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Spatial temporal changes in neighborhoods to predict property prices using street-view images

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Master of Science in Data Science

SPATIAL-TEMPORAL CHANGES IN NEIGHBORHOODS TO PREDICT PROPERTY PRICES USING STREET-VIEW IMAGES

This Thesis is submitted to the Department of Computer Science as partial fulfillment of Master of Science in Data Science degree

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Dedication

Dedicated to my exceptional parents, teachers, husband and adored siblings whose tremendous support and cooperation led me to this wonderful accomplishment.

Acknowledgement

I begin by expressing my deepest gratitude to Allah Almighty, the ultimate source of wisdom and guidance, for His blessings and strength throughout this academic journey. I extend my heartfelt appreciation to my dedicated supervisor, Dr. Tariq Mahmood, whose unwavering support, guidance, and confidence have been instrumental in the completion of this thesis. My profound thanks also go to my family for their constant love, encouragement, and understanding. Their unwavering support has been my anchor, providing the motivation to overcome challenges.

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Abstract

Real estate appraisal is the technique to predict prices of a large number of properties that are similar together and is impossible to calculate without big geographical data. Appraisals are influenced by a multitude of factors, including the physical conditions of neighborhoods. When purchasing a property, abstract factors such as greenery, traffic, and commercialization tend to influence buyers' purchase decision. Understanding how these physical conditions change over time and their impact on property prices is crucial for various stakeholders, such as homeowners, investors, and urban planners. The majority of the research have only focused on spatial features of an area and its impact on sale prices in a single year. The remaining research have predicted property sale prices using temporal models. However, very little research has been done on how image data of a neighborhood varies over the years and its correlation with property prices. This study presents three ideas to overcome these issues: (1) designing a novel spatio-temporal data structure, the Spatial Temporal Abstract Detections (STAD), to quantify the influence of changes in the facilities on property prices, (2) designing a new framework to extract the most important abstract features from street-view images to characterize property prices of each block in a neighborhood, and (3) building a novel YOLO-ML architecture to process Normalized STAD Scores (NSTADS) to predict property prices for a block. The study employs a comprehensive image dataset extracted from Mapillary, comprising physical and abstract attributes of neighborhoods, such as infrastructure, amenities, and environmental factors. The dataset spans multiple years, allowing for a longitudinal analysis of the spatial-temporal changes in two Manhattan neighborhoods: Midtown and Tribeca. The abstract neighborhood features are extracted through image data using YOLO v5 to improve existing property price prediction models. The model's performance is evaluated and compared with the baseline model to predict property prices.

Keywords: Real Estate Appraisal, Street-View Images, Spatio-Temporal Housing Price Prediction, Deep Learning, Machine Learning

Chapter 1

Introduction

Real estate appraisal is the process of identifying the value of many properties using some standard procedures. Real Estate appraisal has been a crucial task for property owners, real estate professionals, governments, taxation organizations, and planning institutions. Government agencies require it to determine the allocation of taxes on properties.

While housing price prediction requires output to be exact future price of a single property, appraisal requires to consider a large group of properties in an area and output a benchmark price. An accurate appraisal of properties is important to ensure fair and equitable taxation for the property owners. It also assists planning departments to budget public services and infrastructure projects (Liu et al., 2018).

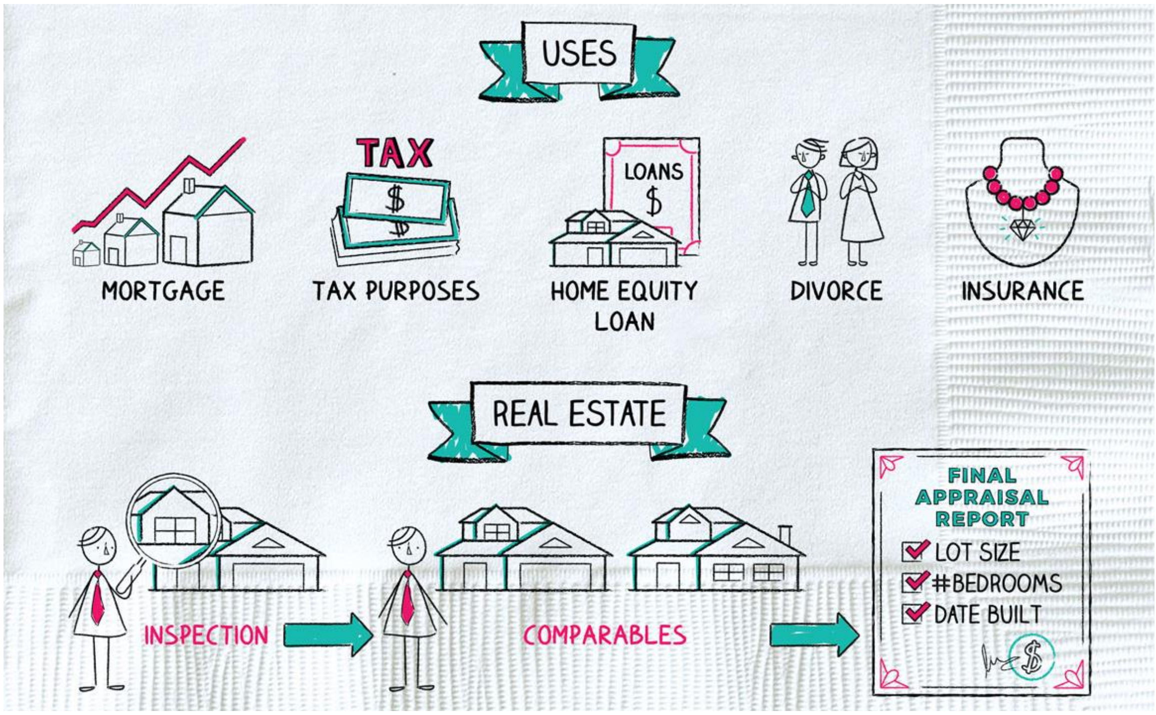


Figure 1: Real Estate Appraisal Process

The most important application of Estate appraisal is for real estate agents to buy, sell, invest in Real Estate. Since the estate values are extremely volatile and sensitive to economic conditions, realtors and buyers need to critically assess the property so they do not end up losing their money on it. A robust price prediction system can potentially cut down the pre-transactions assessment costs for buyers, accelerate estate transactions, and invigorate the estate market (Chiu et al., 2022).

With the rise in Multiple Listing Services (MLS) such as Zillow and Zumper, we see an increase in Big Data techniques being used for property price prediction (Wei et al., 2022). As housing markets adapt technology and digitalization, the need for automated appraisals continues to grow (Liu et al., 2018). In 2006, Zillow introduced its proprietary home value estimator 'Zestimate'. However, Zestimate is heavily dependent on square footage of the property, making home value estimation unreliable (Union Street Media, n.d.). Additionally, Zestimate's algorithm is based on data from a broad range of homes across different markets and can't capture the nuances of local real estate markets. Factors such as neighborhood trends, local amenities, and the desirability of specific schools can significantly affect the value of a home and may not be captured in the algorithm (Union Street Media, n.d.).

With the availability of Zillow transaction data over a range of timestamps, researchers can now perform temporal analysis of pricing trends. What makes real estate appraisal difficult is the characterization of multiple housing attributes such as physical properties, condition of the property, neighborhood in which a property is located, and Point of Interests that are close to a property. Temporal dimension introduces more constraints on the spatial relations.

Existing research have focused on combining Geographic Information System (GIS)-based images with the numerical attributes of the property data (Xue et al., 2020), (Yiorkas & Dimopoulos, 2017), (Noor & Rosni, 2013). The remaining have used property's interior image data to increase the accuracy of price prediction (Liu et al., 2018), (Naumzik & Feuerriegel, 2020), (Law et al., 2019).

Although GIS data and house's features data is easily available, they fail to capture contextual information (Liberti & Petersen, 2019). Both are considered as hard information that can be easily quantified. A lot of research has also been done on utilizing the soft information represented by Image data.

Abstract features in spatial-temporal analysis represent higher-level, derived characteristics that capture underlying patterns not immediately evident in raw data. These abstract features are pivotal in understanding complex phenomena such as real estate valuation, where nuanced attributes like aesthetic appeal or neighborhood vibrancy, inferred from street-view imagery, can significantly impact property prices. This aligns with the work done by authors in (Behnisch &

Ultsch, 2009) conceptualization of abstraction in urban data analysis, which posits that abstracted data layers yield a deeper insight into the spatial dynamics influencing real estate markets.

In (Dubé et al., 2018), (Liu et al., 2020) authors have performed spatio-temporal analysis of the facilities change affecting property prices by using spatial auto-regressive models (SAR) and Geographical and temporal weighted regression (GTWR) respectively. However, utilizing image data to capture changing landscape of the neighborhoods over a period of time hasn't been explored enough yet. In this study, we therefore investigate further spatio-temporal neighborhood changes over the range of 10 years and its impact on Real Estate Appraisal and property prices.

This research contributes to the Real Estate Appraisal problem by primarily answering three questions:

1. Do abstract neighborhood features such as greenery, commercialization, vehicle density and building density affect property prices in an area?
2. Can YOLO identify latent information of a neighborhood from street view images?
3. Can we model temporal changes in a neighborhood through YOLO-ML architecture?

As shown in Figure 2, this thesis performs latent information detection from street-view images using YOLO V5. The soft information obtained from image data is quantified using a novel scoring mechanism. The final step requires aggregation of detection scores and structural information over each block for each year, resulting in a novel data structure that represents latent information of a neighborhood over a decade.

This research encompasses the evaluation of seven traditional machine learning models, namely Multiple Linear Regression, Ridge Regression, Bayesian Ridge Regression, Gradient Boosting Regressor, AdaBoost Regressor, K-Nearest Neighbors Regressor, XGBoost Regressor, and Random Forest Regressor. These models are trained and assessed on aggregated data, aiming to predict property prices for each block.

To further assess the reliability of these models, this study is conducted on two different neighborhoods of Manhattan: Midtown and Tribeca. The rest of the paper is organized as follows. Chapter 2 provides an extensive review of previous related research and performs an analysis of the variables, data types, and models used. Chapter 3 and 4 discuss proposed and experimental methodology adopted in this study and its experimental results. Chapter 5 discusses the outcomes of the spatio-temporal models for both Midtown and Tribeca. Finally, the research concludes with a summary of the research findings in Chapter 6.

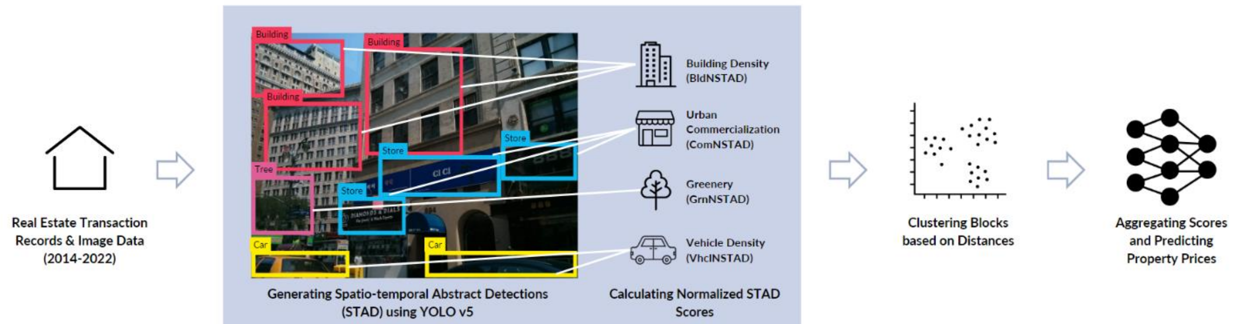


Figure 2: Basic framework presented in this paper

Chapter 2

Related Literature

We have further divided this chapter into 4 sections. The first section explains methodology of paper selection in this thesis. The second section analyzes the variables that were used throughout the selected studies. The third section discusses the image datasets being used in selected papers and the fourth section showcases models that were proposed in papers selected for the literature review.

2.1 Papers selected for literature review

Initially we started off our research from core keywords "housing prices", "mass appraisal", "real estate appraisal" across Publish or Perish database. We queried Publish or Perish database using the following core keywords:

(TS = "Real Estate Appraisal" OR "Mass Appraisal")

This resulted in 520 research papers. However, most of these papers were published before 2010 and were using old methods repeatedly so we filtered out papers pre-2010, reducing relevant papers to 270.

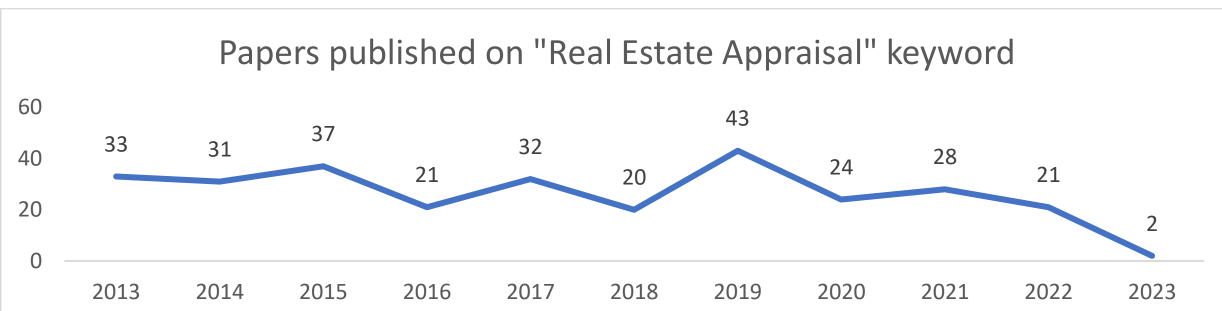


Figure 3: Papers published on "Real Estate Appraisal" keyword

We then further narrowed down our research using our core keyword and spatio-temporal keyword:

(("spatial OR temporal") OR ("spatial" AND "temporal")) AND ("Real Estate Appraisal" OR "Mass Appraisal").

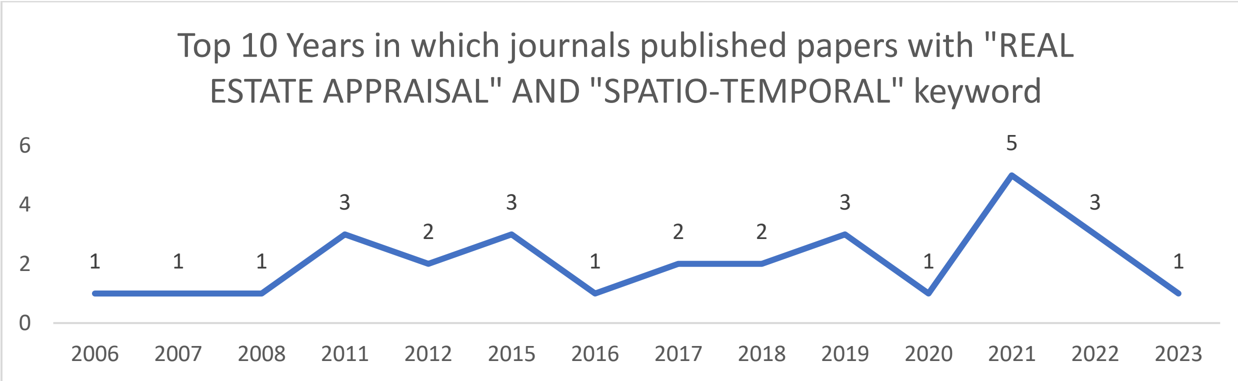


Figure 4: Top 10 Years of journals published with keywords of interest

This query resulted in 28 relevant research papers. However, most of these papers proposed frameworks using old regression methods.

The studies that are shared above enabled us to gain a structural understanding of real estate appraisal. Since our query research for the core keyword resulted in 500 papers, we decided to further categorize them based on the models that were used and the types of data they were using. We included these data types in our literature search as topic keywords to strengthen and support our thesis objective.

Following are the term searches we used for data types + core keyword:

(("GIS" OR "GEO") AND (“Real Estate Appraisal” OR “Housing Price Prediction”))

(("Street-view" OR "satellite") AND “Real Estate Appraisal” OR “Housing Price Prediction”)

("Textual" AND (“Real Estate Appraisal” OR “Housing Price Prediction”))

(("Visual" or "vision") AND (“Real Estate Appraisal” OR “Housing Price Prediction”))

("Remote sense" AND (“Real Estate Appraisal” OR “Housing Price Prediction”))

("Image Data" AND (“Real Estate Appraisal” OR “Housing Price Prediction”))

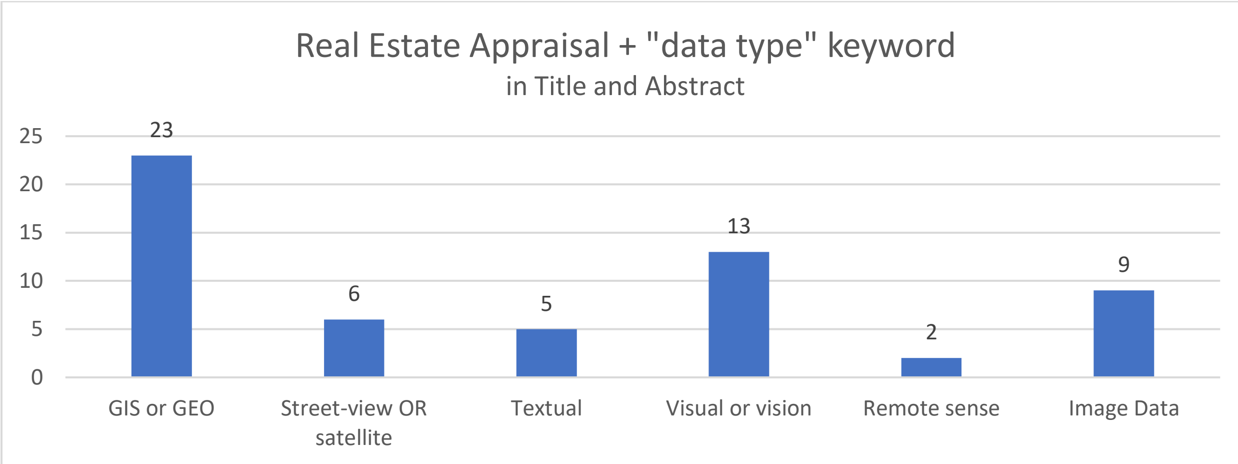


Figure 5: Real Estate Appraisal + "data type" keyword

The searches resulted in 58 research papers. However, for this thesis we narrowed down our focus to image data including street-view images sourced from Mapillary.

Following are the term searches we used for data models + core keyword:

(("Machine Learning" OR "ML" OR "supervised learning") AND ("Real Estate Appraisal" OR "Housing Price Prediction"))

(("Deep Learning" OR "Neural" OR "CNN") AND ("Real Estate Appraisal" OR "Housing Price Prediction"))

(("Regression" OR "Hedonic") AND ("Real Estate Appraisal" OR "Housing Price Prediction"))

(("ARIMA" OR "LSTM") AND ("Real Estate Appraisal" OR "Housing Price Prediction"))

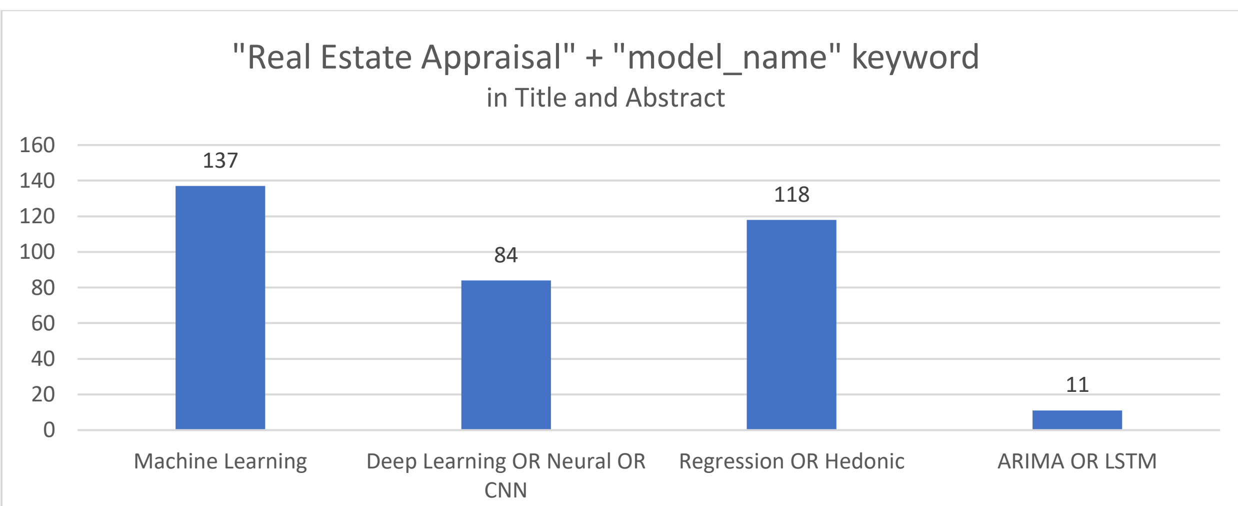


Figure 6: "Real Estate Appraisal" + "model_name" keyword in Title and Abstract

The searches resulted in 350 research papers with most of them containing hedonic pricing model or regression in their title. For the spatial analysis in this thesis, we selected Deep Learning models such as YOLO v5 and for the temporal forecasting we selected Regression and ML models.

	Keyword	# of papers
Core	"Real Estate Appraisal" OR "Mass Appraisal" (REA)	520
Screening	Range of publication 2013 onwards, books and duplicates removed	217
	("spatial and temporal" OR "spatio temporal") AND REA	28
Data type + REA (in title or abstract)	("GIS" OR "GEO") AND REA	23
	("Street-view" OR "satellite") AND REA	6
	"Textual" AND REA	5
	("Visual" or "vision") AND REA	13
	"Remote sense" AND REA	2
	"Image Data" AND REA	9
Model used + REA	("Machine Learning" OR "ML" OR "supervised learning") AND REA	137
	("Deep Learning" OR "Neural" OR "CNN") AND REA	84
	("Regression" OR "Hedonic") AND REA	118
	("ARIMA" OR "LSTM") AND REA	11

Table 1: Keyword selection methodology

We finally shortlisted 10 research papers that had relevant content and would help us build a robust framework on which gap analysis was performed.

The remaining sections of this chapter discuss the variables selected, data type used, and models built for the shortlisted papers.

2.2 Types of variables

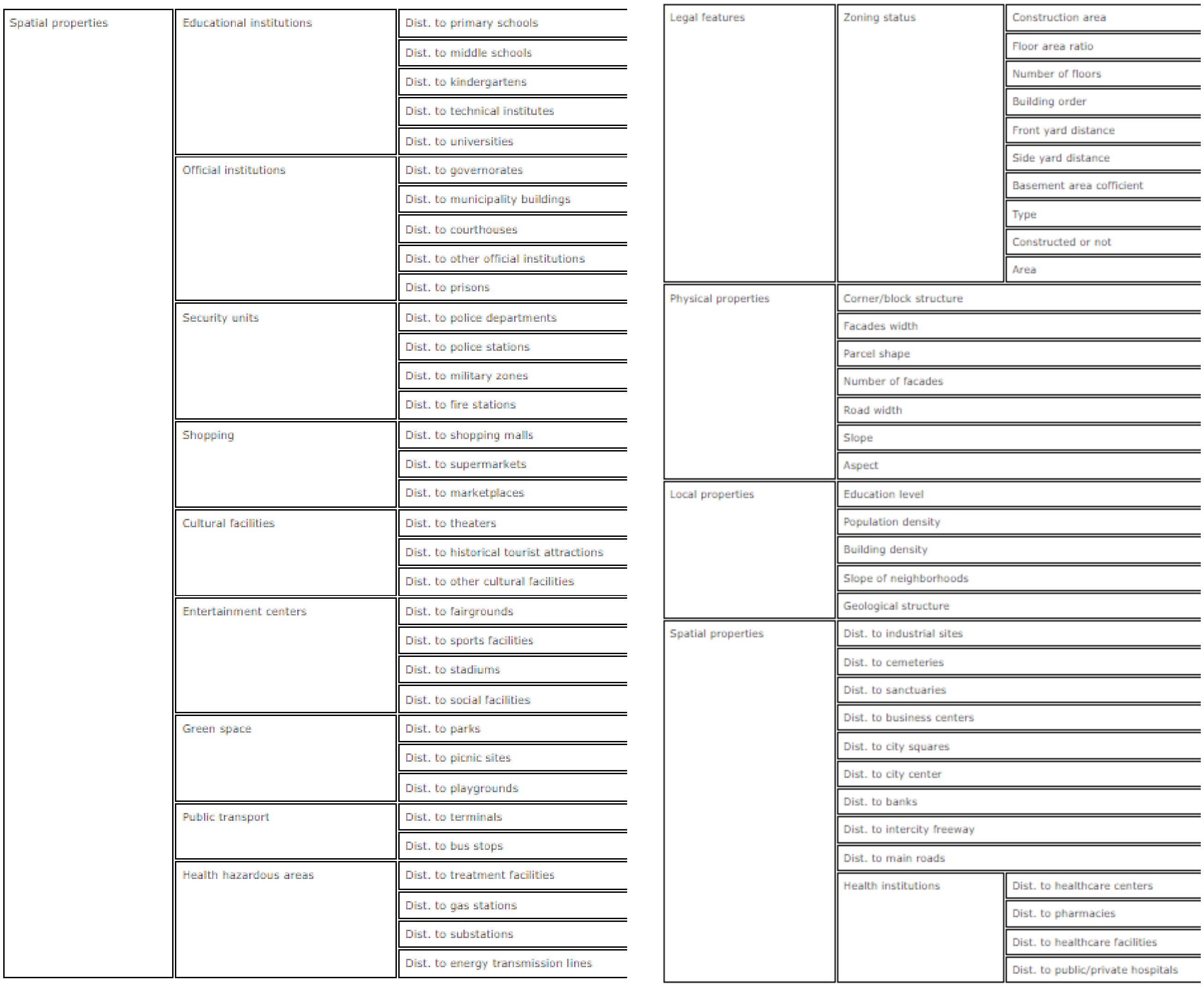
In this section we discuss the two types of variables used in this study: structural and abstract variables.

2.2.1 Structural Variables

It is evident from the numerous studies that have been conducted to solve the appraisal problem, that housing prices are sensitive to the spatial differences of urban facility distributions (Liu et al., 2020). The authors in (Liu et al., 2020) concluded that the more houses are surrounded with commercial buildings, transit routes, and recreational locations, the higher the price.

Numerous empirical studies have examined how the accessibility and quality of urban amenities affect housing prices. For example, Song et al. (Song et al., 2019) analyzed the impact of London's Docklands Light Railway on housing prices and found that public transportation infrastructure has a positive effect, especially in areas with limited access to public transit. Authors in (Bency et al., 2017), (Liu et al., 2020) discovered that the effect of public transportation on housing prices varies depending on the type of system implemented. Subway accessibility was also found to have a positive effect on housing prices, but the degree of impact varied spatially. As for urban green spaces, Wang et. al., and Liu et. al. (Wang, 2023), (Liu et al., 2020) found that the impact of decreasing distance to green infrastructure on housing prices depends on the type and location of the green space. The presence of nearby schools was found to have a positive impact on housing prices (Kucklick et al., 2021), (Bency et al., 2017), (Liu et al., 2020), while cultural heritage localities were found to provide price premiums. The authors in (Bilgilioğlu & Yılmaz, 2021), have compiled a list of all the structural, locational and neighborhood variables that are used frequently (

Figure 7).



Spatial properties	Educational institutions	Dist. to primary schools
		Dist. to middle schools
		Dist. to kindergartens
		Dist. to technical institutes
		Dist. to universities
	Official institutions	Dist. to governorates
		Dist. to municipality buildings
		Dist. to courthouses
		Dist. to other official institutions
		Dist. to prisons
	Security units	Dist. to police departments
		Dist. to police stations
		Dist. to military zones
		Dist. to fire stations
	Shopping	Dist. to shopping malls
		Dist. to supermarkets
		Dist. to marketplaces
	Cultural facilities	Dist. to theaters
		Dist. to historical tourist attractions
		Dist. to other cultural facilities
	Entertainment centers	Dist. to fairgrounds
		Dist. to sports facilities
		Dist. to stadiums
		Dist. to social facilities
	Green space	Dist. to parks
		Dist. to picnic sites
		Dist. to playgrounds
	Public transport	Dist. to terminals
		Dist. to bus stops
	Health hazardous areas	Dist. to treatment facilities
		Dist. to gas stations
		Dist. to substations
		Dist. to energy transmission lines
Legal features	Zoning status	Construction area
		Floor area ratio
		Number of floors
		Building order
		Front yard distance
		Side yard distance
		Basement area cofficient
		Type
		Constructed or not
		Area
Physical properties	Corner/block structure	
	Facades width	
	Parcel shape	
	Number of facades	
	Road width	
	Slope	
	Aspect	
Local properties	Education level	
	Population density	
	Building density	
	Slope of neighborhoods	
	Geological structure	
Spatial properties	Dist. to industrial sites	
	Dist. to cemeteries	
	Dist. to sanctuaries	
	Dist. to business centers	
	Dist. to city squares	
	Dist. to city center	
	Dist. to banks	
	Dist. to intercity freeway	
	Dist. to main roads	
	Health institutions	Dist. to healthcare centers
		Dist. to pharmacies
		Dist. to healthcare facilities
		Dist. to public/private hospitals

Figure 7: List of all independent variables used in housing price studies (Bilgilioğlu & Yılmaz, 2021)

Papers	Citation	Structural Variables
A machine learning-based method for the large-scale evaluation of the qualities of the urban environment	(Liu et al., 2017)	N/A
An application of convolutional neural network in street image classification	(Law et al., 2017)	N/A
Take a Look Around: Using Street View and Satellite Images to Estimate House Prices	(Law et al., 2019)	Year, Bedrooms, Age, Property Type, Size
Quantifying the impact of location data for real a for real estate appraisal – a GIS-based deep learning approach	(Kucklick et al., 2021)	number of rooms/bathrooms/bedrooms), (interior and exterior conditions), technical details (i.e. heating type, air condition), amenities (i.e. number of fireplaces, number of garage spaces), lat/long for each house

Papers	Citation	Structural Variables
The effect of environment on housing prices: Evidence from the Google Street View	(Wang, 2023)	number of rooms/bathrooms/bedrooms, Land Area, Building Area, Total Floors, House Age, Building Type, Parking Space, # of Households, Population Density
Beyond Spatial Auto-Regressive Models: Predicting Housing Prices with Satellite Imagery	(Bency et al., 2017)	latitude, longitude, number of bathrooms, number of bedrooms, number of floors, number of reception rooms, listing status, street address
Past price 'memory' in the housing market: testing the performance of different spatio-temporal specifications	(Dubé et al., 2018)	N/A
Spatial-Temporal Variation in the Impacts of Urban Infrastructure on Housing Prices in Wuhan, China	(Liu et al., 2020)	Plot Ratio Pr floor area /covered area Green Rate Gr Plot green area/Plot area Property Fee Pf property management fee
Estate price prediction system based on temporal and spatial features and lightweight deep learning model	(Chiu et al., 2022)	land shifting total area, build shifting total area, number of bedrooms , number of living/dining rooms, number of bathrooms, Building price, Building age

Table 2: Structural variables used in selected papers

2.2.2 Urban environment latent variables

Where structural variables for housing data are easily available publicly, exogenous variables that are hard to quantify require convolutional networks to structure latent information. Certain characteristics of urban areas are perceivable through photographs, such as the level of activity on a street, the extent of vegetation, or the size of the sidewalk. However, there are other features that are not as easily measurable, such as the perceived status of the neighborhood or the visual appeal of the street (Law et al., 2019).

Nonlinear effects are particularly significant when it comes to intangible factors, such as the overall quality of a neighborhood, as these factors can often have a compounding impact on the value assigned to tangible assets. To illustrate, a broken window in a home might represent an unsafe locality, the amount of greenery in an image can indirectly capture the ambiance and environment of a neighborhood. These intangible differences in an environment can impact house prices throughout the years.

Both Liu et al., 2017 and Law et al. used machine vision techniques to retrieve geographical knowledge such as street frontage quality. According to Liu et al., 2017 if a building is built with high-quality materials, doesn't have any broken windows, dirt, deterioration, corrosion, hanging wires etc. then it has better industrial craftsmanship. Thereby, helping researchers to identify the quality of living in a certain neighborhood. Similarly, continuity of a street wall, i.e., having no building adheres a sense of psychological security in potential buyers (Liu et al., 2017).

Gebru et al. (Gebru et al., 2017) extracted car types, years, and make from 50 million Google Street View images to correlate with socio-economic factors such as income and geographic demographic types across different cities in the United States. The study found that car types, years, and makes can be used as features to predict accurately the income, race, education, and voting patterns at both the zip code and precinct level.

Wang, 2023, trained their convolutional network on street-view images to classify higher and lower scores of a neighborhood's aesthetics. They concluded, with a significant $p<0.001$, that for a one-unit difference in the aesthetic score resulted in a 35% difference in consumer's willingness to pay for the house.

Papers	**Citation**	**Urban environment latent variables**							
		New Buildings	**# of Schools**	**# of Parks**	**# of Shops**	**# of Hospitals**	**Noise**	**Proximity to transit**	**Proximity to Gas stations**
A machine learning-based method for the large-scale evaluation of the qualities of the urban environment	(Liu et al., 2017)								
An application of convolutional neural network in street image classification	(Law et al., 2017)								
Take a Look Around: Using Street View and Satellite Images to Estimate House Prices	(Law et al., 2019)			Yes	Yes				
Quantifying the impact of location data for real a for real estate appraisal – a gis-based deep learning approach	(Kucklick et al., 2021)		Yes	Yes			Yes		
The effect of environment on housing prices: Evidence from the Google Street View	(Wang, 2023)							Yes	Yes
Beyond Spatial Auto-Regressive Models: Predicting Housing Prices with Satellite Imagery	(Bency et al., 2017)		Yes	Yes	Yes	Yes			

Papers	**Citation**	**Urban environment latent variables**							
		New Buildings	**# of Schools**	**# of Parks**	**# of Shops**	**# of Hospitals**	**Noise**	**Proximity to transit**	**Proximity to Gas stations**
Past price 'memory' in the housing market: testing the performance of different spatio-temporal specifications	(Dubé et al., 2018)		Yes						
Spatial-Temporal Variation in the Impacts of Urban Infrastructure on Housing Prices in Wuhan, China	(Liu et al., 2020)		Yes (Primary & Secondary)	Yes	Yes			Yes number of bus lines within 500m	Yes
Estate price prediction system based on temporal and spatial features and lightweight deep learning model	(Chiu et al., 2022)	Yes Categorized over business type, area, height							

Table 3: Latent variables used in selected papers

2.3 Data types

Big data and data storage technologies have made data retention and handling way easier. With respect to real estate the most widely used internet big data types include transactional data, POI data, GIS map data, image data, and text information data (Figure 8).

Papers	**Citation**	**Datasets Used**				
		Street View Image Data	**GIS Data**	**3D - Buildings data (ESRI)**	**Aerial/ Satellite Images**	**Structural Data**
A machine learning-based method for the large-scale evaluation of the qualities of the urban environment	(Liu et al., 2017)	Google Yes				
An application of convolutional neural network in street image classification	(Law et al., 2017)	Google Yes		Yes		
Take a Look Around: Using Street View and Satellite Images to Estimate House Prices	(Law et al., 2019)	Google Yes			Microsoft Bing Yes	Yes
Quantifying the impact of location data for real a for real estate appraisal – a gis-based deep learning approach	(Kucklick et al., 2021)		Yes			Yes
The effect of environment on housing prices: Evidence from the Google Street View	(Wang, 2023)	Google Yes				Yes

Papers	Citation	Datasets Used				
		Street View Image Data	GIS Data	3D - Buildings data (ESRI)	Aerial/ Satellite Images	Structural Data
Beyond Spatial Auto-Regressive Models: Predicting Housing Prices with Satellite Imagery	(Bency et al., 2017)				Google Yes	Yes
Past price 'memory' in the housing market: testing the performance of different spatio-temporal specifications	(Dubé et al., 2018)		Yes			Yes
Spatial-Temporal Variation in the Impacts of Urban Infrastructure on Housing Prices in Wuhan, China	(Liu et al., 2020)		Yes			Yes
Estate price prediction system based on temporal and spatial features and lightweight deep learning model	(Chiu et al., 2022)		Yes			Yes

Table 4: Data type used in selected papers

2.3.1 Structural House/Transaction Data

Transactional data pertains to information about real estate leases or transactions that is obtained from different online platforms acting as intermediaries, or government organizations such as CityofNewYork, or OpenDataPhilly. In most researches, large amounts of transaction data, comprising details about transactions, house prices, building location, and features, were obtained mainly through automatic web crawlers. The data collected by intermediary platforms contains information about the timing and quantity of real estate transactions, which can provide insight into market trends and whether adjustments to real estate prices are necessary based on transaction timing (Wei et al., 2022). Building feature data give information about the features of a house such as building area, construction ratio, room orientation, room layout, house age, and decoration style (among others), as well as community-level features such as community developers, properties, floor-area ratio, and greening rate (Wei et al., 2022).

2.3.2 POI Data

Mainstream internet map platforms have the capability to offer point of interest (POI) data for real estate valuation, which can be available in (or close to) real-time. The POI data consists of latitude and longitude coordinates, names, and addresses, which can provide up-to-date information about the neighborhood and location of the property being appraised. With the help of POI data, users can accurately evaluate the neighborhood and location characteristics of the property based on the location data provided by the internet intermediary platform. For instance, in (Bency et al., 2017) the researchers collected data on the number of infrastructure POI points within a specific radius around a house, as well as the distance from the nearest infrastructure POI point to the house to be appraised, using the Google Places web service. This service allows users to search for and retrieve information on businesses and locations within a designated radius of a specific latitude-longitude coordinate. The places are categorized based on descriptive tags, with 86 different tags available, such as cafes, beauty salons, clothing stores, and post offices etc.

However, finding temporal variations of POI data requires spatial modeling from GIS image data (Kucklick et al., 2021). GIS maps include multiple layers of latitudes and longitudes of each point of interest. For example, a base layer can be a map of your interested region. Users can then overlay other layers of schools coordinates, hospitals coordinates, parks coordinates etc. Tools like ArcGIS and QGIS are commonly used for housing price research.

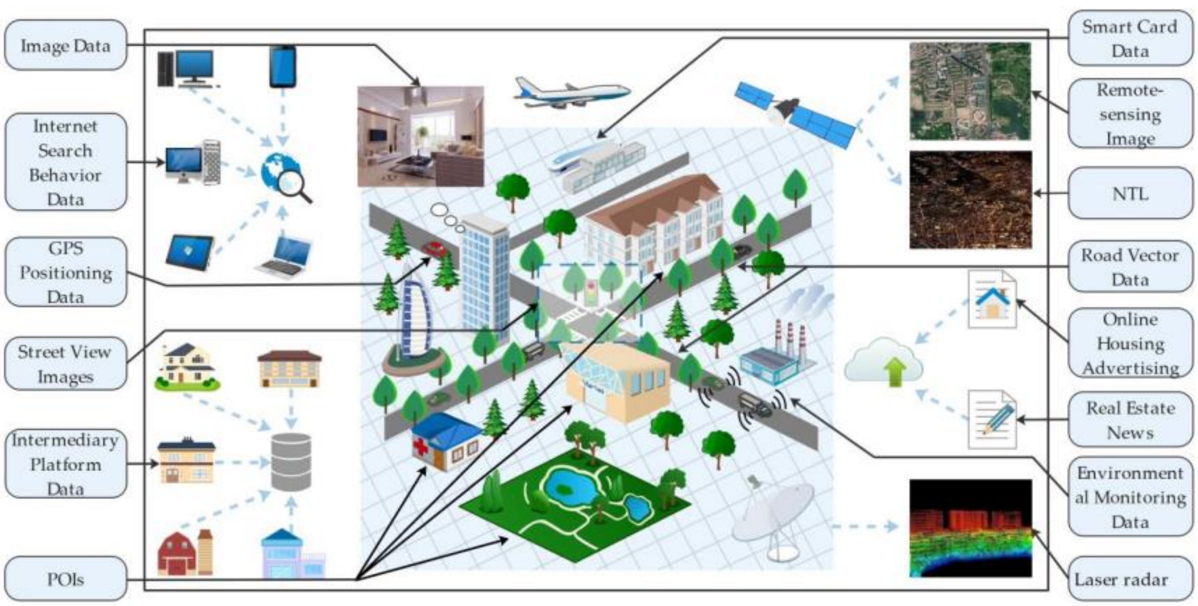


Figure 8: Big data in Real Estate from Wei et al. (Wei et al., 2022)

2.3.3 Street view, Aerial Image Data

Most papers we have considered in this review included Street View Images retrieved from Google Maps API. The information obtained from street-view images represents the characteristics of the surrounding streets close to the house and not the house itself. Remote sensing imagery also serves the same purpose by depicting the surrounding environment of the property. The main difference between the two is the scale at which they gather the information of the neighborhood. In Law et al.'s (Law et al., 2017) research, street-view and satellite images were used to reflect neighborhood characteristics at the street and aerial levels, respectively. Their study helped quantify intangible housing features, such as the visual appeal of a neighborhood, which was challenging to measure previously.

All image data undergoes pre-processing which involves the removal of certain types of images that are deemed invalid. These may include images of the interior of buildings, images that are perpendicular to the street and not front-facing, images that are too dark or not available, and images that are of places under construction or capture cars only. This process is carried out using a combination of automatic functions, convolutional neural network (CNN) classifiers, and manual processes (Law et al., 2019). However, it should be noted that this process may not capture all types of invalid images, such as those that are blocked by large vehicles (Wang, 2023).

2.4 Types of models

Housing price prediction and Appraisal researches have proposed Spatial autoregressive techniques (SAR), Multiple linear regression, and Geographic & Temporal Weighted Regression (GTWR) for more than a decade. Only after 2013 have we seen deep learning models such as CNN, DCNN, LSTM being proposed. In this section, we have discussed models that are used in the papers selected for our review.

2.4.1 GIS Spatial Modeling

In order to model the varying spatial features of a neighborhood, GIS data is required. However, GIS data is available in SHP, or ESRI File format which needs to be quantified using the QGIS, or ArcGIS software. Researchers have used GIS modeling to quantify location-influencing factors such as the distribution of commercial buildings, transit routes, transportation facilities and recreational spaces.

For example, in Kucklick et al. (Kucklick et al., 2021), the authors have identified total number of parks located within the neighborhood by constructing polygons of 400m radius and extracting the overlapping number of parks. As for calculating the proximity to schools, the authors have measured minimum Euclidean distances to elementary and high schools (Kucklick et al., 2021). Lastly, the authors created categories of noise levels for less than 55db, between 55db and 65db, greater than 65db. They used a map that captured noise pollution produced by traffic in urban areas. The same polygons were plotted and assigned decibel levels based on the neighborhood radius and noise level overlap. Similarly, other researchers have used GIS map data to quantify other important spatial features that don't require CNNs.

2.4.2 Hedonic Price Model

The Hedonic price model has been the most proposed framework for appraisal problem suggested by economists, geographers, and real estate economists. Hedonic Price Model is well-known for its scaling capacity and interpretability. The basic principle behind Hedonic Price Model is that the cost of any good can be broken down into its utility-bearing components that influence the cost positively or negatively (Law et al., 2019).

With the number of structural variables increasing and economic factors affecting housing prices more, its easier to add new parameters to a Hedonic Price Model (Wei et al., 2022). However, Hedonic Price Model typically adopts multiple linear regression methods. One common disadvantage of MLR is its over simplicity and inability to capture the non-linear relationships between parameters (Wei et al., 2022).

In Wang et al. (Wang, 2023), the authors have applied a semi-log multiple linear regression model with the following equation:

$$\log P = \beta_0 + L\beta_L + S\beta_S + N\beta_N + G\beta_G + \epsilon,$$

Where P is a vector of house prices, L is a matrix of housing locational attributes, S is a matrix of housing structural attributes, N is a matrix of neighborhood attributes, and G is a vector of aesthetically visual score measured by CNN. The β_0 is the constant term vector, β_L, β_S, β_N and β_G are vectors of the corresponding parameters, and ϵ is a vector of error terms (Wang, 2023).

Using the same simple approach, authors were able to model the price differential by adding more variables and standalone variables. They found that using Base model with PopulationDensity, District and Score variables resulted in the highest R2 value.

2.4.3 Geographic & Temporal Weighted Regression

The two types of most used Hedonic Price Models are Spatial Autoregressive Models (SAR) and Geographic & Temporal Weighted Regression (GTWR). GTWR is the only Hedonic Price Model that takes temporal changes of spatial features into account while continuing to hold explanatory powers.

In Liu et al, 2019, the authors built a GTWR model by combining latitude, longitude, and timestep of the transaction of a house price. The three-dimensional variables allowed GTWR to analyze spatial and temporal relations within the models.

$$\ln y_i = \beta_o(u_i, v_i, t_i) + \sum(X_j\ \beta_k(u_i, v_i, t_i))\ln x_{ij} + \varepsilon_i$$

where i is the index of a spatial-temporal point with (u_i , v_i , t_i) denoting its coordinates. Accordingly, yi , x_{ij}, ε_i are the dependent variable, the j_{th} independent variable, and the error term for the i_{th} observation (point), respectively.

To explain the time series fluctuation of each variable, the authors in (Liu et al., 2020) calculated mean values of the coefficients of each variable and plotted the trend lines to visualize every variable's influence over time. They concluded that the presence of lakes and rivers, green areas such as parks closest to properties, has an increasing influence on the property prices in the range of 2010 to 2018. The impact of hospitals and tourist attractions had a fluctuating increase rather than a steady increase in influence on the prices. Surprisingly the increase in commercial buildings had a decreasing impact on prices over the 8 years. The authors link this trend with the buyers' willingness to move into less commercial areas and more secluded residential areas.

2.4.4 ML Models

Machine Learning models such as Random Forest and Gradient Boosting have been proved to be a significant improvement over the traditional Hedonic Price Model methods (Law et al., 2019). Although hedonic price models have greater interpretability, they are sensitive to influencing factors, resulting in incorrect prices prediction.

Random Forest is an application of Bagging which improves accuracy by building N number of trees from the available data. Instead of using all available features, Random Forest randomly selects a certain number of features leading to decorrelating trees and making RF more reliable in terms of accuracy.

As compared to RF, Gradient Boosting creates inter-dependent trees where every subsequent tree learns from the previous tree. Moreover, RF selects a predicted value generated from the trees based on majority votes whereas GB selects the predicted value generated by the last tree.

In the papers selected for this review, ML models are used as a comparison to the baseline models. Kucklick et al. (Kucklick et al., 2021) performed multiple experiments on their dataset and concluded that baseline random forest model performed 3% better than regression model. Similarly, Wang et al. experimented on Lasso, Ridge Regression, Random Forest and Gradient Boosting. RF performed best for the authors in all types of datasets and all combinations of variables with an R2 of 0.94.

2.4.5 Multi-view CNNs

After Hedonic Models and ML models, the most proposed model in housing price prediction or appraisal related researches has been Deep learning Neural Networks. DL models are mostly implemented by Deep Convolutional Neural Networks that are used to learn the abstract level representations typically in image data.

With multiple types of data available in the housing study, models that can cater to every data type simultaneously and produce compact learned weights are required. Heterogenous data structures such as structural data, image data, and temporal data require multi-view learning strategy (Kucklick et al., 2021). Kucklick et al (Kucklick et al., 2021) trained Structural data, GIS neighborhood data, and Street-view Image data separately on different CNNs with log Price as the dependent variable. The first and the simplest CNN based on a multi-layer perceptron architecture took structural data as an input to predict log prices. After that another CNN is applied on the GIS data. This was also a simpler convolutional network to pass tabular data (obtained through GIS spatial modeling) as input and predict log price. The third CNN is ResNet50 applied on Street-view data to learn an image's relationship with the price. The models were trained using an Adam optimizer with a standard learning rate of 0.001, batch size 32, and a maximum of 80 epochs.

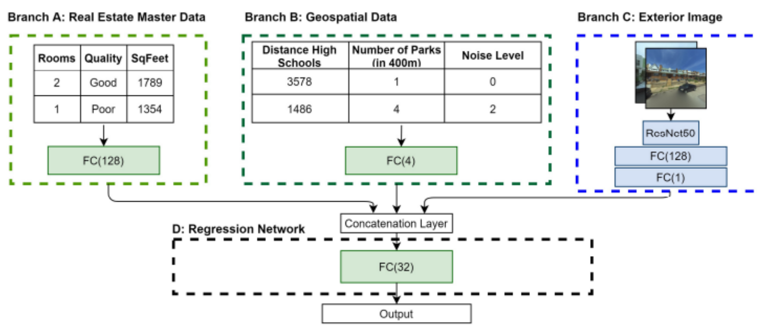


Figure 3. Architecture of the proposed solution. Different combinations of the input branches are combined: (A, B), (A, C), (A, B, C), and (A, B, C, D). The suggested models are trained in an end-to-end fashion. FC = Fully Connected Layer (number of neurons in brackets)

Figure 9: Proposed architecture in (Kucklick et al., 2021)

The three models are then also used together, where instead of predicting log prices, the learned weights produced at the Output layer of each model are concatenated using Concatenate() method in TensorFlow. The concatenated output layer is then passed through another Fully connected layer and is then finally used to predict log price. For the authors in (Kucklick et al., 2021), the lowest RMSE was produced by the concatenated model.

2.4.6 Spatial-Temporal Methods

In this section of the Literature review we have discussed spatio-temporal methods that are only recently getting implemented through Deep Learning methods. The previously discussed methods performed only one form of analysis at a time. In (Law et al., 2019), (Kucklick et al., 2021), (Wang, 2023), (Bency et al., 2017) spatial data is modeled separately by performing GIS spatial analysis on the facilities present in a specified radius of a neighborhood. However, these studies didn't take temporal data into account.

As for research conducted in (Dubé et al., 2018), (Liu et al., 2020) propose a spatio-temporal framework that is based on traditional Hedonic Pricing Model or Regression. The two papers focused on uncovering the linear relationships between log price and spatial-temporal variables. Moreover, regression models are sensitive to the bandwidth parameter which is not an issue in deep learning models.

Of the 20+ papers written using the "spatio-temporal" keyword, only (Chiu et al., 2022) proposed a novel framework based on CNN-LSTM architecture. CNN analyzes the correlation among distinct grids in the housing region and incorporates this correlation to the subsequent LSTM layer that can easily model time series data.

In (Chiu et al., 2022), first GMM clustering is performed on the structural housing price dataset based on the following attributes: total area of the building, number of bedrooms, number of living/dining rooms, number of bathrooms, building age.

Next, they generated spatio-temporal matrices for each Estate A, by selecting a neighborhood radius around estate A and quantifying facilities' changes such as parks, hospitals etc. Each matrix has m x n rows. Where m is the number of facilities near estate A and n is the number of additions, removals, changes in a particular facility. Next the values in the matrix represent the influence of each feature's structural change on the price of estate A using an influence decay function. The degree of this influence decreases as the distance between estate and feature increases.

If estate A has more than 3 transaction records available over a time range of 10 years (i.e., estate A was sold thrice throughout the 10 years at different sale prices), authors have calculated the mean sale price and used that as reference. If estate A has only one record (i.e., estate A was sold only once throughout the 10 years at one sale price), authors have used the single sale price as reference. However, if estate A wasn't sold and was only transferred to another one i.e., there is no price data available for estate A then it's discarded from the dataset. The output will be something like for each estate A there are multiple facilities change matrices. Each matrix will have a corresponding price and a timestamp.

Papers	Citation	Models used						
		Cluster-ing	CNN	Non-Linear MLP	ML models	GIS spatial analysis	Weighted Geographic Regression	MLP
A machine learning-based method for the large-scale evaluation of the qualities of the urban environment	(Liu et al., 2017)		AlexNet + SVR GoogleNet + SVR SIFTHIST + SVR					
An application of convolutional neural network in street image classification	(Law et al., 2017)		Alexnet CNN					
Take a Look Around: Using Street View and Satellite Images to Estimate House Prices	(Law et al., 2019)		Separately for Aerial Images & Street Images	Yes				
Quantifying the impact of location data for real a for real estate appraisal – a GIS-based deep learning approach	(Kucklick et al., 2021)		Yes ResNet50		Yes RF	Yes		Yes
The effect of environment on housing prices: Evidence from the Google Street View	(Wang, 2023)		Yes for image classification only		Yes GB, RF			Yes
Beyond Spatial Auto-Regressive Models: Predicting Housing Prices with Satellite Imagery	(Bency et al., 2017)		Yes for image classification only Inception v3		Yes GB, RF			Yes
Past price 'memory' in the housing market: testing the performance of different spatio-temporal specifications	(Dubé et al., 2018)						Yes (SAR)	
Spatial-Temporal Variation in the Impacts of Urban Infrastructure on Housing Prices in Wuhan, China	(Liu et al., 2020)					Yes	Yes (GTWR)	
Estate price prediction system based on temporal and spatial features and lightweight deep learning model	(Chiu et al., 2022)	Yes	Yes			Yes		

Table 5: Types of models used in selected papers

Finally, the authors have proposed a light-weight CNN-LSTM model, by using drop-out and feature selection method to reduce the training time. The CNN architecture is used to pass m matrices for all estates to the input layer then to the subsequent convolution layers and max-pooling layers. The output of CNN is a set of important features that capture the relationships between the target estate and the surrounding facilities influencing it. After that it is passed to the LSTM layers which finally predicts the estate's price on a future timestamp.

2.5 Gap Analysis

The existing research on predictive systems for Real Estate Appraisals has made commendable strides through the data types, and advanced statistical techniques. Nevertheless, there is still capacity for further exploration, particularly from a spatio-temporal perspective.

Spatio-Temporal Data Exploration: This thesis uniquely leverages spatial-temporal changes in neighborhoods over a decade, integrating dynamic factors like greenery, traffic, and commercialization with property prices. Unlike prevailing research which mainly scrutinizes spatial elements in isolation or temporal aspects without spatial interplay, this study forges a novel path by combining these dimensions, thereby enriching the understanding of their collective impact on Real Estate Appraisals.

Advanced Image Data Utilization: A cornerstone of this research is the advanced utilization of street-view imagery, that is relatively less explored in existing studies. Unlike other studies, this thesis employs a novel YOLO-ML architecture for extracting abstract features that characterize property prices.

In-Depth Longitudinal Analysis: The research distinguishes itself through an intensive longitudinal analysis of specific Manhattan neighborhoods, providing granularity and temporal depth rarely achieved in prior studies. This approach not only aids in understanding the evolution of these areas but also sets a new benchmark in localized, time-sensitive property price analysis.

Practical Implications for Key Stakeholders: The practical applicability of this research extends beyond theoretical realms, offering valuable insights to homeowners, investors, and urban planners. This focus on translating theoretical models to real-world implications provides a unique perspective often missing in academic research.

Chapter 3

Proposed Methodology

In this chapter we explain the framework (

Figure 2) to detect abstract variables using You Only Look Once (YOLO v5), quantify the STADs, aggregate the dataset and cluster the blocks based on distances.

3.1 Study Area

In this research we chose two neighborhoods (Figure 10) in Manhattan: Midtown for the baseline model and Tribeca for comparison due to their distinct characteristics and relevance in understanding urban dynamics in Manhattan.

Midtown, a central commercial and entertainment hub, is marked by high-density development, corporate offices, and significant economic activity. Noteworthy landmarks such as Times Square and the Rockefeller Center contribute to its prominence.

In contrast, Tribeca, located below Canal Street, has evolved from an industrial district to a residential area with historic architecture and a thriving arts scene. The juxtaposition of Midtown's corporate environment and Tribeca's residential and artistic character provides a diverse backdrop for studying urban complexities.

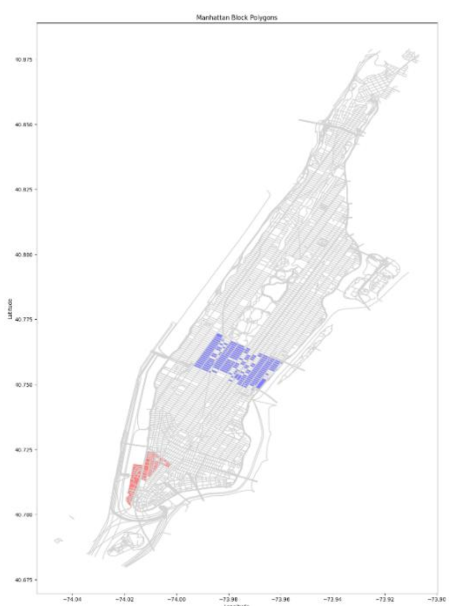


Figure 10: Midtown (blue) and Tribeca (red) blocks

We selected these neighborhoods based on their representation of different aspects of urban life, enabling a pragmatic analysis of the socio-economic factors that shape Manhattan's landscape.

3.2 Dataset Variables

In this section we discuss the variables selected to conduct our property price prediction study.

3.2.1 Structural Variables

In this paper we carry research out from the perspective of a block level in Manhattan's neighborhoods. We utilized Rolling Property Sales Datasets from year 2014 - 2022 publicly available on New York's Data Portal. There are 116 blocks in Midtown and 35 blocks in Tribeca that had sales data available. Each property sale contains the attribute information about the property such as borough, neighborhood, block, lot, building class category, address of the property, number of residential units, number of commercial units in the property, square footage of the property, year it was built, year it was sold, and sale price.

Figure 11 shows the comparison of mean and median sale prices per block in midtown. The mean sale price tends to be higher than the median. This is indicated by the blue distribution extending further to the right.

The median sale price (green distribution) is more centrally located and less spread out. This suggests that the median is less influenced by extreme values or outliers. However, we selected mean Sale Price as our dependent variable after removing outliers since the mean sale price in Tribeca is more centrally located and showed less variability (Figure 12).

Lastly, to incorporate economic factors in the model we included Mortgage Rate, Interest Rate, and Inflation Rate.

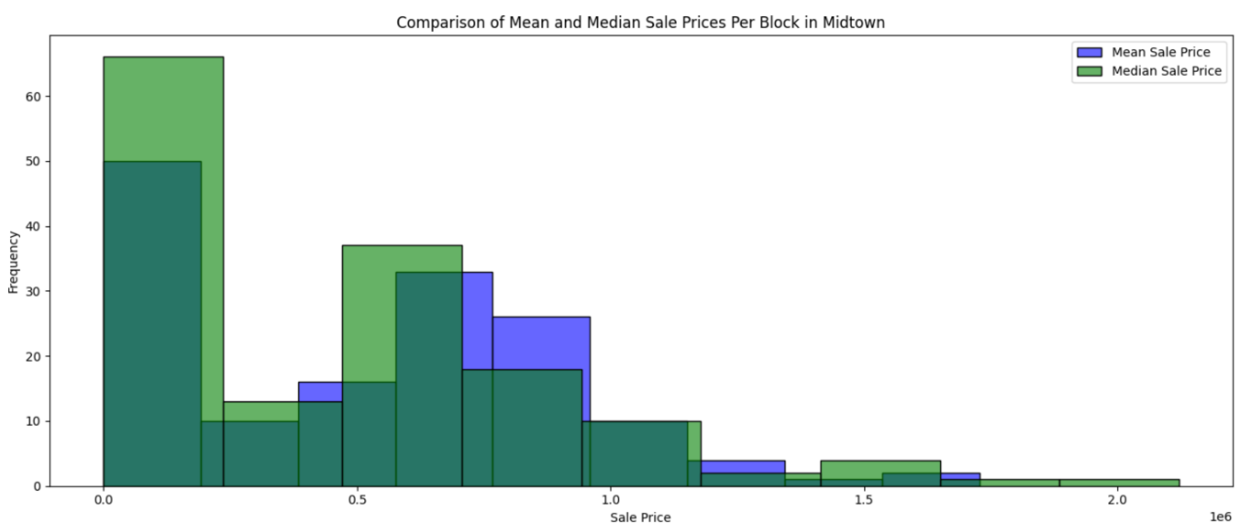


Figure 11: Comparison of Mean and Median Sale Prices Per Block in Midtown

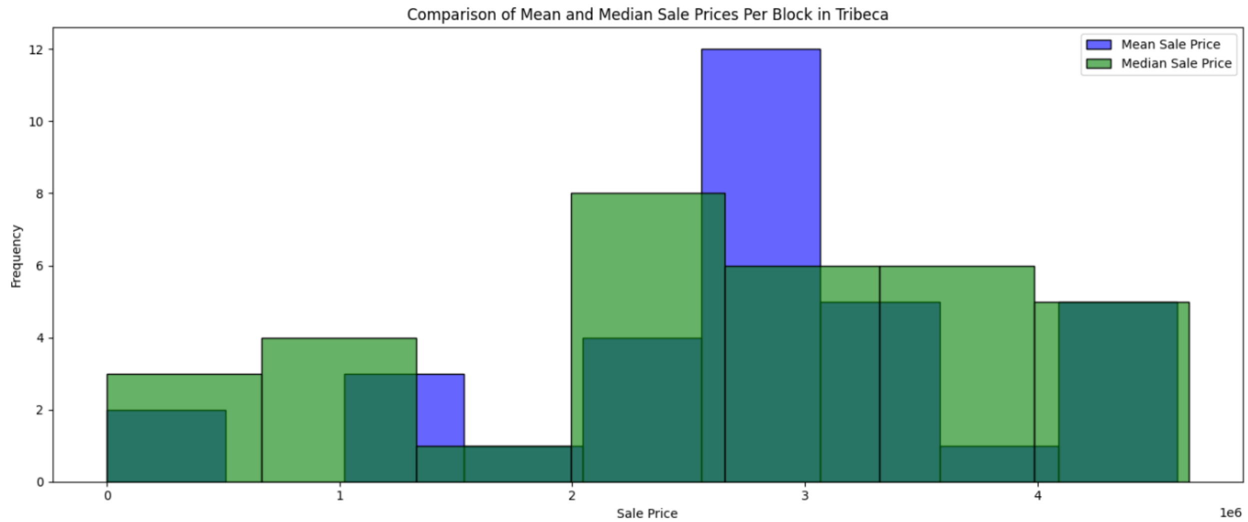


Figure 12: Comparison of Mean and Median Sale Prices Per Block in Tribeca

3.2.2 Spatial Variables

In addition to the structural variables obtained from NYC Data Portal, we extracted spatial data on crime rates in neighborhoods such as number of arrests. We obtained Housing Development data such as new buildings constructed, demolished, and altered each year for Midtown and Tribeca (Figure 16 and Figure 15). Lastly, we added closest facilities and program sites available in a neighborhood using [NYC Capital Planning Explorer]() for Midtown and Tribeca (Figure 14 and Figure 13).

Figure 16: Housing development in Midtown

Figure 15: Housing development in Tribeca

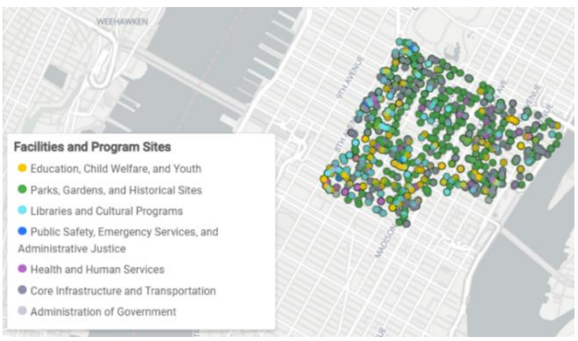


Figure 14: Facilities in Midtown

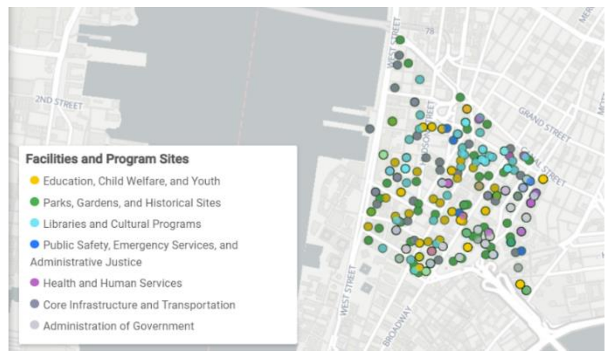


Figure 13: Facilities in Tribeca

3.2.3 Spatio-Temporal Abstract Detections (STAD)

In this section we explain the abstract variables we selected to examine the effects of spatio-temporal changes on neighborhood prices called STAD. Each STAD is a detection that influences the housing prices either positively or negatively over the years 2014-2022.

Most research have been conducted only on the spatial aspect of abstract variables and their impact on housing prices. According to (Kurvinen & Vihola, 2016), the completion of an apartment building has a positive and statistically significant immediate impact on the surrounding apartment values. Similarly, the authors in (Staats & Swain, 2020) established that the number of parked cars and trees in a street influence how the neighborhood is perceived. The number of parked cars in a street influence how the neighborhood is perceived. The research conducted by authors in (Staats & Swain, 2020), participants estimated approximately 5% higher prices for residences when there were trees in the street, as well as rating the neighborhood as more attractive. The data was consistent with the hypothesis that neighborhood appraisal mediates the relationship between cars and affective appreciation of the residence as well as the hypothesis that neighborhood appraisal mediates the relationship between trees and price estimation.

In this paper, our goal is to learn abstract features of a neighborhood such as car ownership, commercial landscape, building density and greenery in a neighborhood and how they impact sale prices over the years. We extracted image data from [Mapillary API] for Midtown and Tribeca from 2014 to 2022.

Figure 17: Street-view images from Mapillary

The four abstract features we studied are:

Building density and housing prices: It is important to note that Manhattan is known for its upscale residential buildings, trendy restaurants, and cultural scene. The actual building density and the changes over time would have significant implications for the real estate market, affecting everything from housing prices to the character and appeal of the neighborhood (Kurvinen & Vihola, 2016).

Vehicle density, and housing prices: A higher vehicle density could either be a sign of vibrancy and accessibility or a detriment due to the associated downsides of heavy traffic. The year-over-year trends in vehicle density would also be telling of the area's development, with increasing scores potentially indicating growing commercial activity or urban development that could lead to changes in the neighborhood's walkability and property values over time (Staats & Swain, 2020).

Commercialization and housing prices: High commercialization can lead to increased property values due to the amenities and conveniences provided by commercial developments, but they can also lead to a less peaceful living environment. The higher the number of stores, malls, and safety markings in an area, the more commercialized it is, which in turn can influence the real estate market trends in the area (Li et al., 2019).

Greenery and housing prices: Higher greenery can generally contribute to higher property values, as they improve not only the visual appeal but also the health and well-being of the residents. A year-over-year increase in greenery scores could also indicate successful urban greening initiatives, which can further enhance the attractiveness of the neighborhood (Staats & Swain, 2020).

3.2.4 Property Sale Price – Dependent Variable

The sale price distribution in Midtown and Tribeca over the years is shown in Figure 18 and Figure 19 respectively.

In Midtown, the median sale price increased from $34,784 in 2014 to $713,887.5 in 2022, which is a substantial increase of approximately 1952.34%. Whereas in Tribeca, the median sale price increased from $1,300,000 in 2014 to $1,745,000 in 2022, marking an increase of approximately 34.23%.

During the 10 years, Midtown consistently showed outliers indicating while the typical sale price might be changing, the presence of exceptional sales remained constant. The presence of more extreme outliers in Tribeca indicated it had a higher number of luxury property sales in the neighborhood.

Type	Variable	Abbreviation	Description
Structural Variables	Borough	Br	The borough in which the property is located.
	Neighborhood	Nb	The neighborhood or district of the property.
	Building Class Category	Bc	Classification of the building based on its use and structure.
	Block	Blk	The city block on which the property is situated.
	Lot	Lot	The specific lot number of the property within the block.
	Address	Adrs	The street address of the property.
	Residential Units	Ru	The number of residential units within the property.
	Commercial Units	Cu	The number of commercial units within the property.
	Land Square Feet	Lsqft	The total area of the land on which the property is built, in sq feet.
	Gross Square Feet	Gsqft	The total interior floor space of the building, in square feet.
	Year Built	Yb	The year in which the building was constructed.
	Sale Price	Sp	The price at which the property was sold.
	Sale Date	Sd	The date on which the sale of the property occurred.

	Interest Rate	Intr	The prevailing rate of interest at the time of the sale.
	Mortgage Rate	Mr	The interest rate charged on a mortgage for the property.
	Inflation Rate	Infr	The rate of inflation in the economy at the time of the sale.
Spatial Variables	Number Of Arrests	Na	The total arrests in the area, indicating the level of crime.
	Buildings Altered	BlndgAlt	The number of buildings that underwent modifications.
	Buildings Demolished	BlndgDemo	The number of buildings that were torn down.
	Buildings Constructed	BlndgConst	The number of new buildings constructed.
	Administration Of Government	GovFac	Facilities related to government administration.
	Core Infrastructure and Transportation	TransFac	Essential transportation and infrastructure facilities.
	Education, Child Welfare, and Youth	EduFac	Facilities related to education and youth services.
	Health And Human Services	HospFac	Facilities dedicated to health and human services.
	Libraries And Cultural Programs	LibFac	Libraries and facilities for cultural programs.
	Parks, Gardens, And Historical Sites	ParkFac	Areas designated as parks, gardens, or historical sites.
	Public Safety, Emergency Services, And Administration of Justice	EmergFac	Facilities for public safety, emergency services, and justice administration.
Abstract Variables	Greenery And Vegetation	GrnSTAD	The presence and extent of green spaces and trees in streets.
	Urban Commercialization	ComSTAD	The presence of stores, ads, banners, markings, traffic rules
	Building Density	BldSTAD	The concentration of buildings in a neighborhood.
	Traffic And Vehicles	VhcSTAD	The number of vehicles such as cars, bikes, trains, and buses

Table 6: Variables selected in this paper

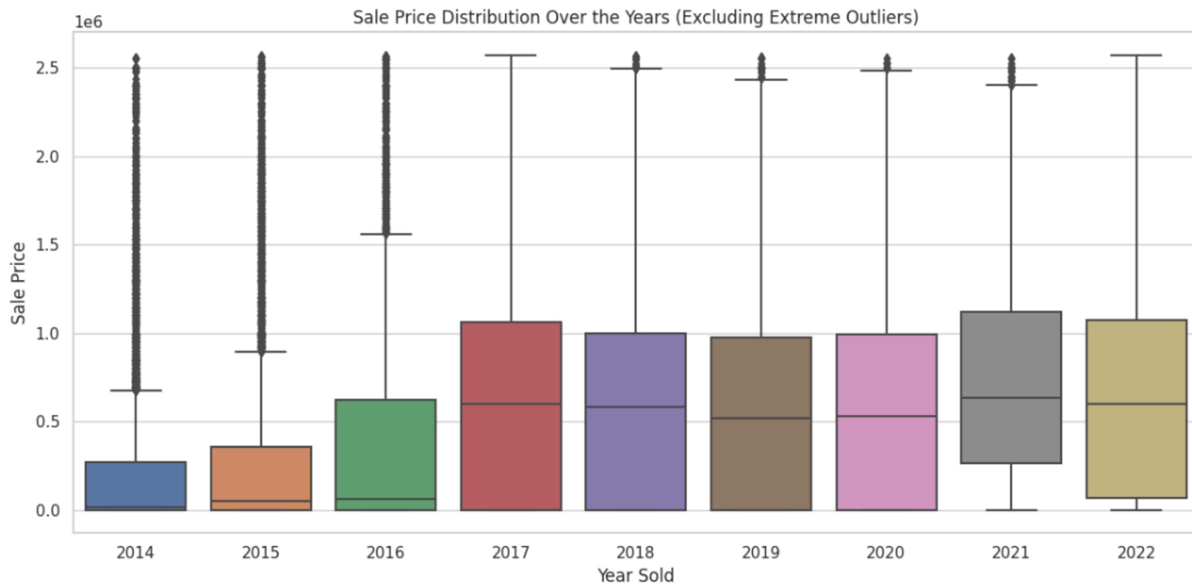


Figure 18: Midtown Sale Price Distribution

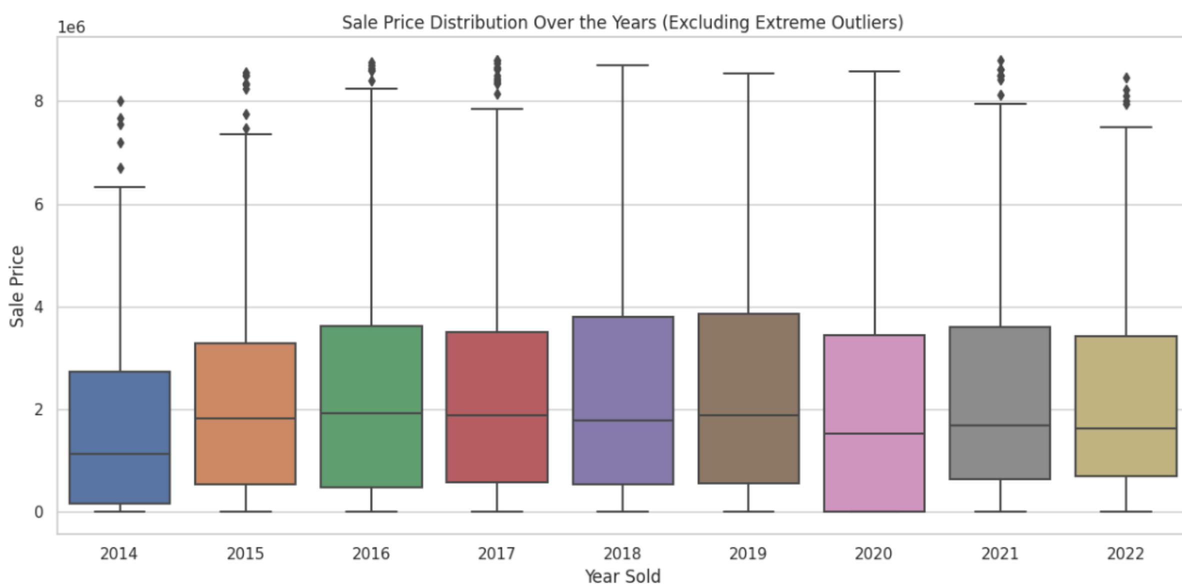


Figure 19: Tribeca Sale Price Distribution

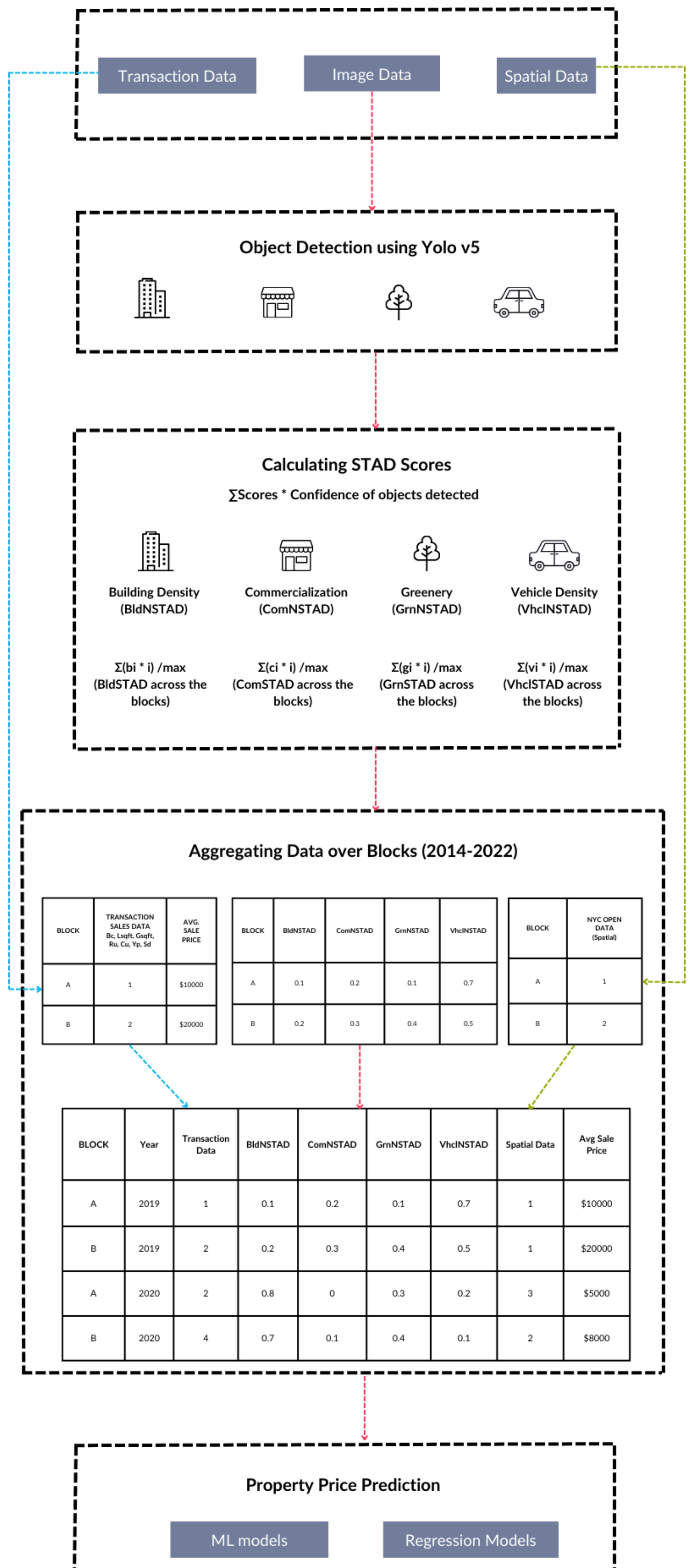


Figure 20: Proposed Framework for Property Price Prediction

3.3 Generating Spatio-Temporal Abstract Detection (STAD) using YOLO v5

In this study, we employed the YOLO v5 architecture, available on the Ultralytics Hub, to conduct image data classification for GrnSTAD, ComSTAD, VhclSTAD and BldSTAD for each year from 2014-2023. The choice of YOLO algorithm was influenced by multiple factors such as: performance, accuracy, availability of pre-trained models, and faster speed.

In assessing the efficacy of object detection algorithms for vehicle recognition, the YOLO v5 model demonstrated superior performance, achieving a 93% accuracy rate, outclassing other methods in speed and precision, making it an optimized choice for real-time applications (Kim et al., 2020).

Furthermore, when comparing YOLO to Mask R-CNN, YOLO displayed a higher capability in detecting small-scale objects, such as human figures, within images that also contain larger, more distinct objects, thereby illustrating its superior detection accuracy in complex scenarios (Kim et al., 2020). Additionally, the development of YOLOv5 in the PyTorch framework has significantly enhanced its production readiness due to PyTorch's flexibility and ease of configuration. Notably, YOLOv5's inference speed marks a substantial improvement over its predecessors, delivering real-time performance at 140 frames per second, a substantial increase from the 50 frames per second of YOLOv4, when both are implemented using the same PyTorch library, highlighting its suitability for high-speed processing requirements (Sumit et al., 2020).

For this paper we leveraged the Ultralytics Hub, which provides a user-friendly and efficient platform for training deep learning models. We successfully trained our model on our comprehensive dataset of street view images. The YOLO V5 architecture, with its state-of-the-art design and optimization, demonstrated remarkable accuracy in detecting and classifying tree species, vehicle types, signages and buildings.

Figure 21: Tree detection using YOLO v5

The graph in Figure 22 indicates the model's performance metrics over time during validation for trees detection. The mAP50 (B) remained consistently high, demonstrating strong model accuracy across the majority of thresholds, while the precision (B) and recall (B) exhibited more variability, suggesting slight fluctuations in model consistency.

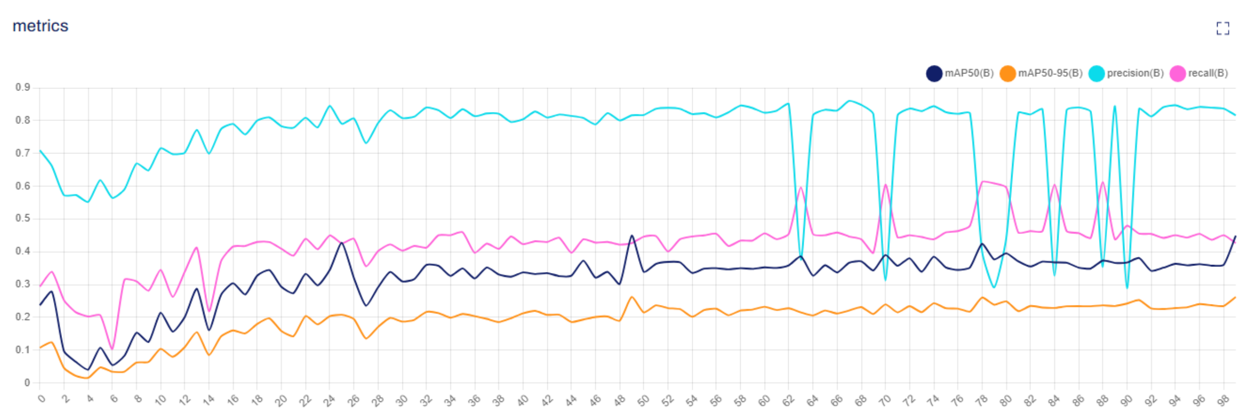


Figure 22: Performance metrics during validation of Tree detection model

In Figure 23, the training loss metrics showed a steady decrease, indicating good model learning during tree detection. There are three metrics displayed in the figure. The box loss (box_loss), which pertains to the accuracy of the bounding box predictions, the class loss (cls_loss), related to the classification accuracy, and the direction or distance loss (dif_loss), potentially related to the accuracy of predicting the object's location or size. The box_loss and cls_loss converged closely, implying that both classification and bounding box predictions improved at a same rate.

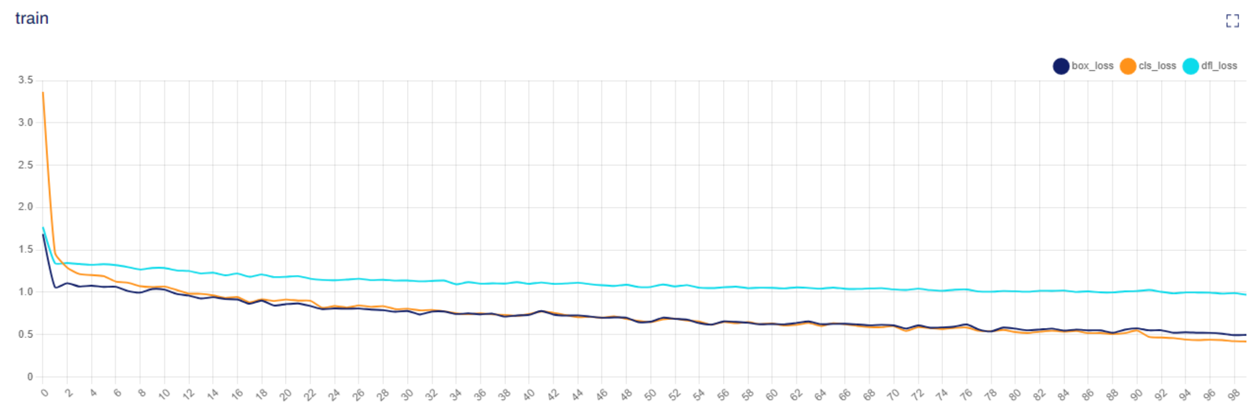


Figure 23: Training loss of tree detection model

During validation, the loss metrics initially peaked and then stabilized at a low level indicating a successful model training processes as shown in Figure 24.

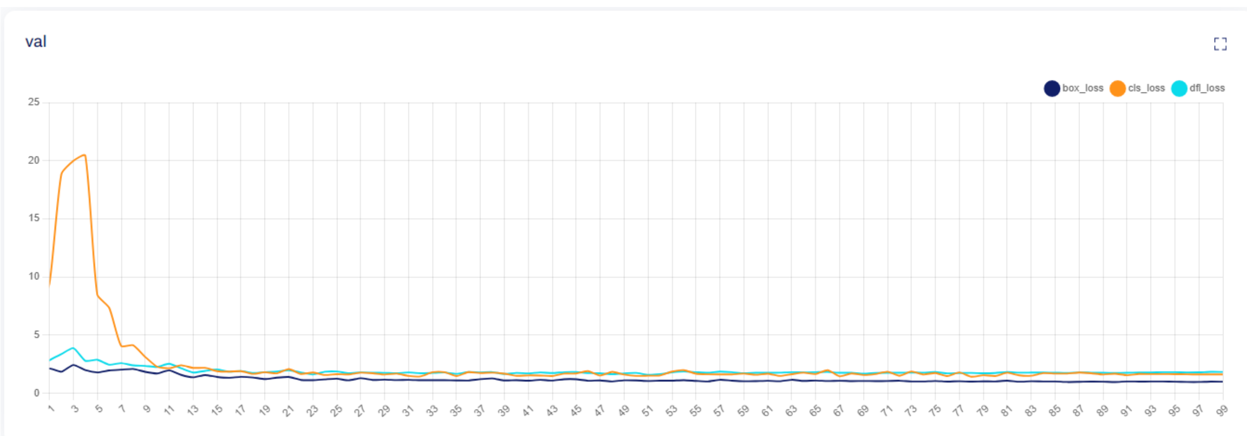


Figure 24: Validation loss of tree detection model

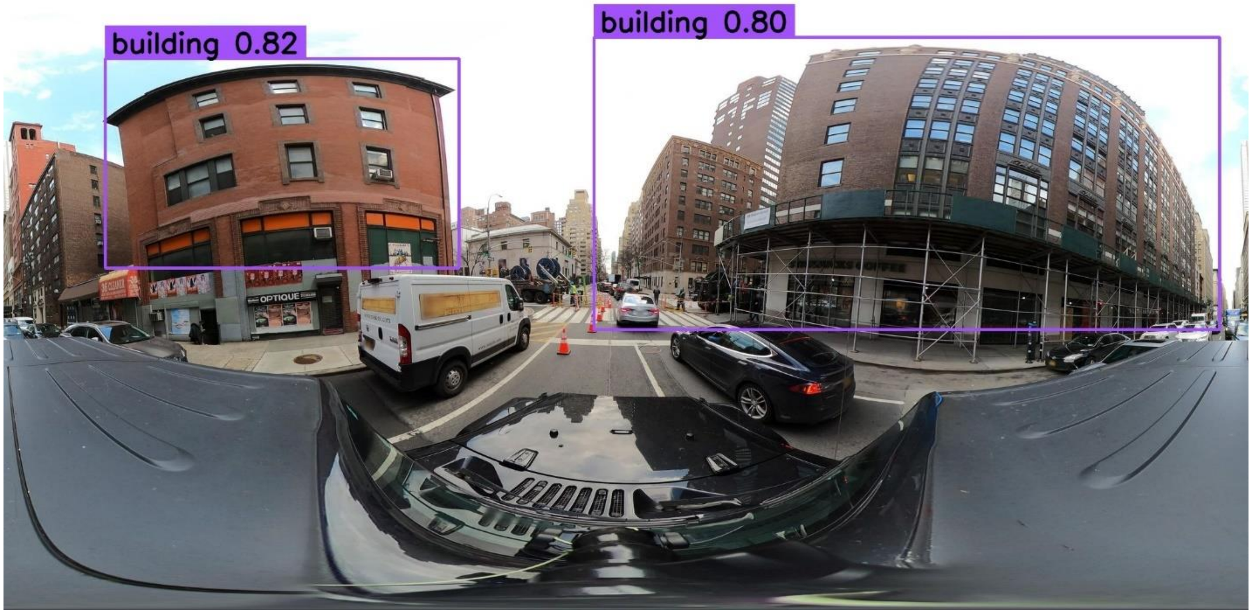


Figure 25: Building detection using YOLO v5

Similarly, for building detections, YOLO v5 performed accurately. The graph in Figure 26 tracks various performance metrics of the model on the validation dataset. The Mean Average Precision at IOU > 0.5 (mAP50) was relatively stable and high, suggesting the model reliably detects objects when the overlap is greater than 50%.

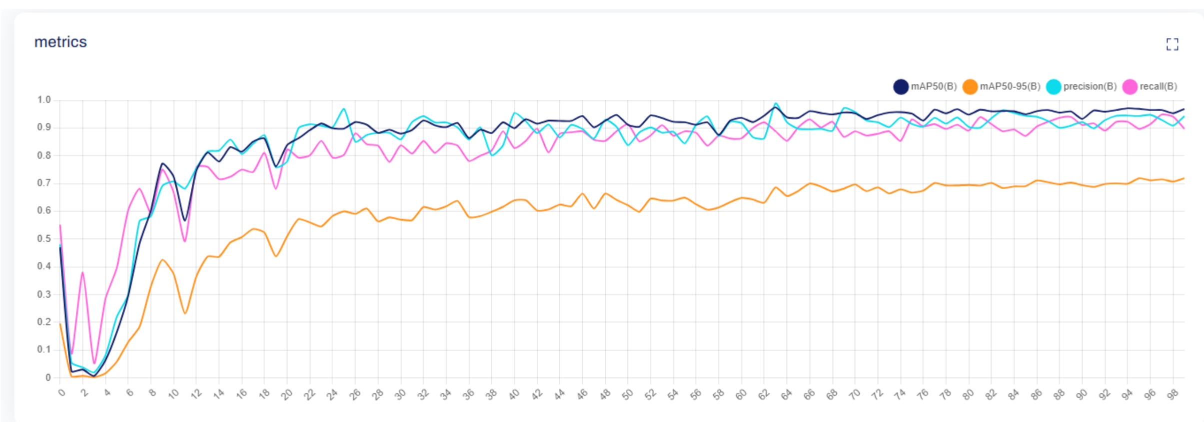


Figure 26: Performance metrics during validation of building detection model

The Figure 27 shows three different loss metrics during the training phase of building detections. All three metrics showed a downward trend, indicating learning and improvement over time.

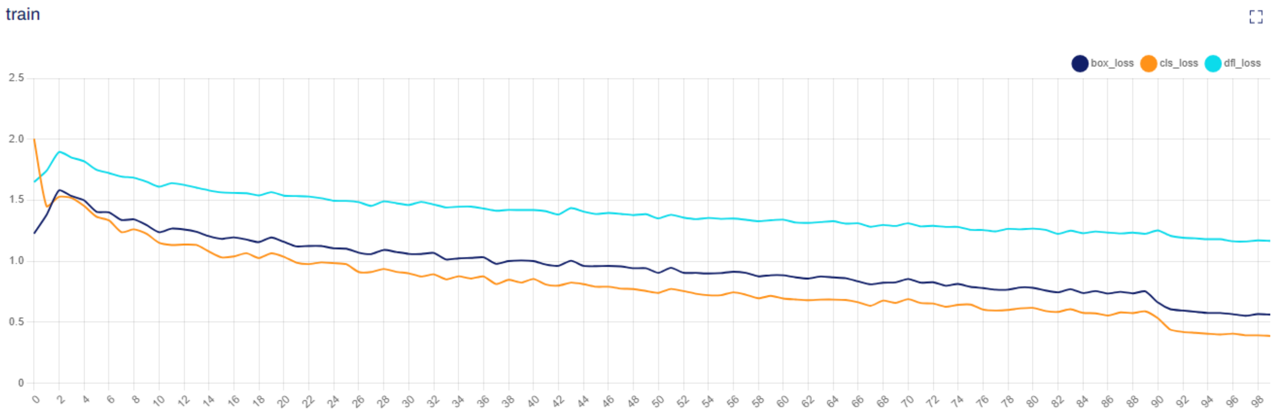


Figure 27: Training loss of building detection model

In

Figure 28, the stabilization at low levels suggests that the model didn't overfit and generalized well to the validation dataset.

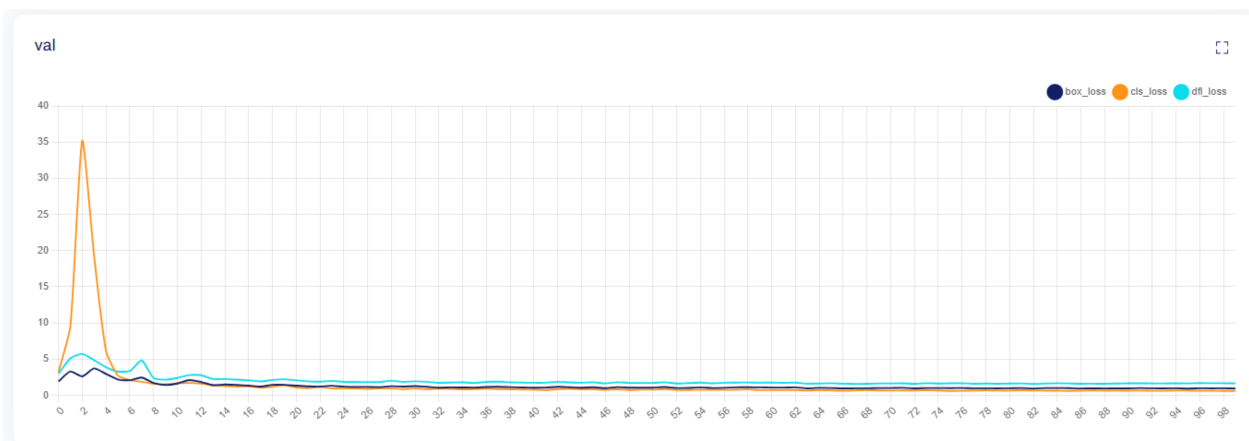


Figure 28: Validation loss of building detection model

For Vehicle detection, we utilized a pre-trained YOLO v5 model using COCO Dataset with the highest accuracy to detect vehicles such as cars, trains, buses, bikes, and trucks.

Figure 29: Vehicle detection using YOLO v5

Lastly for commercialization, we extracted raw features such as objects, stores, advertisements, regulatory markings from Mapillary's internal object detection tool for each image.

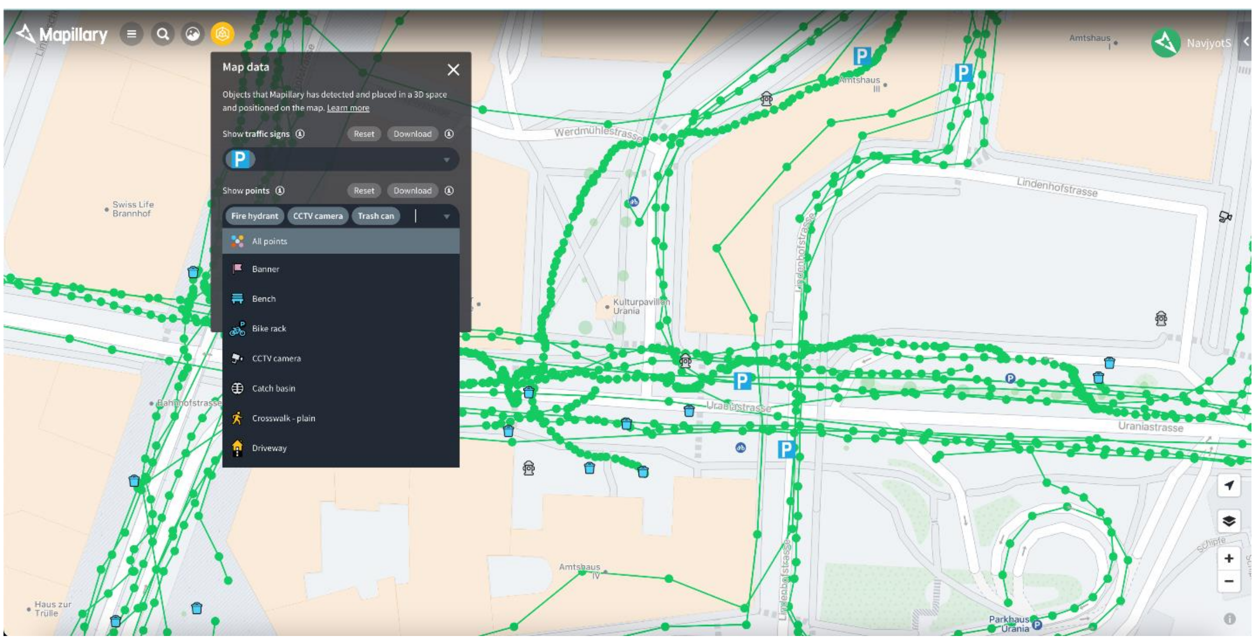


Figure 30: Stores, markings, objects detection from Mapillary API

3.4 Normalized Spatio-Temporal Abstract Detection (NSTAD)

Upon completing the detection of abstract variables within image datasets spanning from 2014 to 2022, we devised an innovative scoring methodology. This method quantifies the abstract variables—Greenery STAD (GrnSTAD), Commercialization STAD (ComSTAD), Vehicle STAD (VhclSTAD), and Building STAD (BldSTAD)—and assesses their respective densities. The

resulting score is intended to serve as an indicator of the neighborhood's aesthetic and abstract urban characteristics, providing a quantifiable measure to represent these features within the scope of our study.
Table 7 shows breakdown of objects detected from Mapillary to form a ComSTAD score. Each object was given a score between 1 and 5, with 1 having the least impact on housing prices whereas 5 score having a positive impact on housing prices.

The Table 8 displays a breakdown of Vehicle density scores that comprised of individual vehicles such as car, bus, bike, truck, and bicycle etc. Like commercialization for vehicles the scores we decided ranged between 1 and 5. With 1 having the least impact on housing prices and 5 having the most positive impact on housing prices.

Object Label	Score	Explanation
marking--discrete--stop-line	5	Properties near intersections with stop lines are often sought after for safety and traffic control, impacting housing prices positively.
object--traffic-cone	2	The presence of traffic cones may indicate temporary road maintenance, with a moderate impact on housing prices.
object--street-light	3	Street lights enhance safety and visibility in neighborhoods, positively influencing housing prices.
object--sign--store	2	Store signs may indicate commercial activity, with potential mixed effects on housing prices due to convenience and increased traffic.
object--sign--advertisement	5	Advertisements suggest commercial activity, which can have varying impacts on housing prices based on buyer preferences.
object--banner	5	Banners may signify temporary events or promotions, likely resulting in a temporary and minimal impact on housing prices.
object--traffic-light--general-upright	1	Well-maintained traffic lights improve safety and traffic flow, positively affecting housing prices.
object--manhole	1	Manholes are part of infrastructure maintenance and have a moderate impact on housing prices compared to other factors.
marking--discrete--crosswalk-zebra	2	Zebra crosswalks enhance pedestrian safety and are typically found in well-regulated areas, positively impacting housing prices.
object--fire-hydrant	2	Fire hydrants are crucial for emergency response, making properties near them safer and more desirable, positively affecting prices.
object--trash-can	2	Trash cans are a basic amenity but are likely to have a minimal impact on housing prices.
object--traffic-light--pedestrians	2	Traffic lights for pedestrians enhance safety and are preferred by families, positively impacting housing prices.
information--parking--g1	3	Information about parking availability can influence housing prices, especially in areas with limited parking options, with a moderate impact.
information--general-directions--g1	3	General directions provide useful information about the area, likely with a moderate impact on housing prices.

Object Label	Score	Explanation
marking--discrete--symbol--bicycle	4	Bicycle symbols indicate bike-friendly areas, potentially attracting cycling enthusiasts and positively impacting housing prices.
object--junction-box	2	Junction boxes are part of infrastructure but are likely to have a minimal impact on housing prices.
construction--barrier--temporary	3	Temporary construction barriers can affect the aesthetics of the area temporarily, with a moderate and short-lived impact on housing prices.
regulatory--priority-road--g1	1	Properties near priority roads are highly sought after due to easy access, significantly impacting housing prices positively.
regulatory--stop--g1	1	Stop signs indicate controlled intersections, enhancing safety, and positively influencing housing prices.
regulatory--yield--g1	1	Yield signs improve traffic flow and safety, positively affecting housing prices.
warning--stop-ahead--g1	1	Warning signs indicating upcoming stops can contribute to traffic safety and positively impact housing prices.
marking--discrete--other-marking	1	Other road markings may have various meanings and impacts, with a moderate influence on housing prices.
construction--flat--driveway	2	The presence of flat driveways is a common feature, likely providing minimal impact on housing prices.
regulatory--lane-control--g1	1	Lane control signs help manage traffic lanes, positively impacting traffic flow and safety, thus affecting housing prices positively.
regulatory--one-way-right--g3	1	One-way right signs affect traffic direction, potentially resulting in smoother traffic flow, positively influencing housing prices.
information--highway-interchange--g1	1	Information about highway interchanges can be valuable for commuters, with a moderate impact on housing prices.
regulatory--stop--g10	1	Stop signs at certain locations are important for safety and positively affect housing prices.
regulatory--no-u-turn--g1	1	No U-turn signs influence traffic behavior, potentially leading to smoother traffic flow and positively impacting housing prices.
regulatory--no-left-turn--g1	1	No left-turn signs affect traffic movement, potentially resulting in smoother traffic flow and positively affecting housing prices.
marking--discrete--text	1	Text markings may provide specific information on roads, with a moderate impact on housing prices.
object--catch-basin	1	Catch basins are part of infrastructure and likely have a minimal impact on housing prices compared to other factors.
object--cctv-camera	3	CCTV cameras can enhance security and safety, with a moderate influence on housing prices.
regulatory--one-way-left--g3	1	One-way left signs affect traffic direction, potentially resulting in smoother traffic flow and positively influencing housing prices.

Table 7: Object scoring for ComSTAD

Object Label	Score	Explanation
car	5	Cars are common on the road and contribute to regular traffic flow. Their impact on traffic is moderate. Housing prices may be influenced by car traffic in terms of convenience and accessibility, but it's not as significant as larger vehicles.
bus	4	Buses, especially public transit buses, have a significant impact on traffic due to their size and frequent stops. They can affect traffic flow and congestion. Housing near bus routes can be convenient for commuters but may experience more traffic-related challenges.
truck	1	Trucks, particularly large freight trucks, have a substantial impact on traffic due to their size and slower speed. They can contribute to congestion and may impact the road's wear and tear. Housing near heavy truck routes may experience increased traffic and noise.
motorbike	2	Motorbikes are smaller and often maneuverable, causing less traffic disruption compared to larger vehicles. While they can contribute to traffic, their impact is relatively low. Housing near motorbike routes may experience some traffic, but it's typically less disruptive.
bicycle	5	Bicycles have a minimal impact on traffic congestion as they take up very little space on the road and move at lower speeds. Housing near bicycle routes is unlikely to be significantly affected by traffic congestion related to bicycles.
train	2	Trains are a distinct mode of transportation with their own dedicated tracks. While they don't directly impact road traffic, they can affect housing prices by providing convenient access to public transportation. Housing near train stations may be more desirable due to transportation accessibility.

Table 8: Object scoring for VhclSTAD

Lastly, for BldnSTAD and GrnSTAD both were individually scored as 4 and 5 respectively on the same scale to quantify their impact on housing prices (
Table 9).

Object Label	Score	Explanation
Building	4	High-density neighborhoods are often sought after for better infrastructure and high market demand. They may increase crowdedness in an area making it less desirable for some.
Tree	5	The presence of greenery and vegetation will increase the perceived value of a neighborhood making it mor eco-friendly hence it will affect prices positively.

Table 9: Object scoring for BldSTAD and GrnSTAD

Next for each image in the dataset we calculated the total score of GrnSTAD, ComSTAD, VhclSTAD and BldSTAD and normalized it.

For an image dataset consisting of numerous street images for a specific year, there are a set of label scores assigned to each image for every object detection as shown in Table 7, Table 8, and Table 9.

$$ImageDataset_{year} = \{Im_1, Im_2, Im_3, \dots, Im_n\}$$

$$LabelScores(Im_n) = \{(Label_1, Score_1), (Label_2, Score_2), \dots (Label_i, Score_i)\}$$

where $Label_i$ is the object label and $Score_i$ represents its corresponding score within a range of 1 to 5 for each STAD.

STEP 1: The weighted scores for each object label (D_j) detected by YOLO v5 in the dataset is calculated by:

$$D_j = Confidence(Label_i) * Score_i$$

Where $Confidence(Label_i)$ is the confidence level of YOLO's detection for each $Label_i$ and $Score_i$ is the score for the object label specified in $LabelScores(Im_n)$ for each STAD.

STEP 2: Next we calculate the total STAD score for each image Im_n in the dataset by summing the weighted scores of object detections for each STAD.

$$STAD_K = \sum_{D_j=1}^{Im_n} D_j \ for \ all \ D_j \ in \ Im_n$$

$$STAD_K(Im_n) = \{(STAD_1, Score_1), (STAD_2, Score_2), (STAD_3, Score_3), (STAD_4, Score_4)\}$$

Where $STAD_1$ is GrnSTAD, $STAD_2$ is ComSTAD, $STAD_3$ is VhclSTAD and $STAD_4$ is BldSTAD and $Score_K$ represents its corresponding score for a single image Im_n.

STEP 3: Finally, we calculate Normalized STAD (NSTAD) Scores for each image. We normalized the total scores of all images by dividing each total score by the maximum total score in the dataset of the specific year.

$$NSTAD_K(Im_n) = \frac{STAD_K(Im_n)}{Max(STAD_K)}$$

Where $Max(STAD_K)$ is the maximum total score among all images in the dataset.

Table 10 displays pseudo code for the normalized STAD scores for all the images in Midtown.

Psuedo code of Normalized STAD Score Calculation

Input: $ImageDataset_{year}$ consisting of $\{Im_1, Im_2, Im_3, \dots, Im_n\}$, $LabelScores(Im_n)$ for each image, consisting of $\{(Label_1, Score_1), (Label_2, Score_2), \dots (Label_i, Score_i)\}$

Output: Normalized STAD (NSTAD) scores for each image

For each image Im_n in $ImageDataset_{year}$ **do**

  Initialize $STAD_1$, $STAD_2$, $STAD_3$, $STAD_4$ to 0

  For each label $Label_i$ with $Score_i$ in $LabelScores(Im_n)$ **do**

    Confidence Level of YOLO Detection = Confidence($Label_i$)

    $D_j = Confidence(Label_i) * Score_i$

    Update STAD score for the corresponding STAD based on $Label_i$

  End For

  $STAD_K(Im_n) = \{ STAD_1, STAD_2, STAD_3, STAD_4 \}$

  For each $STAD_K$ in $\{ STAD_1, STAD_2, STAD_3, STAD_4 \}$ **do**

    $STAD_K = \sum_{D_j=1}^{Im_n} D_j \; for \; all \; D_j \; in \; Im_n$

  End For

  $STAD_K(Im_n) = \{(STAD_1, Score_1), (STAD_2, Score_2), (STAD_3, Score_3), (STAD_4, Score_4)\}$

End For

For each Im_n in $ImageDataset_{year}$ **do**

  For each $STAD_K$ in $STAD_K(Im_n)$ **do**

    $NSTAD_K(Im_n) = \frac{STAD_K(Im_n)}{Max(STAD_K)}$

  End For

End For

Return $\{ NSTAD_K(Im_1), NSTAD_K(Im_2), \dots, NSTAD_K(Im_n)\}$

Table 10: Psuedo code of Normalized STAD Score Calculation

3.5 Aggregation of NSTAD Scores & Transaction Data over Neighborhood Blocks

After calculating the NSTAD Scores for GrnSTAD, ComSTAD, VhclSTAD and BldSTAD of each image we aggregated the scores over blocks in the neighborhood.

For each neighborhood selected in this paper, N_A = Midtown, N_B = Tribeca, we have a set of blocks within the neighborhood such that block IDs for a neighborhood are represented by

$$B_{Midtown} = \{A_1, A_2, \dots, A_M\} \,\&\, B_{Tribeca} = \{B_1, B_2, \dots, B_T\}$$

Each block is further geographically represented by a polygon of coordinates

$$Polygon(B_{Midtown}) = \{[(Lat, Lon), (Lat, Lon), \dots, (Lat, Lon)]_{A1}, \dots, [(Lat, Lon), (Lat, Lon), \dots, (Lat, Lon)]_{AM}\}$$

STEP 1: Assign block to each image

For each image Im_n in the image dataset corresponding to a specific year $ImageDataset_{year}$

there are geographical coordinates such that:

$$Point_{Im_n} = \{ (Lat, Lon)_{Im_1}, (Lat, Lon)_{Im_2}, \dots, (Lat, Lon)_{Im_n} \}$$

To assign these images to the blocks, we check whether the geographical coordinates (Lat, Lon) of each image Im_n fall within the polygon boundaries of any of the blocks in the neighborhood.

$$if\ Polygon(Block_{Midtown})\ coordinates\ contains\ Point_{Im_n}\ coordinates:$$
$$Im_n[BlockID] = A_M$$

STEP 2: Aggregate mean values for each NSTAD: GrnNSTAD, ComNSTAD, VhclNSTAD and BldNSTAD

For each image Im_n belonging to Block A_M in Neighborhood N_A calculate mean value of each $NSTAD_K$ such that:

$$NSTAD_K(A_M) = \frac{\sum_{NSTAD_K=1}^{Im_n} NSTAD_K\ for\ all\ NSTAD\ in\ Im_n}{\sum N(Im_j)}$$

Where $N(Im_j)$ is the total number of images spatially located in each block A_M of neighborhood N_A.

STEP 3: Aggregating remaining variables

Similar to NSTADs, the remaining structural and spatial variables will get averaged based on the blocks assigned to the images in the dataset. Lastly, all variables are concatenated to form the final dataset. To compile the full dataset, we concatenated by stacking individual datasets of each year over one another for both Midtown and Tribeca.

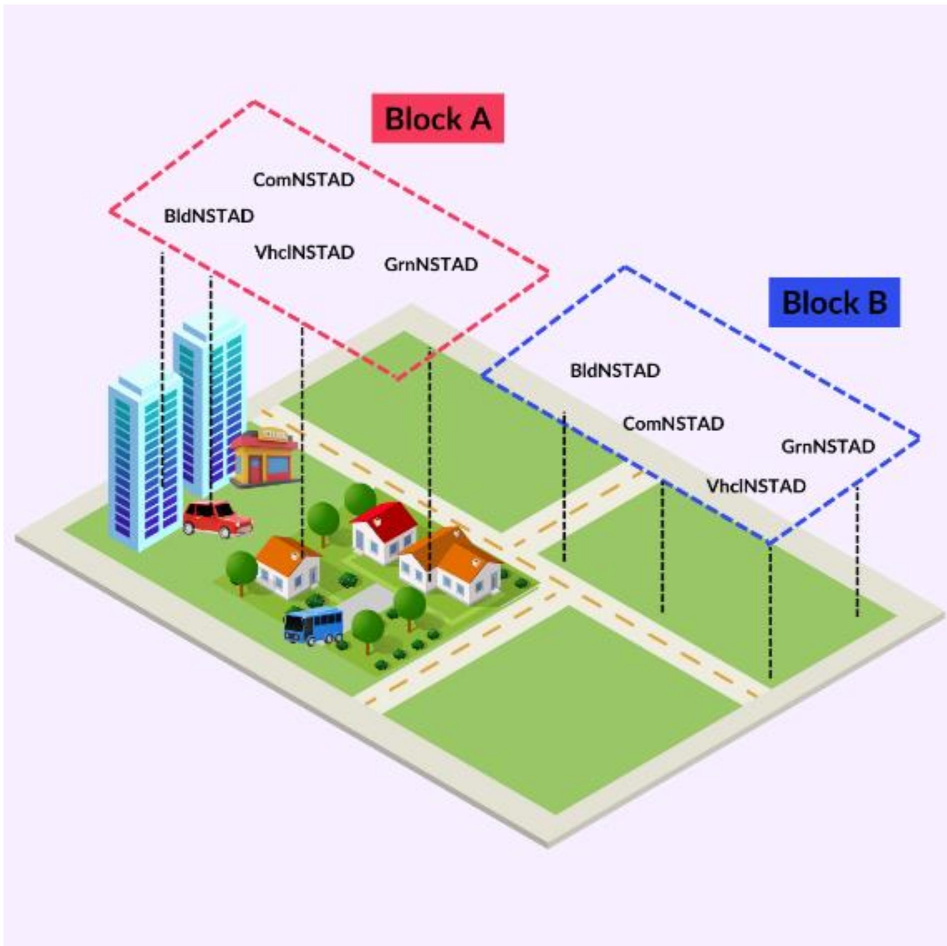


Figure 31: Aggregation of NSTAD scores over each block for each year

Psuedo code of Aggregated NSTAD Scores Over Blocks

Input:	$ImageDataset_{year}$ consisting of $\{Im_1, Im_2, Im_3, \dots, Im_n\}$ with associated NSTAD Scores, Blocks in Midtown with IDs: $B_{Midtown} = \{A_1, A_2, \dots, A_M\}$, Polygons representing Midtown blocks: $Polygon(B_{Midtown})$, Point coordinates representing each image in $ImageDataset_{year}$: $Point_{Im_n}$
Output:	Aggregated NSTAD scores for each block in Midtown

For each image Im_n in $ImageDataset_{year}$ **do**
    IF $Polygon(Block_{Midtown})$ **contains** $Point_{Im_n}$ coordinates **do**
        $\mathrm{BlockImages_{Midtown}[BlockID].add(A_M)}$
        Break
    End IF
End For
Aggregated Sores$_{Midtown}$ = {}
For each Block A_M of Midtown **do**
    Total Score = 0
    For each Im_n in $ImageDataset_{year}$ of Midtown **do**
        Total Score += $NSTAD_K(Im_n)$
    End For
    Aggregated Sores$_{Midtown}$[$\mathrm{A_M}$] = Total Score // n where n is total number of images
End For
Return { $NSTAD_K(A_1)$, $NSTAD_K(A_2)$, … , $NSTAD_K(A_m)$}

Table 11: Psuedo code of Aggregated NSTAD Scores Over Blocks

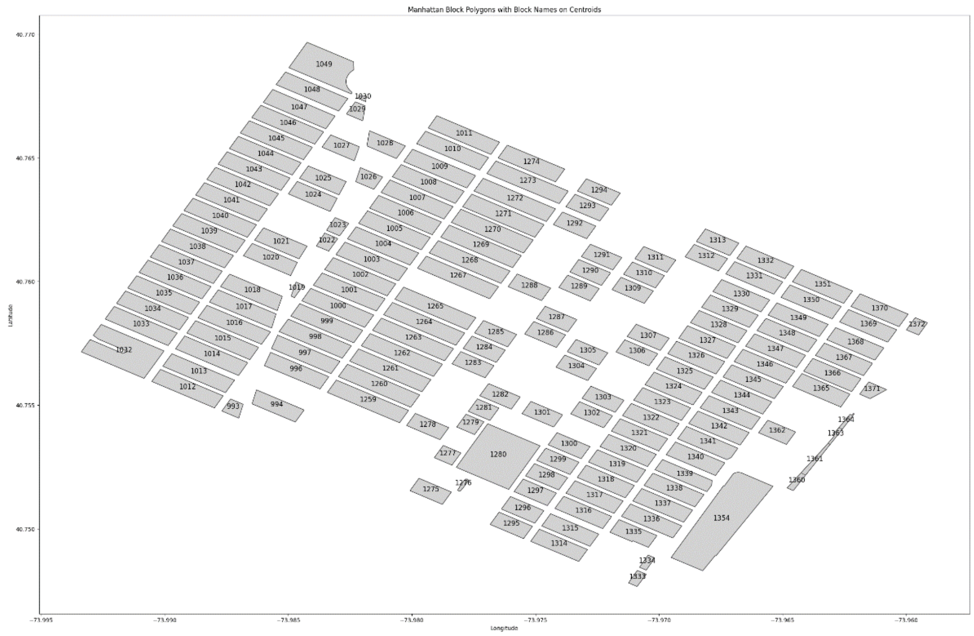


Figure 32: Blocks selected for Midtown

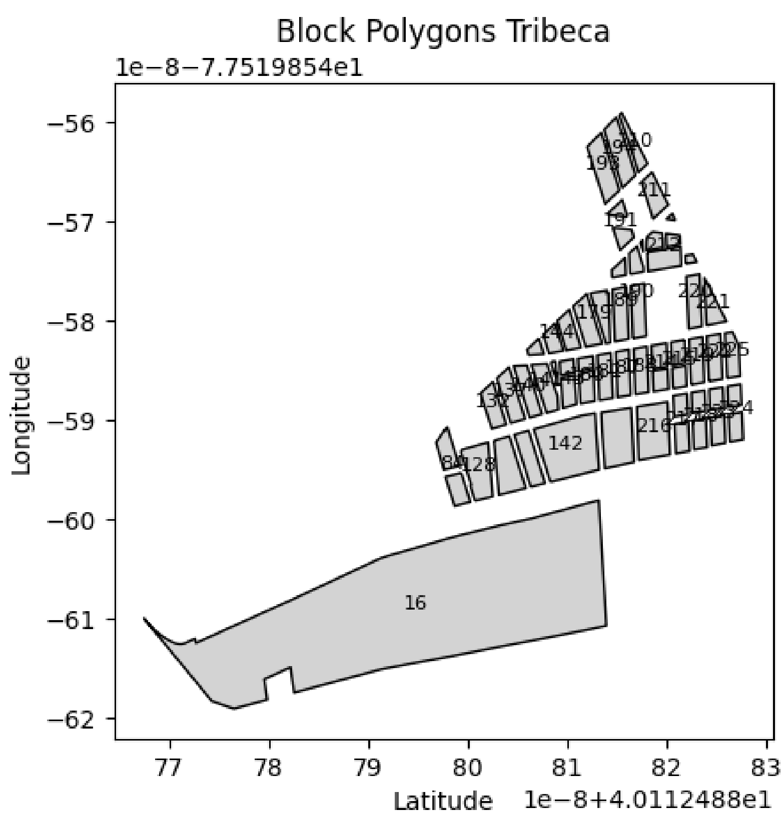


Figure 33: Blocks selected for Tribeca

3.6 Distance Based Clustering of Neighborhood Blocks

In this paper, we have performed distance-based clustering of blocks in a neighborhood as an interpolation strategy. Due to lack of availability of image data samples, 10% of the blocks had no NSTAD scores. In our study we compared the performance of both KMeans Clustering (n = 4) and Density-Based Spatial Clustering of Applications with Noise - DBSCAN clustering (epsilon = 0.003). Where KMeans segmented blocks adequately for both Midtown (Figure 34) and Tribeca, DBSCAN on the other hand failed to segment Tribeca's blocks as shown in Figure 35.

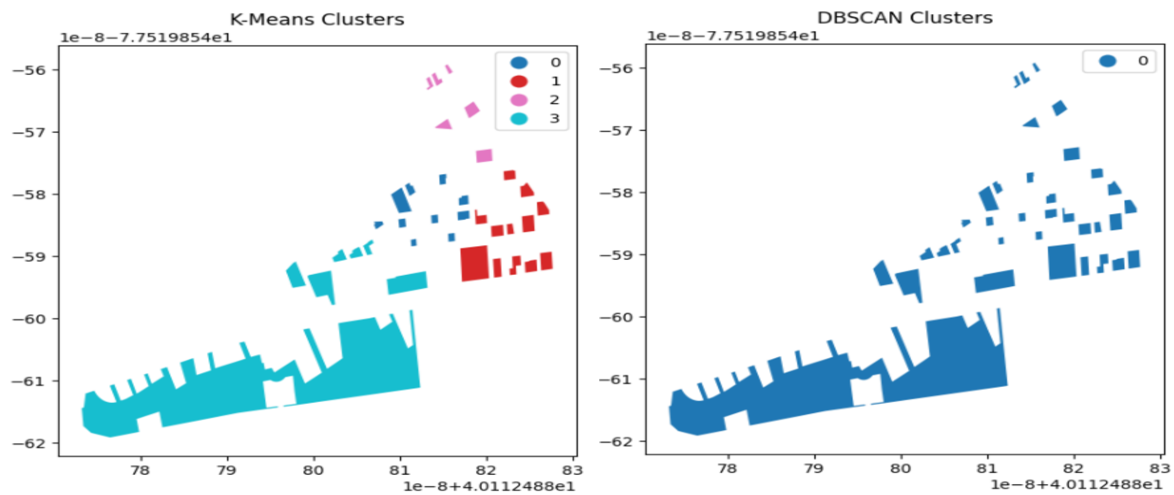


Figure 35: KMeans vs DBSCAN clustering in Tribeca blocks

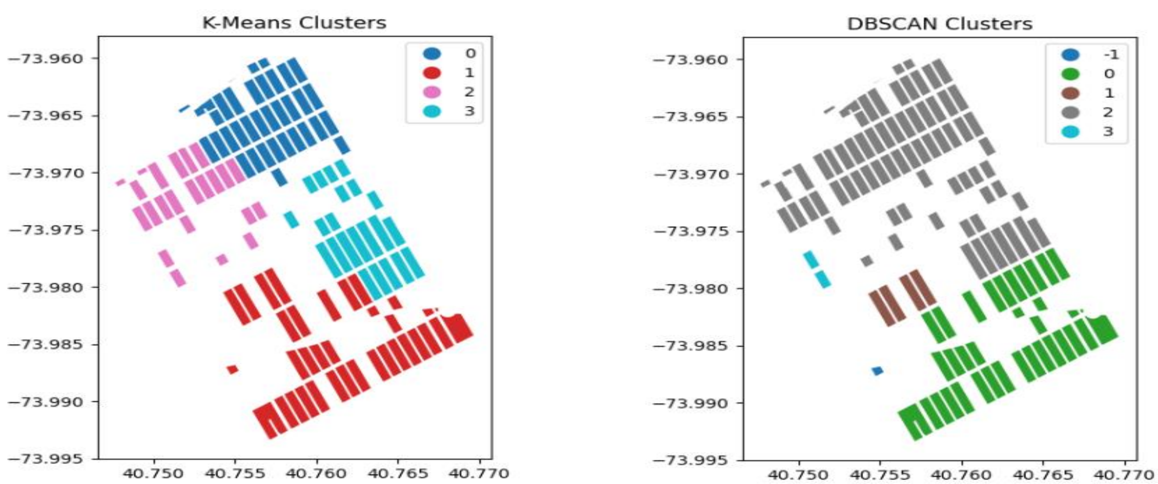


Figure 34: KMeans vs DBSCAN clustering in Midtown

Chapter 4

Model Performance

In this paper we selected a mixture of regression, ML, and Deep learning models. The selected regression models include Multiple Linear Regression, Ridge Regression, Bayesian Ridge Regression, Gradient Boosting Regressor, AdaBoost Regressor, K-Nearest Neighbors Regressor, XGBoost Regressor, and Random Forest Regressor for time series data. The evaluation metrics chosen to assess the performance of these models are:

- Mean Squared Error (MSE) for both training and testing datasets.
- Root Mean Squared Error (RMSE) for both training and testing datasets.
- Mean Absolute Error (MAE) for both training and testing datasets.
- R-squared (R^2) Score for both training and testing datasets.

These metrics provide a comprehensive view of the models' accuracy, precision, and ability to fit the data. MSE and RMSE measure the average squared errors between predicted and actual values, MAE measures the average absolute errors, and R^2 Score assesses the goodness of fit.

The choice of these metrics allowed us for a thorough evaluation of model performance, enabling comparisons between different regression models to determine which one performs best for the specific dataset and problem at hand.

4.1 Parameter estimation summary of hedonic price model

Firstly, the Hedonic Price Model (HPM) based on ordinary least squares (OLS) regression was built in linear form to gauge the importance of each variable.

As shown in

Table 12, the spatial and temporal abstract variables GrnSTAD, ComSTAD, and BldSTAD had p-values of 0.04, 0.001, 0.027 respectively in Midtown. However, VhclSTAD showed an insignificant p-value of 0.116. Similarly, Table 13 displays p-values of STADs in Tribeca for GrnSTAD, ComSTAD, VhclSTAD and BldSTAD to be significant. It is important to note that in both Midtown and Tribeca the coefficient of BldSTAD is negative around -0.028 and -0.003 respectively.

Variable	Coefficient	Standard Error	t-value	P-value
Const	0.011	0.004	-5.138	0.876
Ru	-0.0071	0.034	0.755	0.45
Cu	0.0028	0.023	3.019	0.003
Lsqft	-0.9668	0.073	4.035	0.002
Gsqft	1.0523	0.041	-10.4	0.008
Bc	-0.0511	0.045	0.082	0.935
Na	-0.0008	0.028	2.296	0.022
BlndgAlt	-0.0001	0.008	6.904	0.001
BlndgDemo	-0.0067	0.02	7.609	0.005
BlndgConst	-0.0013	0.01	6.447	0.007
GovFac	-0.0128	0.011	-0.771	0.441
TransFac	-0.0161	0.006	8.631	0
EduFac	0.0003	0.009	-2.772	0.006
HospFac	0.0014	0.017	1.173	0.241
LibFac	-0.0017	0.013	2.019	0.044
ParkFac	0.0117	0.007	-3.325	0.001
EmergFac	0.0179	0.026	-0.397	0.691
Intr	-0.0084	0.006	5.068	0
Mr	0.0045	0.006	-9.149	0
Infr	-0.0031	0.007	-1.633	0.103
TreeFreq	-0.2167	0.104	1.519	0.129
GrnNSTAD	0.0315	0.094	1.97	0.049
MarkFreq	-0.0183	0.03	-1.854	0.064
RegFreq	0.0068	0.032	-0.448	0.654
InfoFreq	0.0146	0.021	-2.738	0.006
ObjFreq	-0.006	0.042	0.705	0.481
StoreFreq	-0.0374	0.057	-0.28	0.78
ComNSTAD	0.0599	0.044	3.48	0.001
VhclNSTAD	0.0277	0.127	1.574	0.116
BldnFreq	-0.0072	0.038	-2.228	0.026
BldNSTAD	-0.0285	0.092	-2.22	0.027

Table 12: Midtown HPM OLS SIGNIFICANCE

Variable	Coefficient	Standard Error	t-value	P-value
Const	0.0079	0.003	-0.686	0.493
Ru	0.0211	0.011	6.945	0.23
Cu	-0.01	0.01	-1.842	0.066
Lsqft	1.1753	0.025	2.997	0.003
Gsqft	-0.4412	0.025	-8.786	0.017
Bc	-0.0005	0.008	-3.862	0.3
BlndgAlt	6.51E-12	1.36E-11	3.12E+10	0.387
BlndgDemo	-3.5302	19.993	2.478	0.013
BlndgConst	29.6731	19.597	-5.178	0
GovFac	-0.0011	0.002	-0.164	0.87
TransFac	-0.0016	0.003	-7.216	0.356
EduFac	-0.0022	0.004	0.41	0.682
HospFac	-6.51E-05	0.002	6.071	0.543
LibFac	-0.0017	0.003	3.288	0.001
ParkFac	0.0054	0.004	-4.174	0.342
EmergFac	0.001	0.003	-0.744	0.457
Intr	-0.0064	0.002	-2.257	0.024
Mr	-0.0118	0.003	3.719	0.0018
Infr	0.008	0.003	-2.727	0.007
GrnNSTAD	0.0031	0.004	4.933	0.003
ComNSTAD	0.0003	0.003	-3.993	0.04
BldNSTAD	-0.0035	0.005	2.228	0.026
VhcNSTAD	0.0061	0.006	-3.569	0.017

Table 13: Tribeca Hedonic Pricing Model OLS Significance

4.2 Model Performance with NSTAD Scores

After establishing variable significance full datasets of Midtown and Tribeca were evaluated on seven models.

Models incorporating NSTAD scores, such as Ridge Regression and Bayesian Ridge Regression, exhibit enhanced predictability and better R^2 scores, underscoring the efficacy of NSTAD variables in capturing market dynamics.

The positive impact of NSTAD scores is evident in the consistent performance improvement across various models, including MLR and Random Forest.

In Table 14, Bayesian Ridge Regression for Midtown shows a slight improvement in R^2 with NSTAD scores (R^2: 0.3973 with NSTAD vs. 0.3866 without NSTAD). The model also shows a 1% reduction in RMSE with NSTAD scores for the Bayesian Ridge regression model. However, for the remaining models both with and without NSTAD scores show poor results.

Model	With NSTAD Scores		Without NSTAD Scores	
	RMSE	R2	RMSE	R2
MLR	0.0307	0.3657	0.0306	0.3707
Ridge Regression	0.028	0.4288	0.029	0.4347
Bayesian RR	0.0299	0.3973	0.0302	0.3866
GB Regressor	0.0681	-2.1222	0.0657	-1.9046
AdaBoost Regressor	0.0671	-2.0296	0.0798	-3.282
KNN Regressor	0.0396	-0.055	0.0379	0.0328
XGBoost Regressor	0.0642	-1.7762	0.0639	-1.7432
RF Regressor	0.0341	0.1478	0.0356	0.1476

Table 14: Midtown model performance on full dataset without imputation

On the contrary, Table 15 shows improvement in all models especially Adaboost Regressor and RF regressor by an increase in R2 scores of 2.77% and 34.33% respectively.

Model	With NSTAD Scores		Without NSTAD Scores	
	RMSE	R2	RMSE	R2
MLR	0.0716	0.3579	0.0681	0.4192
Ridge Regression	0.0794	0.2106	0.0793	0.2126
Bayesian RR	0.0731	0.3309	0.0716	0.3581
GB Regressor	0.0752	0.2919	0.075	0.2962
AdaBoost Regressor	0.0728	0.3373	0.0774	0.2511
KNN Regressor	0.0863	0.0684	0.0857	0.0804
XGBoost Regressor	0.0732	0.3296	0.0735	0.3231
RF Regressor	0.0716	0.3579	0.0769	0.2596

Table 15: Tribeca model performance on full dataset without imputation

4.3 Model Performance with DBSCAN vs KMeans

After handling the missing values using clustering, the imputed datasets were evaluated on the seven models again.

Table 16 and Table 17 show improved performance of NSTADs in Midtown after imputation. However, KMeans shows better performance in terms of R2 as compared to DBSCAN. Almost all models show an increase in R2 scores, whereas a decrease in RMSE with the inclusion of NSTAD scores in both KMeans and DBSCAN imputation.

Model	With NSTAD Scores		Without NSTAD Scores	
	RMSE	R2	RMSE	R2
MLR	0.0547	0.3227	0.0549	0.3179
Ridge Regression	0.0554	0.3044	0.0556	0.2999
Bayesian RR	0.0549	0.3178	0.055	0.3158
GB Regressor	0.0564	0.2814	0.0561	0.289
AdaBoost Regressor	0.0642	0.0664	0.0618	0.136
KNN Regressor	0.0682	-0.052	0.0627	0.1118
XGBoost Regressor	0.0571	0.2625	0.0629	0.1059
RF Regressor	0.0547	0.3227	0.0549	0.3179

Table 16: Midtown model performance using DBSCAN epsilon = 0.003

Model	With NSTAD Scores		Without NSTAD Scores	
	RMSE	R2	RMSE	R2
MLR	0.0547	0.3227	0.0549	0.3179
Ridge Regression	0.0554	0.3044	0.0556	0.2999
Bayesian RR	0.0549	0.3178	0.055	0.3158
GB Regressor	0.0563	0.2826	0.0563	0.2819
AdaBoost Regressor	0.0635	0.0878	0.0624	0.1195
KNN Regressor	0.0682	-0.052	0.0627	0.1118
XGBoost Regressor	0.0571	0.2625	0.0629	0.1059
RF Regressor	0.0549	0.3187	0.0549	0.3179

Table 17: Midtown model performance using Kmeans n = 4

Since Midtown was referred to as a baseline in this paper, Kmeans with n = 4 was selected as the best methodology and applied on the dataset for Tribeca. Table 18 shows a significant improvement of R2 scores on the Tribeca dataset using NSTADs and a significant decrease in RMSE.

Model	With NSTAD Scores		Without NSTAD Scores	
	RMSE	R2	RMSE	R2
MLR	0.0681	0.4192	0.0716	0.3579
Ridge Regression	0.0793	0.2126	0.0794	0.2106
Bayesian RR	0.0716	0.3581	0.0731	0.3309
GB Regressor	0.075	0.2962	0.0752	0.2919
AdaBoost Regressor	0.0774	0.2511	0.0728	0.3373
KNN Regressor	0.0857	0.0804	0.0863	0.0684
XGBoost Regressor	0.0735	0.3231	0.0732	0.3296
RF Regressor	0.0769	0.2596	0.0785	0.228

Table 18: Tribeca model performance with Kmeans n = 4

The improvement in model performances with NSTAD scores is more pronounced in Tribeca than in Midtown. This suggests that Tribeca's real estate market dynamics are more closely tied to the neighborhood-specific features captured by NSTAD scores.

The inclusion of NSTAD scores uniformly enhances model accuracy across both regions, though the degree of improvement varies, reflecting the varying sensitivity of real estate markets to local attributes.

Chapter 5

Results

In this chapter we discuss the insights and results of the experiments we discussed before.

5.1 Impact of Spatio-temporal neighborhood changes on sale prices in Midtown

In this section we analyze how well NSTAD scores can explain price variation in Midtown. After applying KMeans Clustering as a data imputation strategy, we analyzed the spatial patterns of changing NSTAD scores for each cluster.

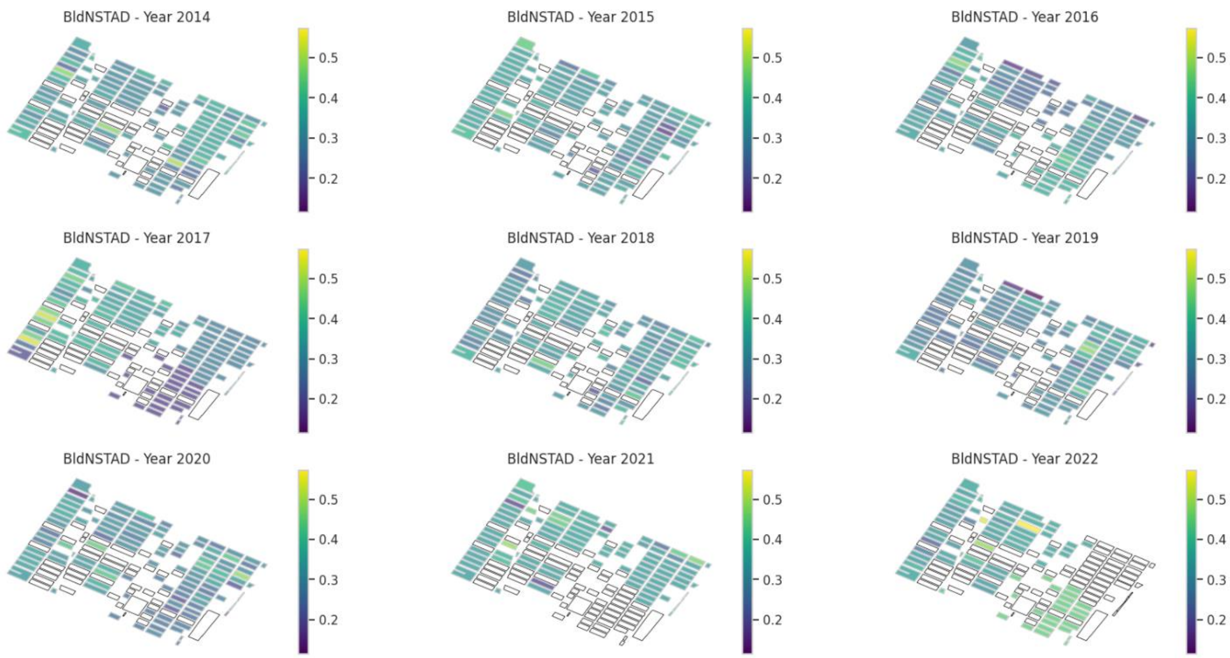


Figure 36: Spatio-temporal changes in BldNSTAD in Midtown

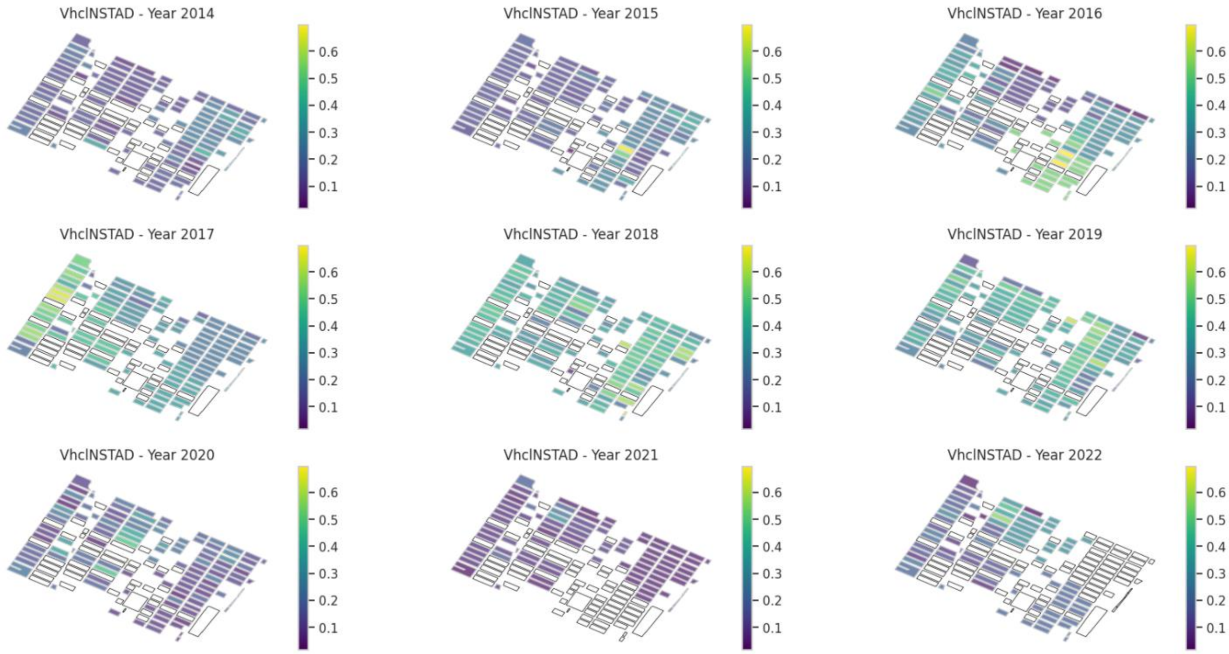


Figure 37: Spatio-temporal changes in VhclNSTAD in Midtown

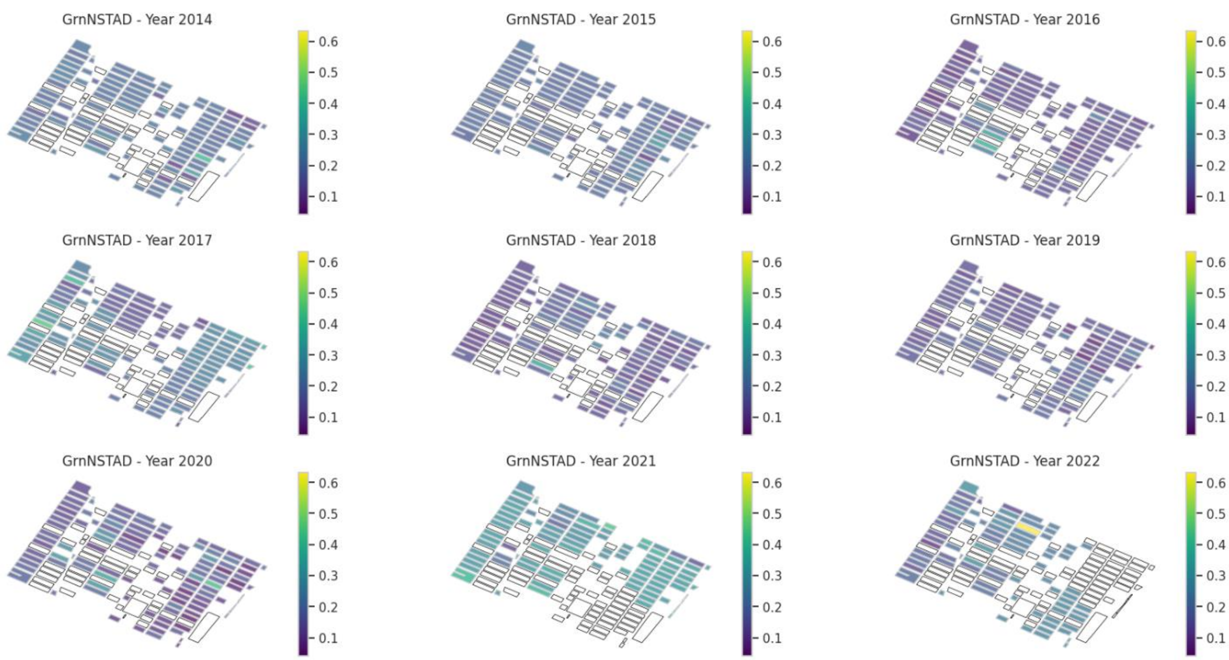


Figure 38: Spatio-temporal changes in GrnNSTAD in Midtown

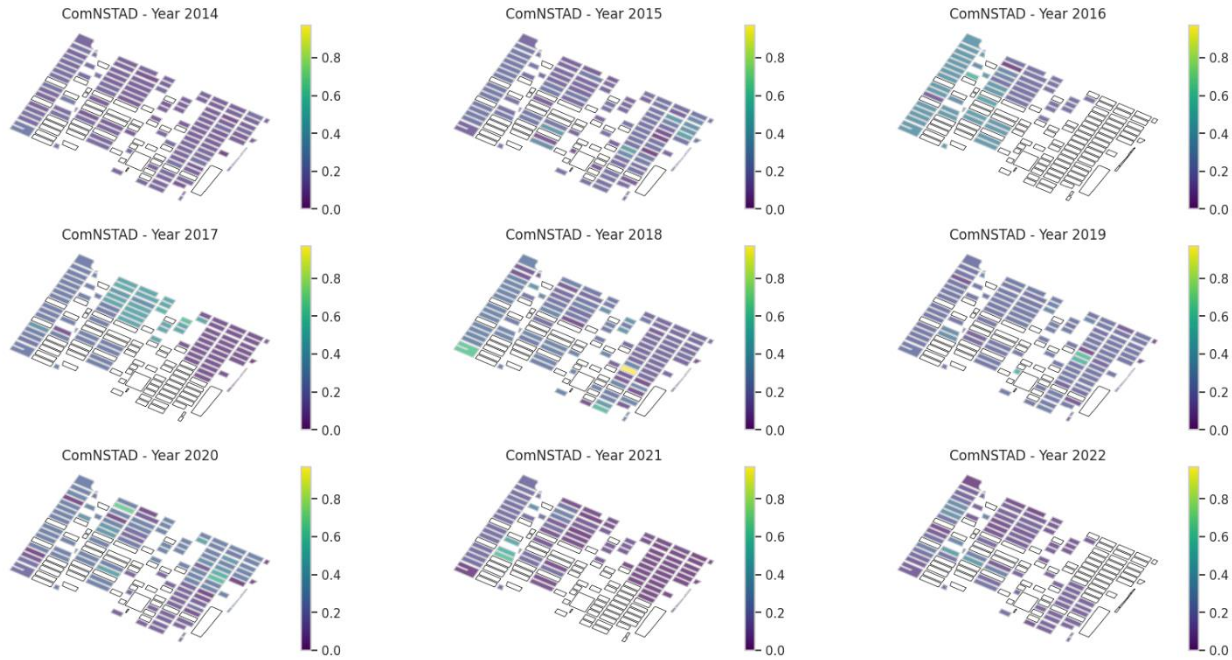


Figure 39: Spatio-temporal changes in ComNSTAD in Midtown

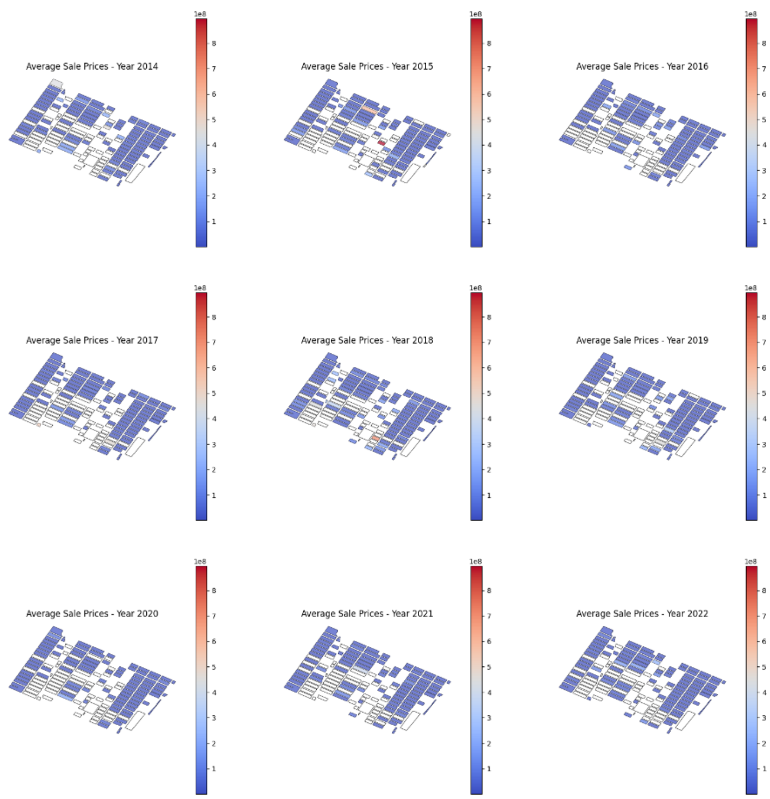


Figure 40: Average Sale Prices in Midtown blocks (2014-2022)

5.1.1 Cluster 0

Following are the observations for Cluster 0:

Consistent building densities: Cluster 0, color-coded as dark blue in Figure 34, shows consistent building scores throughout the years between 0.2 and 0.35. The consistent higher density scores for Block 1049 (between 0.4 and 0.5) indicate sustained construction or redevelopment efforts, attracting higher real estate values over $4bn. Figure 36 displays a significant drop in building density scores to 0.1 in 2016 and the corresponding decrease in average sale price by 900% reflecting a market downturn, affecting construction and sales. In 2022, Block 1272 displayed the highest building density in all years throughout Midtown around 0.6 and the sale price increased from $0.4 to $0.7bn. The rise in sale price could be due to new developments, renovations, or an upswing in the market attracting more investments and higher property values.

Steady traffic: Blocks in this cluster with vhclNSTAD scores consistently ranging from 0.2 to 0.35 might represent stable residential areas with moderate traffic (Figure 37). Block 1049 scored consistently around 0.4 to 0.5 indicating a higher vehicle density, suggesting it might be a minor commercial area or a roadway with steady traffic throughout the years.

Well-maintained green areas: Blocks with GrnNSTAD scores consistently between 0.3 and 0.5 (Figure 38) could suggest well-maintained residential areas with parks or green spaces. The peak score approaching 0.6 in 2022 may indicate blocks with substantial public green spaces or heavily treed areas.

Minimal Commercial influence: With consistent ComNSTAD scores ranging from 0.2 to 0.3 (Figure 39), Cluster 0 suggests minimal commercial influence on housing prices. This could be indicative of residential areas with necessary but low-impact commercial features like streetlights and pedestrian traffic lights.

Moderate sale prices: The consistent building and vehicle densities in Cluster 0, along with stable greenery scores, suggest a well-maintained residential environment. The average sale prices for this cluster stayed between $1bn -$2bn. However, Figure 40 shows a few blocks such as Block 1049, showed a high increase of $4bn average sale price in 2014. The drop in average sale prices in 2016 across this cluster reflects the broader market downturn that year.

5.1.2 Cluster 1

Following are the observations for Cluster 0:

Variable building density: Cluster 1 **color-coded as red** in Figure 34 shows variability in the blocks of cluster 1 throughout the years in Figure 36. From 2016 to 2017, the building density reduced from 0.4 to 0.1, and then back to 0.4 in 2018. This indicates a cycle of demolition followed by reconstruction or redevelopment within these blocks as compared to the rest of the neighborhood. The peak density of 0.5 in 2022 could signify a recent push for development, possibly due to favorable market conditions or changes in zoning policies encouraging denser construction.

High traffic volume: The variation of vhclNSTAD scores from 0.4 to 0.1 (Figure 37) and back to 0.4 could represent areas under construction or areas that experience seasonal traffic changes, such as near schools or event venues. A peak score of 0.5 in 2022 might indicate the completion of infrastructure that supports higher traffic volume or a new attraction that has increased vehicle presence.

Established landscaping: Scores that consistently range from 0.1 to 0.3 (Figure 38) in this cluster could indicate commercial zones with established landscaping or residential areas with consistent tree cover and public gardens. This indicates there were no new environmental initiatives taken for the blocks in cluster 1 as compared to the rest of the blocks in the neighborhood.

High commercial activity: The steady ComNSTAD scores between 0.2 and 0.3 (Figure 39), except for 2022, suggest a stable presence of commercial elements with moderate impact on housing prices — indicating well-regulated areas with essential infrastructure such as zebra crosswalks and street lighting. The deviation in 2022 could indicate either a temporary decrease in commercial activity or the introduction of higher-impact commercial elements that have yet to influence housing prices significantly.

Fluctuating sale prices: The fluctuating building densities and low greenery scores in Cluster 1 lead to variable sale prices over the years. The dip in building density in 2017 followed by a recovery in 2018 suggests a potential temporary decline in sale prices by 30%, with a rebound as new developments complete. The peak in building density in 2022 due to the recent push for development, and the elevated ComNSTAD scores for this year indicate the average sale price increase from $1bn to $4bn.

5.1.3 Cluster 2

Following are the observations for Cluster 2:

High building density: The blocks representing cluster 2, color-coded as pink in Figure 34, remained consistent throughout the years with an average building density score varying between 0.37 and 0.5 as shown in Figure 36. The relative stability of the building density scores in cluster 2 suggests it's a well-established area with continuous demand. In 2017, a few blocks in cluster 2 displayed higher building density scores as compared to the remaining blocks in the entire neighborhood. This could have been due to a localized development initiative or a response to specific demand within the neighborhood.

High traffic volume: With scores between 0.37 and 0.5 (Figure 37), this cluster 2 likely represents commercial zones or main thoroughfares that consistently attract a higher volume of traffic. A score of 0.5 is relatively high, possibly indicating a commercial district or a major intersection with consistent traffic throughout the day.

Temporary green spaces: A fluctuation in GrnNSTAD scores from higher to lower values and back could indicate redevelopment that temporarily affects green spaces, such as construction projects that remove vegetation but later incorporate landscaping. Figure 38 shows the score peaking at 0.5 in 2021 might be due to the maturation of plantings or seasonal variations in foliage.

High commercialization scores: Cluster 2 had ComNSTAD scores that are consistently higher between 0.4 and 0.5, indicating a more substantial commercial influence on housing prices Figure 39. This might reflect areas with a mix of residential and commercial properties, where features like store signs and street markings positively affect the desirability of the neighborhood.

High sale prices: This cluster's stable building densities and higher commercial scores are likely correlated with consistently higher sale prices, as the presence of commercial amenities is generally desirable. The average sale prices in this cluster stayed stable between \$1bn - \$2bn, reflective of the continuous demand and the commercial influence on housing values within the cluster.

5.1.4 Cluster 3

Following are the observations for Cluster 3:

Steady increasing building densities: As compared to the remaining clusters, the blocks in cluster 3, color-coded as light blue in Figure 34, show a consistent increase in building scores throughout the years. Figure 36 shows the BldNSTAD scores have increased steadily from a score of 0.3 to 0.4 from 2014 to 2021. Whereas the year 2022, had no image samples for cluster 3 hence there is blank space.

Growing traffic volume: A steady increase in VhclSTAD scores from 0.3 in 2014 to 0.4 in 2021 suggests a growing traffic volume (Figure 37). This might reflect a developing commercial area or increased population leading to more vehicles on the road. The lack of data for 2022 means we cannot confirm if this trend continues or if there has been a change in traffic patterns.

Improvement in urban greenery: A steady rise in GrnNSTAD scores from 0.2 to 0.4 (Figure 38) over several years might suggest an improvement in urban greenery, possibly due to city initiatives to plant more trees or improve community parks and gardens.

Increase in commercial influence: Cluster 3 shows an upward trend in ComNSTAD scores over the years, suggesting an increase in commercial influence on housing prices as shown in Figure 39. This could be due to the development of new commercial zones, or the introduction of traffic and safety features that are highly valued in urban settings, such as stop lines at intersections and well-maintained traffic signals.

Low sale prices: Despite the increasing trend in building and vehicle densities from 2014 to 2021 in Cluster 3 suggesting an area of growth, the average sale prices of the blocks in this cluster remained stable at $1 - $1.5bn.

5.2 Impact of Spatio-temporal neighborhood changes on sale prices in Tribeca

In this section we analyze how well NSTAD scores can explain price variation in Tribeca. After applying KMeans Clustering as a data imputation strategy, we analyzed the spatial patterns of changing NSTAD scores for each cluster.

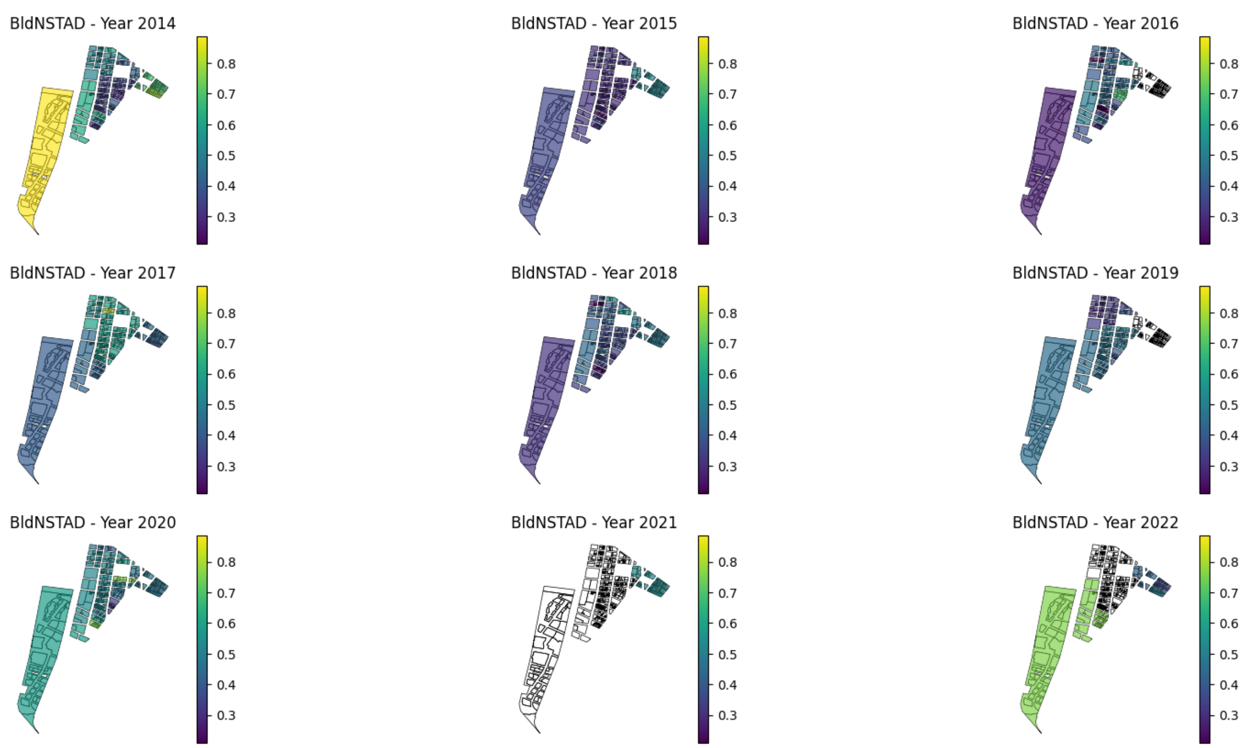


Figure 41: Spatio-temporal changes in BldNSTAD in Tribeca

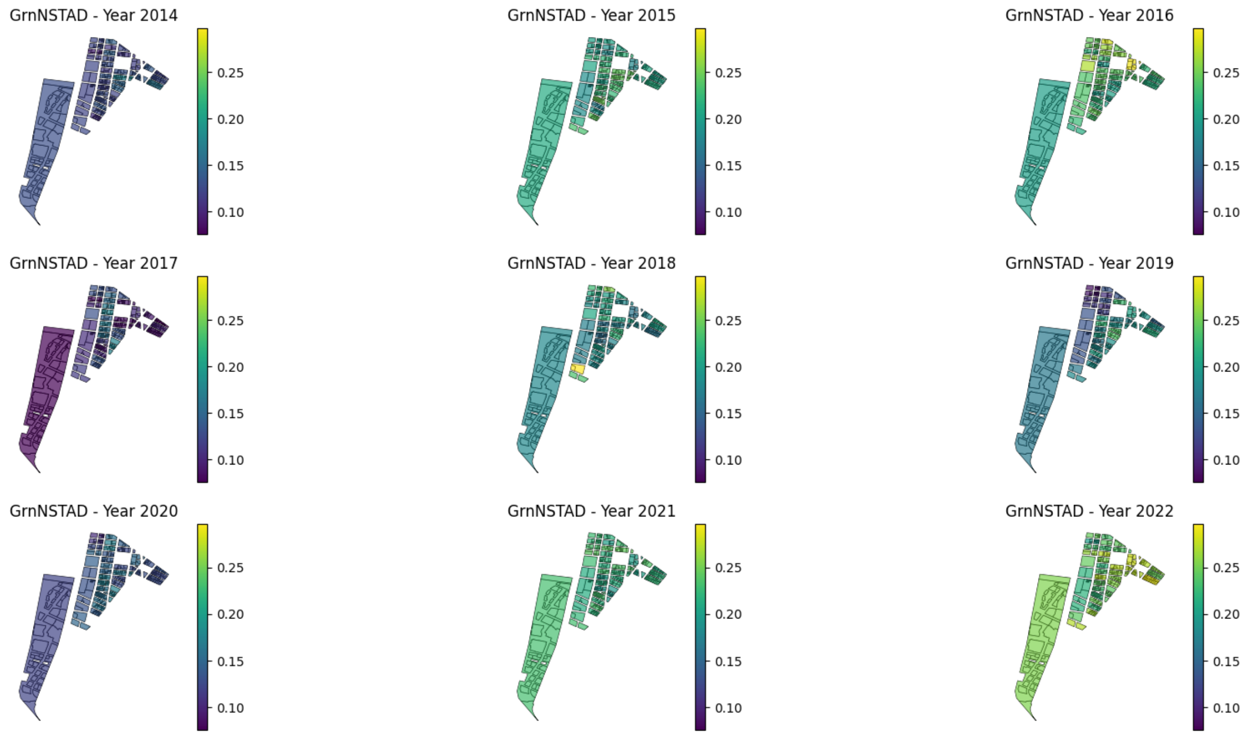


Figure 42: Spatio-temporal changes in GrnNSTAD in Tribeca

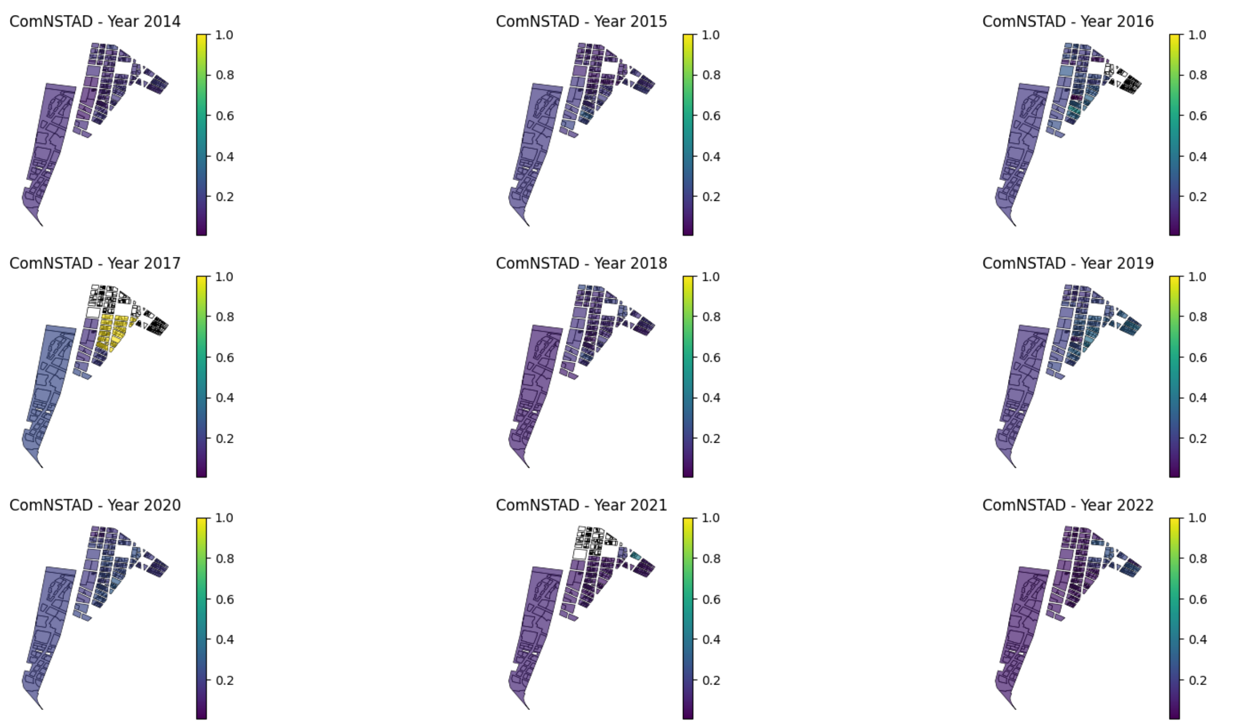


Figure 43: Spatio-temporal changes in ComNSTAD in Tribeca

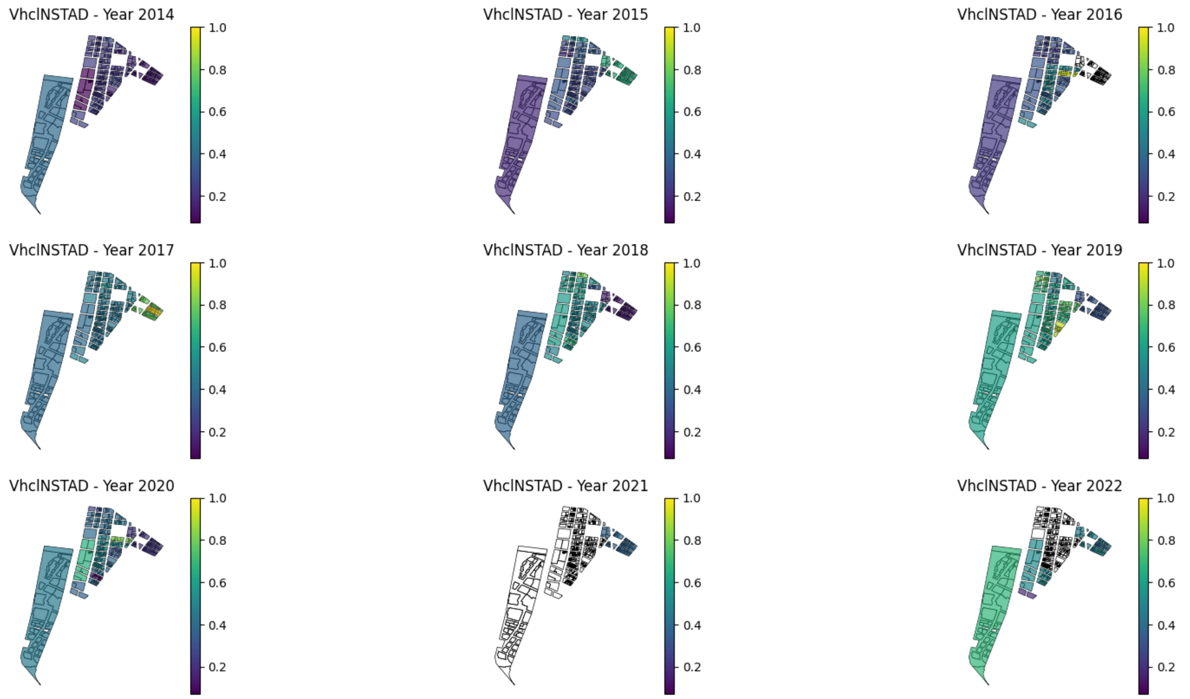


Figure 44: Spatio-temporal changes in VhclNSTAD in Tribeca

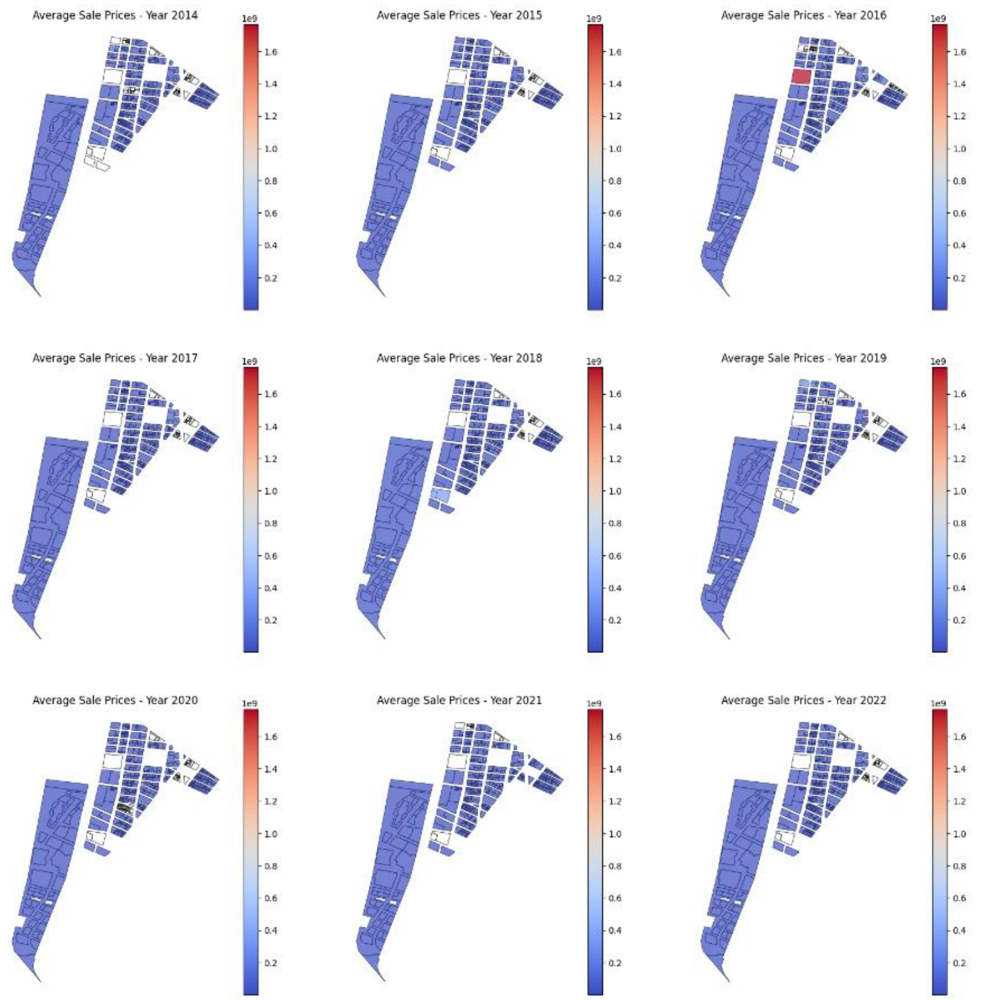


Figure 45: Average Sale Prices in Tribeca blocks (2014-2022)

5.2.1 Cluster 0

Following are the observations for Cluster 0:

Low building density: Cluster 0, color-coded as dark blue in Figure 35, had BldNSTAD scores ranging from approximately 0.3 to 0.5 across the years (Figure 41). The relatively low building density indicates a prevalence of smaller buildings, possibly residential or mixed-use, with fewer high-rise developments. This suggests a stable or slightly growing real estate value, reflecting a demand for this type of property in Tribeca.

Densely built areas: This cluster displayed the lowest GrnNSTAD scores, around 0.1 to 0.15 (Figure 42) indicating it has limited green spaces, which could correspond to more densely built-up areas with a focus on commercial or residential use. Lower greenery scores might affect the desirability for those seeking green living environments but could be offset by urban amenities.

Limited commercial activity: Cluster 0 showcased the lowest ComNSTAD scores, around 0.2 or less (Figure 43). The blocks in cluster 0 likely consist of residential blocks or areas with minimal commercial establishments. Lower ComNSTAD scores indicate quieter streets with fewer shops, restaurants, or offices, which may be preferred by residents seeking a more subdued neighborhood atmosphere. This could lead to higher property values for those looking for less busy areas.

Low traffic: This cluster had the lowest VhclNSTAD scores, around 0.2 or less (Figure 44). The blocks in cluster 0 likely experience low traffic, which might correlate with quieter residential streets or areas with restricted vehicle access. The low vehicle density is generally preferred for living due to reduced noise and air pollution, possibly making these areas more desirable for residents, and positively influencing real estate values.

Low average sale prices: With low traffic, low building density and limited green spaces, cluster 0 had a stable and low sale price throughout the years In Tribeca. Average sale prices here have been consistently between $900 million to $1.8 billion, indicative of a sustained demand for residential spaces. A notable peak in 2017 of $0.4 billion may reflect luxury developments or a prime location.

5.2.2 Cluster 1

Following are the observations for Cluster 1:

Moderate building density: Cluster 1, color-coded as red in Figure 35, displayed BldNSTAD scores hovering around 0.5 to 0.6 (Figure 41) indicating a moderate level of building density. This corresponds to an area with a balanced mix of residential and commercial properties. The moderate density is likely to attract a consistent market interest, reflecting in steady or moderately increasing property values over the years.

Moderate greenery: Cluster 1 displayed mid-range GrnNSTAD scores, approximately 0.15 to 0.20 (Figure 42). This cluster may have some green spaces such as small parks, street trees, or community gardens. The moderate level of greenery can contribute positively to residential desirability and may reflect a balanced urban design that supports both development and quality of life.

Low commercialization: With scores between 0.2 and 0.4, Cluster 1 suggests a balanced mix of residential and commercial spaces (Figure 43). This level of commercialization might provide residents with convenient access to stores, malls and amenities while still maintaining a residential feel. It could potentially attract a diverse range of buyers, reflecting positively on real estate values.

Balanced level of traffic: Moderate scores in this cluster approximately 0.4 to 0.6 (Figure 44), suggest a balanced level of traffic that could be associated with mixed-use areas that have both residential and commercial properties. This could indicate good accessibility while still maintaining a livable environment, potentially having a neutral to slightly positive impact on housing prices.

Rising sale prices: With moderate level of commercial activity, traffic, and limited green spaces in cluster 1 reflect increasing average sale prices over the years. Over the years prices of the properties in cluster 1 have increased from \$0.1 billion to \$0.3 billion. A notable peak in 2016 of \$1.6 billion may reflect renewed interest and investment in the specific block.

5.2.3 Cluster 2

Following are the observations for Cluster 2:

High building density: This cluster, color-coded as pink in Figure 35, showcases the highest BldNSTAD scores, ranging from 0.7 to 0.8 (Figure 41), indicating a high density of buildings which are likely to include commercial and residential high-rises. Areas with high building density in urban settings like Tribeca are often associated with higher property values, due to the desirability of the location and the concentration of amenities and services.

Substantial green spaces: While cluster 0 and 1 displayed low green scores, cluster 2 on the other hand, showcases higher greenery scores. This suggests substantial green spaces like large parks, green roofs, or extensive tree covers as shown in Figure 42. This is often attractive in urban environments, potentially increasing property values and providing environmental and social benefits.

High footfall: Blocks in Cluster 2 appear to be highly commercial with plenty of shops, eateries, and businesses having scores between 0.6 and 0.8 (Figure 43). This indicates a vibrant, possibly downtown area with a high footfall, which might appeal to investors or those who enjoy living in dynamic urban environments. However, it could also mean more noise and traffic, which might not be as attractive to some residents.

High traffic density: Higher scores in Cluster 2 roughly 0.6 to 0.8 point to significant traffic (Figure 44), likely due to main thoroughfares, commercial districts, or areas with popular attractions. While this means better access to amenities and public transport, it might also come with increased noise and congestion, which could have a mixed impact on property values.

Stable sale prices: The blocks within Cluster 2, showed stable high building densities and significant commercialization scores, indicating a robust commercial district. However, the average sale prices remained stable and same as remaining clusters around $0.2 billion. This indicates market saturation where supply exceeds demand. If new constructions are not met with equivalent demand, this could drive sale prices down despite the area's development.

5.2.4 Cluster 3

Following are the observations for Cluster 3:

Varying building densities: Color-coded as light blue in Figure 35, Cluster 3 displays a wide range of BldNSTAD scores over the years. The scores vary from 0.4 to 0.7 (Figure 41), this indicates a transitioning area within Tribeca that may be experiencing development, demolition of old properties and construction of new ones.

Significant green infrastructure: The highest scores as shown in Figure 42 indicate cluster 3 has areas with significant green infrastructure. In an urban context like Tribeca, this could mean the presence of landmark parks or waterfront green spaces, which are highly valued for recreation and aesthetic appeal, often correlating with premium property prices.

Vibrant commercial areas: The highest scores in Cluster 3 close to 1 (Figure 43), suggest extremely high levels of commercial activity, which could correlate with major commercial hubs or tourist areas within Tribeca. Properties in such locations might command premium prices due to their prime location and potential for business or rental income, despite the downsides of living in such bustling areas.

Major traffic hub: The highest vehicle density scores close to 1 suggest, the blocks in this cluster are major traffic hubs, possibly with arterial roads or highways (Figure 44). These areas might be less desirable for residential purposes due to high noise and pollution levels, but they could be attractive for commercial real estate or for those who prioritize transport accessibility.

Moderate sale prices: Despite the trends indicating growth in building and vehicle densities from 2014 to 2022, the sale prices in Cluster 3 have remained relatively stable, with a range from $0.1 billion to $0.25 billion. This could suggest that while the area is developing and becoming denser, the market has adjusted to these changes, maintaining stable property values. The consistent demand for living in Tribeca, coupled with its reputation as a desirable location, likely contributes to this stability.

These assessments for Manhattan's real estate market are reflective of the interplay between urban development indicators and market valuation, where development trends, commercial activity, and greenery all play significant roles in shaping property values. Each cluster's unique composition offers insights into the localized real estate dynamics within the broader context of Manhattan’s luxury market.

Chapter 6

Conclusion

This thesis, centered on analyzing spatial-temporal changes in neighborhoods to predict property prices and Real Estate Appraisal using street-view images, has demonstrated significant findings. Employing advanced methodologies like YOLO v5 for image processing and creating a unique Spatial-Temporal Data structure (STAD), the study has quantified the correlation between neighborhood characteristics and property price trends in areas like Midtown and Tribeca.

The model analysis distinctly shows that NSTAD scores are pivotal in enhancing the accuracy and robustness of regression models in both Midtown and Tribeca. On average the RMSE was reduced between 1% to 5% when including NSTAD scores for both Tribeca and Midtown. Similarly, the R2 scores showed a consistent increase between 10% to 15%.

The inclusion of NSTAD scores not only improves model fit but also provides a deeper insight into the complex relationship between neighborhood characteristics and property values. Key results indicate a notable percentage increase in property prices over the years, correlating strongly with changes captured in various STADs such as GrnSTAD, ComSTAD, VhclSTAD, and BldSTAD. These findings suggest the importance of incorporating localized and detailed features in real estate market analysis, thereby reinforcing the value of NSTAD scores in predictive modeling.

However, the study's reliance on street-view images presents certain limitations. These images may not fully encapsulate the dynamic and multi-faceted nature of neighborhood changes. Additionally, the data's scope, limited to specific regions, might affect the generalizability of the findings across different urban settings.

Future research should aim to expand the dataset to include a more diverse range of neighborhoods. Integrating additional data types, like satellite imagery or social media data, could offer a more comprehensive view of neighborhood dynamics. Advancements in image processing techniques could further refine the accuracy of property price predictions.

In conclusion, this thesis contributes significantly to the field of real estate economics and urban development. It highlights the potential of using spatial-temporal data and image processing in understanding property market dynamics, paving the way for more informed decision-making in urban development and investment strategies. The findings of this research suggest a measurable impact of neighborhood evolution on real estate values, offering valuable insights for urban planners, investors, and homeowners.

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ADDITIONAL COMMENTS

All above contents of the thesis were found in compliance to the approved format.

OFFICIAL NOTES

Date: 15 October 2024	Revision: I	Check by: Khola Modi
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