometer is the official API used on Twitter. There are posts with commercial or mechanical characteristics on SNS, not articles expressing individual emotions or opinions, such as advertisements or automatically posting bots. This API helps remove false or exaggerated information from advertising or auto-posting bots. Since these tweets can affect the research results, an API called Complete Automation Probability (CAP) was used to remove them. CAP is called Botometer due to research by Center for Complex Networks and Systems Research, Rudy School, and Indiana University Network Science Institute, and it is an API that calculates bot probability through machine learning models. To calculate the score, the account is compared with tens of thousands of examples, and scores are calculated by extracting more than 1000 functions, such as profiles, friends, and activity patterns, derived from public profiles and hundreds of public tweets using Twitter API. The higher the CAP score, the higher the probability of being a bot.

4.3.4. Sentiment Analysis and Multiple Regression Analysis

The emotional analysis is the process of measuring or comprehending the market image of a product, service, or brand. It interprets nuances such as customer reviews, financial news, and social media to analyze human emotions. By providing transparency on the good and bad aspects of people's brands, products, and services, emotional analysis can predict users' tendencies and tastes.

Emotional analysis has a method for directly constructing keyword data that enters the dictionary or using an external dictionary. After extracting noun, adjective, and verb keywords, positive/negative labeling is performed to build emotional dictionary data. In addition, we used an external dictionary, the AFINN lexicon dictionary, in our research. Since it does not manually score each word, it is easy to apply to the analysis. The AFINN lexicon is a collection of English terms that have been manually rated for valence using an integer between −5 (negative) and +5 (positive) [68].

To measure residential satisfaction, an emotional analysis was conducted to determine the level of Twitter emotion. About 120,000 tweets were filtered through CAP and residential distribution and were scored through Python with the AFINN lexicon dictionary; filtered tweets were classified as positive, neutral, and negative. Tweets with positive values were processed as positive, tweets without emotional language were processed as neutral, and tweets with negative values were processed as negative [29]. Among the calculated tweets, neutral tweets were removed, leaving only positive and negative tweets. Since each tweet contains location data, it was possible to estimate the sensitivity of each census tract using this method. Then, the sensitivity of each census tract was calculated by processing the negative-to-positive ratio. To observe the rate of change between 2011 and 2017, it was processed and analyzed as an increasing rate. Residential satisfaction was selected as the dependent variable, which refers to the degree of sensitivity for each tract as determined by emotional analysis, and it was calculated by converting it to a positive-to-negative ratio (Table 4).

Table 4. Sentiment of Tweets by Year.

Y	Total #	Total # (After Filtering, %)	Positive (%)	Negative (%)	Neutral (%)
2011	156,119	58,866	16,896 (28.7)	12,473 (21.2)	29,497 (50.1)
2017	180,820	62,162	20,450 (32.9)	6788 (10.9)	34,924 (56.2)

Multiple regression examines how several independent variables affect the dependent variable and is used when there is one dependent variable with more than one independent variable. Using the IBM SPSS Statistics 26 program, multiple regression was used to understand the relationship between residential satisfaction and basic statistics (including land bank properties) based on the sensitivity of Twitter data. The equation used is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + e \quad (1)$$

(X: Independent variable, Y: Dependent variable, β: Regression coefficient, β_0: Y-intercept (constant term), β_1~β_k: Slope coefficients for each explanatory variable, e: the model's error term).

5. Results

5.1. Residential Distribution and CAP Filtering

Visitors such as office workers and travelers were identified and removed through the residential distribution process. In the process, 9159 users decreased to 4141 as of 2011, and 156,119 tweets decreased to 137,400. As of 2017, the number of users decreased from 20,764 to 7613 through residential distribution, and 180,820 tweets decreased to 159,932. As such, the number of users decreased by about 5000 and about 13,000 in 2011 and 2017, respectively, but the change in the number of tweets was not significant. Although the number of visitors was higher in 2017 than in 2011, the number of tweets posted by residents did not drop significantly in 2011 and 2017, indicating that the number of visitors was much higher than that of residents.

Previous studies revealed tweets with a CAP score of 0.5 or higher as bots and removed them (CAP scores under 0.5 were selected and used in the analysis) [29,69]. The number of users selected through the filtering process was 1748 in 2011 and 4506 in 2017. Compared to the number of users filtered out by resident distribution, the number of users decreased by 3000 each. The number of tweets also dropped sharply, with 58,866 in 2011 and 62,162 in 2017, down from about 80,000 and 100,000 tweets, respectively (Table 5). As the number of users filtered through CAP filtering is quite large, it can be seen that there are many bots for advertising and promotion purposes.

Table 5. Residential Distribution and CAP(0.5) Filtering.

Y	Users	Total_Tweets	Residents	Residents_Tweets	CAP_Under 0.5_Users	CAP_Under 0.5
2011	9159	156,119	4151	137,400	1748	58,866
2017	20,764	180,820	7613	159,932	4506	62,162

5.2. Multiple Regression Analysis

A correlation analysis was conducted before performing a multiple regression analysis to confirm the multicollinearity between the variables. Correlation analysis can numerically confirm what and how variables are related to each other. If the correlation coefficient is high, it has the potential to influence the outcome and should be eliminated.

In this study, IBM SPSS Statistics 26 was used to analyze the Pearson correlation coefficient (Table 6). The variables with the highest Pearson correlation coefficient are Poverty and Per Capita Income, indicating a coefficient of −0.467. Next are Poverty and Unemployment, which have a correlation coefficient of 0.388. Since the correlation coefficient between the three variables was not high enough to affect the results, the analysis was conducted without removing the variables.

The emotional level of each census tract was identified through sentiment analysis on Twitter to fully understand the land bank program's influence. The sensitivity of each tract was set as a dependent variable. Basic statistics and land bank properties were set up as independent variables. Multiple regression analysis was used to understand the relationship between the dependent variable and the independent variable using the SPSS program.

As shown in Table 7, Adj. = 0.347, and explanatory ability was 34.7%. Among a total of 13 variables, Home Ownership, Built Year, House Value, and Land Bank were the variables that affected residential satisfaction by satisfying the significance probability *p*-value ($\beta = -10.505$, $\beta = -0.114$, $\beta = 1.217$, $\beta = -0.140$, respectively), rejecting the null hypothesis and adopting the alternative hypothesis, which significantly affects residential satisfaction. First, in the case of Home Ownership, β was negative, so if Home Ownership increases by 1%, the negative emotion increases by 10.505%. Second, in the case of Built Year, β is negative, so if Built Year increases by 1%, the negative emotion increases by 0.114%. Third, in the case of House Value, β is positive, so if House Value increases by 1%, the positive emotion increases by 1.217%. Finally, Land Bank has β as negative, so if *Land Bank* increases by 1%, negative emotion increases by 0.140%.

To investigate the relative influence on residential satisfaction, it was compared through the standardized coefficient value (β). It can be said that Home Ownership ($\beta = -0.562$), *Built Year* ($\beta = -0.100$), House Value ($\beta = 0.120$), and Land Bank ($\beta = -0.167$) have a high impact on residential satisfaction in the order of Home Ownership, Land Bank, House Value, and Built Year.

It was found that negative emotions increased as the percentage of *Home Ownership* increased. In the process of selecting variables, the results were contrary to what was expected. Homeownership ratio was able to improve residential satisfaction because previous research on residential satisfaction quantified residential satisfaction using census-based socioeconomic statistics such as income and housing prices. However, unlike previous studies, the homeownership ratio had a negative effect on residential satisfaction in our study for two reasons: (1) more people live in their own dwellings and homeowners have a greater interest in the local environment than tenants; (2) noise, traffic problems, and dust caused by land bank program. Furthermore, the findings might indicate that newly arriving homeowners' socioeconomic circumstances through land bank programs are not necessarily superior to those of their prior residents. This is judged to be due to the high crime rate, low land prices, and the deterioration of buildings in Detroit. Buildings deteriorate in internal and external conditions as they age, increasing the cost of remodeling an old building. Additionally, as a building's age rises, so do its disadvantages, which lowers residential satisfaction. This was the same result obtained as expected in selecting variables. An increasing house price leads to an increase in holdings, which increases positive emotions. The increase in negative emotions due to the increase in Land Bank might be attributed to noise during remodeling, relocation, and environmental changes due to moving in, and movement between classes caused by the land bank program.

Furthermore, the influx of additional people exacerbates the present situation. The existence of a demographically diverse population would impede social capital formation because newcomers would not share communally sustained norms, such as the entry of singles into a middle-class electorate [70].

Table 6. Correlation analysis (Pearson).

Pearson	Minority	Home Ownership	Vacancy	Less than High School Diploma	Unemployment	Second Industry	Per Capita Income	Built Year	House Value	Poverty	Composition	Mortgage	Land Bank
Minority	1	−0.116	0.007	0.016	0.103	−0.029	0.024	−0.002	−0.036	0.032	0.006	0.022	−0.026
Home Ownership		1	0.023	−0.178 **	−0.135 *	0.104	0.285 **	−0.097	0.144 *	−0.139 *	−0.114	−0.062	0.179 **
Vacancy			1	−0.042	0.081	−0.018	0.006	−0.168 **	−0.068	−0.016	−0.075	−0.096	−0.044
Less than High School Diploma				1	0.068	0.008	−0.188 **	0.230 **	−0.042	0.114	0.105	−0.077	−0.141 *
Unemployment					1	0.044	−0.267 **	−0.116	−0.006	0.388 **	0.039	0.013	−0.020
Second Industry						1	0.081	−0.017	0.027	−0.008	0.005	−0.034	0.048
Per Capita Income							1	0.004	0.028	−0.467 **	−0.308 **	0.073	0.135 *
Built Year								1	0.108	−0.085	0.079	−0.009	−0.039
House Value									1	0.012	0.191 **	0.155 *	0.286 **
Poverty										1	0.197 **	0.003	−0.086
Composition											1	−0.024	−0.033
Mortgage												1	0.336 **
Land Bank													1

* $p < 0.05$ ** $p < 0.01$.

Table 7. Multiple Regression analysis.

Model	Unstandardized Coefficients		Standardized Coefficients	t(*p*)	Sig	TOL	VIF
	b	Std. Error	Beta				
(Constant)	1.922	0.668		2.877	0.004		
Minority	−0.011			−0.218	0.827	0.986	1.014
Home Ownership ***	−10.505	0.942	−0.562	−11.152 ***	0.000	0.948	1.055
Vacancy	0.052			1.035	0.302	0.967	1.034
Less than High School Diploma	−0.060			−1.170	0.243	0.911	1.097
Unemployment	−0.004			−0.086	0.932	0.964	1.037
Second Industry	0.059			1.200	0.231	0.988	1.012
Per Capita Income	0.037			0.715	0.475	0.908	1.101
Built Year ***	−0.114	0.057	−0.100	−1.999 ***	0.047	0.972	1.029
House Value *	1.217	0.526	0.120	2.312 *	0.022	0.893	1.120
Poverty	−0.088			0.078	−0.108	0.962	1.039
Composition	0.016			0.749	0.020	0.936	1.068
Mortgage	0.019			0.720	0.022	0.866	1.155
Land Bank *	−0.140	0.044	−0.167	−3.217 *	0.001	0.896	1.116
F(*p*)	36.957 ***						
adj.R^2	0.347						
Durbin-Watson	2.2021						

* $p < 0.05$, *** $p < 0.001$.

6. Conclusions

The primary purpose of this study was to understand how the land bank project affected the residential satisfaction of nearby residents. Opinions derived from Detroit were collected through SNS, and only residents were identified by filtering. The filtered tweets were then analyzed using emotional analysis to determine the level of sensitivity among residents and classified by census tract to assess the level of sensitivity by region. Then, multiple regression analysis was used to determine how land bank data and basic statistical data affect residential satisfaction.

The factors that influenced the relationship between residential satisfaction and land bank were homeownership, built year, house value, and land bank. Furthermore, basic statistics on quality of life in Detroit rose compared to the comparative year (2011–2017), while residential satisfaction decreased. Since most land bank sites are already distressed areas where people who want to leave have been unable to do so, the small number of reconstructions through the land bank program can limit increasing residential satisfaction. Contrary to expectations, statistical analysis proved that the increase in land banking sold property was found to have a negative effect on neighborhood satisfaction in Detroit. This can be taken into account in relation to the finding that satisfaction declines even as home ownership increases. About 28.5% of the vacant homes among the land banking sold properties between 2011 and 2017 were taken over by new owners via auction and own it now. A significant portion of them (18.4%) are sold on own it now for USD 1000 in their 'as is' condition. Although studies on the degree of improvement of homes sold through land banking have not been conducted, the results may indicate that the socioeconomic status of newly arriving homeowners is not likely to be better than that of previous landlords or current residents. Therefore, it is possible that the level of improvement in reoccupied homes falls short of expectations. In addition, according to [71], 54% of Detroit homeowners in 2011 paid more than 30% of their income to housing costs. This suggests that many Detroit homeowners, whose income levels are lower than the national average, would find it challenging to improve their homes' interior and exterior conditions. In places such as Detroit, where housing prices are low and are anticipated to remain low, it may not be necessary to become a homeowner, or it may not have an impact on the neighborhood [72]. Furthermore, side lots, which make up the majority of the land banking sold properties, would be expected to improve the residential environment of the neighborhood, such as well-kept gardens and playgrounds. However, there is no specific requirement for when and how such action should be completed. Lastly, there might be an inconvenience in the land bank program to surrounding residents due to new construction (noise and dust) and the influx of additional lower-income residents.

Therefore, to present management guidelines in the policy, it is necessary to investigate how side lots are used. Furthermore, the land bank needs to expand its policy and urban regeneration role to address shrinking urban issues, such as increasing the residential population, local environment, and regional atmosphere. However, not much time has passed since the land bank project began; therefore, further research on Detroit residents' residential satisfaction and standard of living will be needed in the coming years. The most detrimental impact of homeownership is that "Most of those who wish to move out have been unable to do so." [73]. In the case of underdeveloped areas, it is judged that there will not be many positive emotions due to the land bank's business. As a result, new entrants and programs, such as side lots sold in the region, may not appear to help improve the region's conditions. Compared to the era when the land bank properties sold the most, in 2017, this was still in its early stages; therefore, it was soon to feel the effect. The land bank program policy shows a lack of understanding of the region. It is critical to identify which residents depart and which remain and to investigate the cause. Detroit is now more advanced than when the research was conducted, and the number of visitors is increasing. Therefore, it is necessary to determine whether the land bank program contributed to this development.

7. Discussion

Based on the opinions of SNS users, this study examined the factors that affect residential satisfaction in Detroit. It is meaningful in that we were likely to access social media (big data), which expresses opinions, rather than surveys or interviews from previous studies. As a result, we were able to approach them from a sociological standpoint. In addition, it can be effectively interpreted based on existing opinions or evaluations, and it can be meaningful in that a new methodology is used to determine residential satisfaction and living standards through SNS and the land bank program.

Despite the merits of this study, some limitations should be further addressed in future research. First, this research collects specific opinions on SNS, and it might not represent the opinions or emotions of all residents in Detroit. Since some people could be disconnected from digital services and tools, the Twitter data might only represent younger and highly educated groups with relatively substantial technology assets. In addition, words extracted from Twitter have the disadvantage of being difficult to understand the surrounding environment or situation accurately.

Second, the criteria for determining residents were applied through Twitter, but there is still insufficient evidence that the user who posted the tweet resides in Detroit. In future studies, it is necessary to determine residents based on tweets occurring within the same census tract or to set and reflect on new criteria for deciding residents based on tweets occurring in residential areas.

Third, there is a possibility of errors in emotional analysis and filtering. Although the dictionary of emotional analysis is used, slang and foreign words used by each user are different, which can affect the results of the emotional analysis.

Finally, there is a possibility of intervention of factors other than the land bank program in measuring residential satisfaction. It can be influenced by policy or economic conditions in measuring residential satisfaction and living standards.

To further clarify what may affect the results of this study, residents' distribution standards can be strengthened, and additional data can be collected from more SNS platforms to measure residential satisfaction. Furthermore, SNS can be crawled to compare the frequency and sensibility of each word and to understand the needs of the residents. Based on the results of this study, it is also necessary to identify the characteristics that affect residents' residential satisfaction in terms of land bank projects or policies, observe the inconveniences that residents experience, and identify the problems that arise.

Some Detroit residents want to leave but are unable to do so due to financial constraints. As a result, even though the land bank provides low-cost housing, moving to a new location is difficult. Due to issues such as moving costs, remodeling costs, and maintenance costs, residents may find themselves in more difficult situations. As a result, the land bank should shift its focus to reducing the number of sales and conducting business from a micro rather than a macro perspective.

We believe it is important to lessen the burden on individuals by improving the living environment or supporting the cost of moving to land bank-owned property (or supporting remodeling costs). In addition, as in the broken window theory, a single negative image can spread to the entire town. Therefore, for the land bank to improve residential satisfaction, it will be possible to improve the surrounding environment (painting, cleanliness improvement), road maintenance, streetlamp maintenance, and CCTV installation in vulnerable areas.

Author Contributions: Conceptualization, S.P. and J.L.; methodology, Y.P.; writing—original draft preparation, S.P.; writing—review and editing, supervision, J.L.; funding acquisition, Y.P. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant KAIA001434041G0003186).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. Rybczynski, W.; Linneman, P.D. How to save our shrinking cities. *Public Interest* **1999**, *135*, 30–44.
2. Wang, K.; Lee, S. Policy Responses to Shrinking Cities in the United States and Some Implications for Urban Regeneration. *J. Korea Plan. Assoc.* **2019**, *54*, 159–172. [CrossRef]
3. Kim, Y. Land and Housing Bank to Cope with New Normal of Global Financial Crisis: Focusing on US Cases. *SpaceEnvironment* **2017**, *27*, 12–52. [CrossRef]
4. Park, J.; Kang, Y. An Analysis of Spatial characteristics of Residential Satisfaction in Seoul Using Tweet Data. *Korean Urban Geogr. Soc.* **2014**, *17*, 43–56.
5. Kim, S.; Lee, S. Determinants of Residential Environment Satisfaction in the Second-Generation New Towns of the Seoul Metroplitan Area Using Web Crawling and Text Mining. *J. Korea Plan.* **2020**, *55*, 5–20.
6. Bourne, L.S. Alternative perspectives on urban decline and population deconcentration. *Urban Geogr.* **1980**, *1*, 39–52. [CrossRef]
7. Lima, M.F.; Eischeid, M.R. Shrinking cities: Rethinking landscape in depopulating urban contexts. *Landsc. Res.* **2017**, *42*, 691–698. [CrossRef]
8. Slach, O.; Bosák, V.; Krtička, L.; Nováček, A.; Rumpel, P. Urban shrinkage and sustainability: Assessing the nexus between population density, urban structures and urban sustainability. *Sustainability* **2019**, *11*, 4142. [CrossRef]
9. Stryjakiewicz, T. The Process of Urban Shrinkage and its Consequences. *Rom. J. Reg. Sci.* **2013**, *7*, 29–40.
10. Hollander, J.B.; Pallagst, K.; Schwarz, T.; Popper, F.J. Planning shrinking cities. *Prog. Plan.* **2009**, *72*, 223–232.
11. Wiechmann, T.; Pallagst, K.M. Urban shrinkage in Germany and the USA: A comparison of transformation patterns and local strategies. *Int. J. Urban Reg. Res.* **2012**, *36*, 261–280. [CrossRef]
12. Hollander, J.B. Moving toward a shrinking cities metric: Analyzing land use changes associated with depopulation in Flint, Michigan. *Cityscape* **2010**, *12*, 133–151. [CrossRef]
13. Friedrichs, J. A theory of urban decline: Economy, demography and political elites. *Urban Stud.* **1993**, *30*, 907–917. [CrossRef]
14. Silva, D.A. Land banking as a tool for the economic redevelopment of older industrial cities. *Drexel Rev.* **2010**, *3*, 607.
15. Negro, S.E. You Can Take It to the Bank: The Role of Land Banking in Dealing with Distressed Properties. *Zoning Plan. Law Rep.* **2012**, *35*, 41176986.
16. Whitaker, S.; Fitzpatrick, T.J. Land Bank 2.0: An Empirical Evaluation. *J. Reg. Sci.* **2016**, *56*, 156–175. [CrossRef]
17. Bozgo, L.; de Wit, J.; Haradon, S. *Genesee County Land Bank Side Lot Transfer Program Evaluation*; University of Michigan Library: Ann Arbor, MI, USA, 2006.
18. Knoechelmann, A.; Seifert, N.; Guenther, S.; Moor, I.; Richter, M. Income and housing satisfaction and their association with self-rated health in different life stages. A fixed effects analysis using a German panel study. *BMJ Open* **2020**, *10*, e034294. [CrossRef]
19. Gerdtham, U.-G.; Johannesson, M. The relationship between happiness, health, and socio-economic factors: Results based on Swedish microdata. *J. Socio-Econ.* **2001**, *30*, 553–557. [CrossRef]
20. Elsinga, M.; Hoekstra, J. Homeownership and housing satisfaction. *J. Hous. Built Environ.* **2005**, *20*, 401–424. [CrossRef]
21. Ibem, E.O.; Aduwo, E.B. Assessment of residential satisfaction in public housing in Ogun State, Nigeria. *Habitat Int.* **2013**, *40*, 163–175. [CrossRef]
22. Li, Z.; Wu, F. Residential satisfaction in China's informal settlements: A case study of Beijing, Shanghai, and Guangzhou. *Urban Geogr.* **2013**, *34*, 923–949. [CrossRef]
23. Kim, A.E.; Hansen, H.M.; Murphy, J.; Richards, A.K.; Duke, J.; Allen, J.A. Methodological Considerations in Analyzing Twitter Data. *J. Natl. Cancer Inst. Monogr.* **2013**, *2013*, 140–146. [CrossRef] [PubMed]
24. Odabaş, M. 10 Facts about Americans and Twitter. Available online: https://www.pewresearch.org/fact-tank/2022/05/05/10-facts-about-americans-and-twitter/ (accessed on 4 September 2022).
25. Abbasi, A.; Rashidi, T.H.; Maghrebi, M.; Waller, S.T. Utilising location based social media in travel survey methods: Bringing Twitter data into the play. In Proceedings of the 8th ACM SIGSPATIAL International Workshop on Location-based Social Networks, Bellevue, WA, USA, 3 November 2015; pp. 1–9.
26. Luhmann, M. Using big data to study subjective well-being. *Curr. Opin. Behav. Sci.* **2017**, *18*, 28–33. [CrossRef]
27. Nguyen, Q.; Kath, S.; Meng, H.-W.; Li, D.; Smith, K.R.; VanDerslice, J.; Wen, M.; Li, F. Leveraging geotagged Twitter data to examine neighborhood happiness, diet, and physical activity. *Appl. Geogr.* **2016**, *73*, 77–88. [CrossRef] [PubMed]
28. Zivanovic, S.; Martinez, J.; Verplanke, J. Capturing and mapping quality of life using Twitter data. *GeoJournal* **2020**, *85*, 237–255. [CrossRef]
29. Park, Y.; Kim, M.; Seong, K. Happy neighborhoods: Investigating neighborhood conditions and sentiments of a shrinking city with Twitter data. *Growth Chang.* **2020**, *52*, 539–566. [CrossRef]
30. Durahim, A.O.; Coşkun, M. #iamhappybecause: Gross National Happiness through Twitter analysis and big data. *Technol. Forecast. Soc. Chang.* **2015**, *99*, 92–105.

31. Crump, J.; Newman, K.; Belsky, E.S.; Ashton, P.; Kaplan, D.H.; Hammel, D.J.; Wyly, E. Cities Destroyed (again) For Cash: Forum on the U.S. Foreclosure Crisis. *Urban Geogr.* **2008**, *29*, 745–784. [CrossRef]
32. Gu, D.; Newman, G.; Kim, J.-H.; Park, Y.; Lee, J. Neighborhood decline and mixed land uses: Mitigating housing abandonment in shrinking cities. *Land Use Policy* **2019**, *83*, 505–511. [CrossRef]
33. Wachter, S.M.; Zeuli, K.A. *Revitalizing American Cities*; University of Pennsylvania Press: Philadelphia, PA, USA, 2013.
34. Fee, K.; Hartley, D. Economic trends: Growing cities, shrinking cities. *Fed. Reserve Bank Cleveland. April.* **2011**, *14*, 14.
35. Lee, J.; Newman, G. Forecasting urban vacancy dynamics in a shrinking city: A land transformation model. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 124. [CrossRef]
36. Tate, E. Social vulnerability indices: A comparative assessment using uncertainty and sensitivity analysis. *Nat. Hazards* **2012**, *63*, 325–347. [CrossRef]
37. Berke, P.; Newman, G.; Lee, J.; Combs, T.; Kolosna, C.; Salvesen, D. Evaluation of Networks of Plans and Vulnerability to Hazards and Climate Change: A Resilience Scorecard. *J. Am. Plan. Assoc.* **2015**, *81*, 287–302. [CrossRef]
38. Amos, J. *Dropouts, Diplomas, and Dollars: US High Schools and the Nation's Economy*; Alliance for Excellent Education: Washington, DC, USA, 2008.
39. Chuang, W.-C.; Gober, P. Predicting hospitalization for heat-related illness at the census-tract level: Accuracy of a generic heat vulnerability index in Phoenix, Arizona (USA). *Environ. Health Perspect.* **2015**, *123*, 606–612. [CrossRef]
40. Mortensen, D.T.; Nagypal, E. More on unemployment and vacancy fluctuations. *Rev. Econ. Dyn.* **2007**, *10*, 327–347. [CrossRef]
41. Rufat, S.; Tate, E.; Emrich, C.T.; Antolini, F. How Valid Are Social Vulnerability Models? *Ann. Am. Assoc. Geogr.* **2019**, *109*, 1131–1153. [CrossRef]
42. Chen, W.; Cutter, S.L.; Emrich, C.T.; Shi, P. Measuring social vulnerability to natural hazards in the Yangtze River Delta region, China. *Int. J. Disaster Risk Sci.* **2013**, *4*, 169–181. [CrossRef]
43. Lee, J.; Newman, G.; Lee, C.J.S. Predicting Detached Housing Vacancy: A Multilevel Analysis. *Sustainability* **2022**, *14*, 922. [CrossRef]
44. Armaş, I.; Gavriş, A. Census-based Social Vulnerability Assessment for Bucharest. *Procedia Environ. Sci.* **2016**, *32*, 138–146. [CrossRef]
45. Helpman, E.; Itskhoki, O.; Redding, S. Inequality and Unemployment in a Global Economy. *Econometrica* **2010**, *78*, 1239–1283.
46. Park, I.K.; Ciorici, P. Determinants of vacant lot conversion into community gardens: Evidence from Philadelphia. *Int. J. Urban Sci.* **2013**, *17*, 385–398. [CrossRef]
47. Lee, J.; Newman, G.; Park, Y. A Comparison of Vacancy Dynamics between Growing and Shrinking Cities Using the Land Transformation Model. *Sustainability* **2018**, *10*, 1513. [CrossRef]
48. Nolan, B.; Whelan, C.T. *Resources, Deprivation, and Poverty*; Clarendon Press: Walton, UK, 1996.
49. Deaton, A. *Measuring Poverty*; Oxford University Press: Oxford, UK, 2006; pp. 3–15.
50. Holcombe, R.G.; Lacombe, D.J. The Effect of State Income Taxation on Per Capita Income Growth. *Public Financ. Rev.* **2004**, *32*, 292–312. [CrossRef]
51. Hasan, M.S. The long-run relationship between population and per capita income growth in China. *J. Policy Model.* **2010**, *32*, 355–372. [CrossRef]
52. Farris, J.T. The barriers to using urban infill development to achieve smart growth. *Hous. Policy Debate* **2001**, *12*, 1–30. [CrossRef]
53. Dupuis, A.; Thorns, D.C. Home, home ownership and the search for ontological security. *Sociol. Rev.* **1998**, *46*, 24–47. [CrossRef]
54. Van Zandt, S.; Peacock, W.G.; Henry, D.W.; Grover, H.; Highfield, W.E.; Brody, S.D. Mapping social vulnerability to enhance housing and neighborhood resilience. *Hous. Policy Debate* **2012**, *22*, 29–55. [CrossRef]
55. Fatemi, F.; Ardalan, A.; Aguirre, B.; Mansouri, N.; Mohammadfam, I. Social vulnerability indicators in disasters: Findings from a systematic review. *Int. J. Disaster Risk Reduct.* **2017**, *22*, 219–227. [CrossRef]
56. Oulahen, G.; Mortsch, L.; Tang, K.; Harford, D. Unequal vulnerability to flood hazards:"ground truthing" a social vulnerability index of five municipalities in Metro Vancouver, Canada. *Ann. Assoc. Am. Geogr.* **2015**, *105*, 473–495. [CrossRef]
57. Hollander, J.B.; Graves, E.; Renski, H.; Foster-Karim, C.; Wiley, A.; Das, D. *Urban Social Listening: Potential and Pitfalls for Using Microblogging Data in Studying Cities*; Springer: Berlin, Germany, 2016.
58. Backlinko. How Many People Use Twitter in 2022? [New Twitter Stats]. Available online: https://backlinko.com/twitter-users (accessed on 6 June 2022).
59. Yoon, D.K. Assessment of social vulnerability to natural disasters: A comparative study. *Nat. Hazards* **2012**, *63*, 823–843. [CrossRef]
60. Lee, Y.-J. Social vulnerability indicators as a sustainable planning tool. *Environ. Impact Assess. Rev.* **2014**, *44*, 31–42. [CrossRef]
61. Guillard-Gonçalves, C. Vulnerability Assessment and Landslide Risk Analysis: Application to the Loures Municipality, Portugal. Ph.D. Thesis, Universidade de Lisboa, Lisboa, Portugal, 2016.
62. Lee, J.Y.; Van Zandt, S. Housing tenure and social vulnerability to disasters: A review of the evidence. *Planing Lit.* **2019**, *34*, 156–170. [CrossRef]
63. Karaye, I.M.; Horney, J.A. The impact of social vulnerability on COVID-19 in the US: An analysis of spatially varying relationships. *Am. J. Prev. Med.* **2020**, *59*, 317–325. [CrossRef] [PubMed]
64. Zahran, S.; Brody, S.D.; Peacock, W.G.; Vedlitz, A.; Grover, H. Social vulnerability and the natural and built environment: A model of flood casualties in Texas. *Disasters* **2008**, *32*, 537–560. [CrossRef]
65. Kain, J.F.; Quigley, J.M. Measuring the value of housing quality. *J. Am. Stat. Assoc.* **1970**, *65*, 532–548. [CrossRef]

66. Wood, N.J.; Burton, C.G.; Cutter, S.L. Community variations in social vulnerability to Cascadia-related tsunamis in the U.S. Pacific Northwest. *Nat. Hazards* **2010**, *52*, 369–389. [CrossRef]
67. Kovacs-Gyori, A.; Ristea, A.; Havas, C.; Resch, B.; Cabrera-Barona, P. #London2012: Towards Citizen-Contributed Urban Planning Through Sentiment Analysis of Twitter Data. *Urban Plan.* **2018**, *3*, 75–99.
68. Nielsen, F.Å. A New ANEW: Evaluation of a Word List for Sentiment Analysis in Microblogs. Available online: http://corpustext.com/reference/sentiment_afinn.html (accessed on 17 August 2022).
69. Juhász, L.; Hochmair, H. Comparing the Spatial and Temporal Activity Patterns between Snapchat, Twitter and Flickr in Florida. *GI_Forum* **2019**, *1*, 134–147. [CrossRef]
70. Robson, G.; Butler, T. Coming to terms with London: Middle-class communities in a global city. *Int. J. Urban Reg. Res.* **2001**, *25*, 70–86. [CrossRef]
71. Poethig, E.C.; Schilling, J.; Goodman, L.; Bai, B.; Gastner, J.; Pendall, R.; Fazili, S. *The Detroit Housing Market: Challenges and Innovations for a Path Forward*; Urban Institute: Washington, DC, USA, 2017.
72. Grinstein-Weiss, M.; Yeo, Y.; Anacker, K.; Van Zandt, S.; Freeze, E.B.; Quercia, R.G. Homeownership and Neighborhood Satisfaction among Low- and Moderate-Income Households. *J. Urban Aff.* **2011**, *33*, 247–265. [CrossRef]
73. Kasl, S.V.; Harburg, E. Perceptions of the neighborhood and the desire to move out. *J. Am. Inst. Plan.* **1972**, *38*, 318–324. [CrossRef]