Analyzing the impact of COVID-19 on property prices in the Rotterdam

MARYAM AKBARI LOR
June 2022

SUPERVISORS:
Dr. Mila Koeva
Dr. Monika Kuffer

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Enschede, The Netherlands, June 2022

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.

Specialization: Urban planning and management

SUPERVISORS:
Dr. Mila Koeva
Dr. Monika Kuffer

THESIS ASSESSMENT BOARD:
Prof. dr. R.V. Sliuzas (Chair)
Dr. M.N. Koeva
Dr. M. Kuffer
Dr. M.N. Daams (External examiner)

ABSTRACT

Worldwide, the housing market that represents the assets of people and a country experienced a shock and uncertainty due to the strike of Covid-19. The spread of this disease caused fluctuation in the price of residential properties especially in the big cities which have been occupied by high-rise buildings, which leads to the alteration of people's preferences regarding the type and location of the house they are willing to purchase. Therefore, assessing the micro-level transactions in the housing market (as an influential factor in the economy) is vital. This study aims to determine what is effects of the outbreak of the Covid-19 disease on the spatial pattern of property prices and the factors that determine the price of a property in Rotterdam.

This research elaborates on the quantitative property valuation methods to assess both 2D and 3D data influencing a residential property price. For the 2D data, two different methods (Random Forest (RF) and Hedonic Pricing Model (HPM)) have been applied to evaluate the changes in the importance of influential indicators on the house price. Also, the spatial pattern of property prices has been visualized based on the executed feature importance in HPM. For the 3D data, due to a lack of detailed information per property transaction, only four indicators (sky view, road view, water view, and green view) were executed, and due to the low number of sample data, only the Hedonic pricing model was used for the assessment of data in the 3rd dimension.

The result of the micro-level housing transaction for the 2D data in the Rotterdam, from February 2019 to December 2021, indicates that the importance of some indicators experiences a change. One of the visible changes in both RF and HPM was related to the alteration of feature importance of the distance to the Central business districts (CBD) in 2020. The value of the coefficient in HPM shows that the CBD indicator lost around 50% of its value compared to the time before the pandemic, and its value was relatively back to the former value in 2021. But, the analysis of the data in the 3rd dimension illustrates that the value of feature importance for the applied indicators related to the view has remained constant for the time before and during the pandemic.

This research demonstrates that although the percentage growth of house prices has increased significantly in the year 2021 compared to previous years, the changes in the spatial pattern of residential property prices occurred in Rotterdam in 2020. The analysis of the changes in the percentage growth of house prices in Rotterdam shows that there is not any significant evidence to prove that Covid-19 affected the house price properties. Besides, the changes in the spatial pattern of the properties in Rotterdam in the first year of the pandemic are mainly due to the difference in the importance of the “distance to CBD and road” indicators. Apart from the distance to CBD and roads indicators, the influence of other indicators on the residential property prices was not significant, or in some cases, the value was constant within all the three assessed years. At the same time, the result of the feature importance in the 3rd dimension HPM model illustrates that the value of high-quality views does not change within the three years. Still, in the first year of the pandemic strike, the price of residential properties decreases with the building height increase. As a result, the outcome of all the executed models indicates that changes in the Dutch housing market are slow compared to other countries, and predicting the effects of a short-term crisis does not reflect the changes accurately.

Keywords: Covid-19, Housing market, feature importance

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my supervisors Dr. Mila Kovea and Dr. Monika kuffer, for their support and constructive feedback throughout my thesis writing. I would also like to thank my supervisors in Kadaster, Dr. Paul de Vries and Dr. Lianne Hans, who gave me warm help and guidance during my study. Their productive feedback helped to shape my thesis.

Finally, I would love to thank my dear family for their support throughout different steps of my life.

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1. INTRODUCTION

1.1. Background and justification

Since 2020, the global COVID-19 pandemic has affected many aspects of the economy, including the housing market (Bryson and Vanchan, 2020; Herwany et al., 2021; Hu et al., 2021). The policies of governments such as social distancing, home office work, and restricting business operations to control the spread of the virus have led to the alteration of people's behavior regarding the demand for housing and property purchasing. One of the reasons for these changes in the real estate market at the beginning of the pandemic is that many individuals chose to leave their flats in metropolitan areas since they could not afford the cost of living after the closure of many industries during the pandemic (Balemi et al., 2021). Furthermore, the new routine of home office work caused individuals to require more space in their homes for their activities (such as office spaces). Houses with a big area were not often available in inner-city locations due to high housing prices (De Toro et al., 2021). Hence, almost in all countries, the volume of the deals in the housing market reduced in the first six months of the COVID-19 spread, negatively impacting house prices (Cheung et al., 2021).

On the other hand, the trend for real estate prices changed after the first six months. Although most countries were experiencing severe negative economic impacts, the Global House Price Index, which evaluates the changes in the property values of 56 countries, showed that house prices increased in the second half of 2020. In the following, based on the report of Knight Frank (2020), the Global House Price Index indicates that the average annual change for the studied countries is around 4.7%. It further presents the changes within six months in the Netherlands (quarter 4 of 2019- quarter 2 of 2020), which is 4.5%.

As a result of the identified changes in the gradient of housing prices during the pandemic, several studies have been conducted to examine the dynamic of prices in residential areas. In these studies, the Hedonic Pricing Model (HPM), which can estimate the house price gradient by interpreting the physical and locational factors of a property, has been commonly applied (Cheung et al., 2021, Kim, 2021, Qian et al., 2021, Wang, 2021). In this traditional valuation approach, mainly 2D data have been used to interpret the factors related to the property price. However, 3D elements of a building (both indoor and outdoor) can also significantly influence property valuation (Ying, 2019), which is commonly neglected. Appling 3D data that reflects the impact of height (such as view, sunlight condition, or noise level) can provide more factors affecting property valuation (in high-rise buildings). In this era, the demand for high-rise buildings in many cities has increased due to the rise in land value prices. Thus, considering these 3D factors are inevitable. These factors can significantly affect the house price during this pandemic due to the isolation of individuals or families in their homes. During the pandemic, issues related to indoor property quality attracted more buyers' attention since people spend most of their time in their homes. It should be noted that the features of a property in a high-rise building alter with height (such as view and noise level). As a result, according to Yamani et al. (2021), using 2D and 3D indicators to obtain more precise information on the factors that impact property prices can assist buyers, real estate agents, and the government in gaining a thorough picture of the property valuation process.

1.2. Research problem

As mentioned above, the spread of the respiratory disease called COVID-19 has affected all sections of the economy globally, and real estate market is one of them (M. R. Hu et al., 2021). The spread of this disease influenced house prices due to its spatial spreading characteristic. People may prefer to avoid the risk of getting the disease by avoiding crowded areas (epicenters) (Cheung et al., 2021). This can lead to fluctuation in house prices due to the invasion of people to purchase properties in the periphery area; therefore, this affects the trend related to the real estate market, which represents the assets of people and a country (Wang, 2021). Hence, it is significantly vital to identify how people react in spatially sorting themselves within the cities when a risk such as the current pandemic occurs.

Even though the pandemic began more than two years ago, only a few studies have examined real estate price dynamics in micro-level transactions (Del Giudice et al., 2020, Yoruk, 2020, Zhao, 2020). These studies determine people's reactions, which may lead to the alteration of the spatial pattern of property prices in these new circumstances compared to the past. Furthermore, none of them have considered the influence of the 3rd dimension, which can significantly impact property prices in high-rise buildings, and examined if there are any changes in their importance. Besides, to the best of our knowledge, none of these studies have investigated the property price dynamics in the Netherlands during the pandemic.

As a result, the study aims to identify any alteration in the spatial pattern and the feature importance of property prices during the spread of COVID-19 across the city of Rotterdam (in the Netherlands), emphasizing on applying both 2D and 3D data to the property valuation methods. Rotterdam is chosen as a case study since this city has towering residential structures. Moreover, the gradient of housing price charts has shown an upward trend from 2013 due to the Credit Crunch (the Bank crisis which is the cause of the housing crisis) in the Netherland (Figure 1-1). Hence, it makes the changes trackable if there are any alterations in the house prices during the pandemic. The mentioned reasons make this city an ideal case study to assess the influence of the pandemic on the property prices, especially in height, and its possible changes in people's behavior in choosing their settlement area.

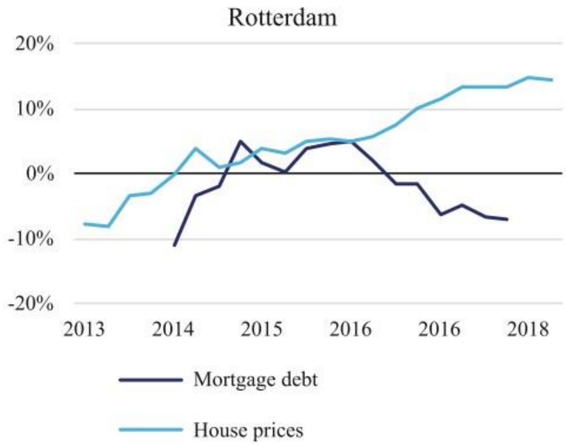

Figure 1-1: Growth of mortgage debt and house prices (Nijskens et al., 2019)

1.3. Research objectives

1.3.1. General objective

To analyze the impact of COVID-19 on property prices in the Netherland. Case study the city of Rotterdam.

1.3.2. Specific objectives and research questions

1- To identify the impacts of COVID-19 on property prices by literature review.
    - What modeling method is suitable for analyzing the patterns of property prices?
    - What are the current common factors that are used for property valuation?
    - What are the common factors for the residential area to quantify the property prices in the Netherland?
    - What are the factors that can affect the buyer's behavior during pandemics?

2- To analyze the property prices in 2D within Rotterdam before and during the pandemic.

- What is the short-term result of the COVID-19 outbreak due to stay-at-home regulations on micro-level transactions in the housing market in the study area?
- What are the possible changes in the importance of the influential indicators on property prices during the pandemic?
- What is the possible influence of COVID-19 on the spatial pattern of property prices in Rotterdam?

3- To compare the result of high-rise buildings' property prices with applying 3D data in the selected neighborhood before and during the pandemic.

- What are the relationships between factors and property prices?
- What are the possible changes in the importance of the influential indicators on property prices during the pandemic?

1.4. Conceptual framework

The figure indicates the main concepts of the research. As mentioned above, based on the previous studies, the outbreak of COVID-19 can significantly impact property prices and the influential indicators for property price. Hence, property price patterns may change due to the creation of new circumstances and routines.

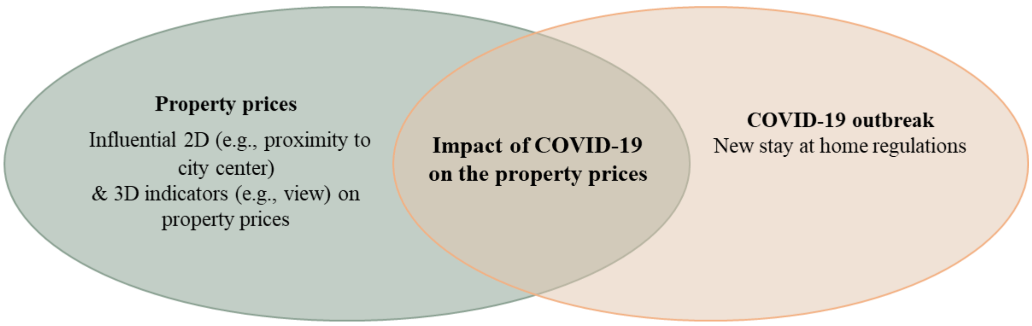

Figure 1-2: Conceptual framework

2. LITERATURE REVIEW

2.1. Methods to quantify the influential factors on housing prices

2.1.1. Hedonic price model

Estimating the price of an exchanged property at a certain period is known as property valuation (RICS, 2012). The main idea behind property valuation modeling is to consider the value and contribution of each feature affecting the total price of a property. Although there are multiple methods for estimating property value, the Hedonic Pricing Model (HPM) is the most often used approach for valuation (Schläpfer et al., 2015). The fundamental concept behind the HPM model is that price of residential properties is made up of a complex variety of features. These factors include both qualitative and quantitative features and can be categorized into three groups such as structural, locational, and environmental attributes. In this model, the property price is considered the dependent variable, and the house attributes as the explanatory variables (Chin & Chau, 2003, Williams, 1991). Based on the hedonic price regression, the individual effects of each housing characteristic can be estimated through the coefficient of the regression (importance of indicators) while all other factors held constant.

Many studies use the hedonic model to assess and quantify the value of different factors in the housing market. In a research conducted by Jim & Chen (2010), the HPM was used to assess the effect of neighborhood parks on the price of high-rise private residential units. This study reveals that the existence and proximity to neighborhood parks can positively affect the property price by up to nearly 15% compared to other landscape elements. Chen et al. (2012) also applied the HPM to assess the sky view factors, which can be used to quantify the air temperature in different cities and its effects on the price of a high-rise property in Jong kong. Another similar study that has been conducted by Czembrowski & Kronenberg (2016) focuses on the value of different types and sizes of urban green spaces by capturing these green spaces into nine categories.

The equation of the hedonic model, which explains the importance of various indicators on the price of a property, can be used in many functional forms. For example, it can be used as the linear, log-linear, the Box-Cox form to improve the model's fitness.

2.1.2. Mashing learning

Machine Learning Algorithms (MLA) have recently become a common method in housing price estimation. This trend is due to the limitations of the hedonic price model in handling the nonlinear relationship between the house price and the explanatory variable of a house. Hence, many studies have examined alternative methods such as MLA to enhance the accuracy of their pricing model. L. Hu et al. (2019) have applied six machine learning algorithms to analyze housing rental prices, including Random Forest regression (RF), extra-trees regression (ETR), gradient-boosting regression (GBR), support vector regression (SVR), multi-layer perceptron neural network (MLP-NN) and *k*-nearest neighbor algorithm (k-NN). The result shows that random forest regression and extra-trees regression provide more accurate results among the executed outcomes. According to Fan et al. (2006), the decision tree approach as a statistical pattern recognition tool can be used to predict the influence characteristics of a house on its price. In this study, the Singapore housing market has been considered as a case study to examine the relation of the qualitative characteristics of the property to the price. Another research conducted by Segal (2004) uses an ensemble classification and regression approach. The RF algorithm, introduced by Breiman (2001), combines random processes of bootstrapping and random feature selection. The algorithm builds new datasets in the RF procedure by selecting rows from the original data. The number of rows in each dataset is the same as the original dataset. The process of creating new data is called bootstrapping. The train decision tree on each bootstrap dataset selects a subset of features for each tree independently and uses them only for training. The mentioned process combines all the predictions, and then the algorithm takes a majority of the voting. The privilege of RF is that it considers the individual classifiers' strength and reduces the generalization error. Besides, it is less sensitive to noise and the overfitting problem in the datasets.

In another research conducted by Li (2020), the relationship between the street visual features and the property value was assessed by applying the RF method. It further explains that RF's advantage is its capability to handle multidimensional data and multicollinearity. Yoo et al. (2012) also compared the performance of two rule-based machine learning regression methods (Cubist and Random Forest (RF)) with the Hedonic pricing model. This research illustrated that the RF model provides the highest accuracy compared to the other models.

2.2. Common housing price attributes

The price of a residential property is related to the wealth and the economic status of a nation, and the changes in the housing sector can affect many economic sectors. Hence, studying the indicators that can affect the price of a property is very important since purchasing a residential property can be considered both an investment decision and a consumption decision (Chin & Chau, 2003). According to (Wittowsky et al., 2020), a house is a multidimensional heterogeneous good that commands the price based on the elements inherent in a property, such as the number of rooms, size, or presence of a balcony or garden. As a result, the reason that causes the price of a property to differ compared to another home is the summation of all the marginal and implicit attributes of a house. It further explains that the most influential factors affecting the price of a property can be different in each continent, country, and city. Hence, many scholars in different countries have been conducted regarding the identification of these factors and potential ways of quantifying them .In the literature conducted by Li (2020), housing characters are categorized into three groups: structural, locational, and environmental.

Structural characteristic refers to the physical attributes of the property. These characteristics can be the area or age of the building, the number of rooms, or the specific room's size, such as the size of the kitchen (Chin & Chau, 2003). The structural characteristic that can give value to a property can change during the time or based on the nation (Kohlhase, 1991). For example, in different countries, based on their climate, the type of material or usage of sustainability factors in the facade can positively or negatively impact the property's price. Different researches have also revealed that an extra-functional room in a house can increase the value by about 7 %, and an extra bathroom collects twice that premium. Commonly, buyers are willing to pay extra to buy a house with a more extensive area and additional room or bathroom to improve the quality of their life (Carroll et al., 1996, Foye, 2017 Garrod & Willis, 1992). On the other hand, the increase in the age of a property can negatively impact the price. The reason is that owner has to spend extra money for the maintenance and the refurbishment of the electrical or mechanical utilities of the building (Chin & Chau, 2003, Clapp & Giaccotto, 1998).

Locational characteristic refers to the property's geographical location and quantifies the house's relation with urban areas and its accessibility to the urban amenities. Proximity to the various transport mode, Central Business District (CBD), social networks, and educational and commercial centers are some of the common locational factors. For example, (Zheng et al., 2016) have been mentioned that proximity to the subway and railway station (in the buffer of 400m) has a positive effect on the price of a house. Easy commuting, which is related to the proximity to the transport facilities, leads buyers to pay more for a house to reduce their future transport costs (Adair et al., 2010); hence, proximity to the good public transport service has a positive impact on the residential property price. Based on the study that has been conducted in Japan, it is also possible that the factor of commuting is not influential on the house price since companies usually are responsible for paying the cost of transportation to the work (Chin & Chau, 2003). Another research that has been conducted in England proves that proximity to high reputation schools can cause a rise of 16 to 20% in the price of the house. One of the reasons for this trend is that schools with good reputations get full quickly, and based on the regulation of the UK, schools have to register a student who lives in the same neighborhood (Leech & Campos, 2003).

Environmental characteristics refer to the surrounding landscape near the property, such as a river, lake, and vegetation. These elements can improve the life quality and well-being of the residents. Studies have shown that quality of view can cause the price of a property to rise up to 8 to 10% (Luttik, 2000). Benson et al. (1998) also noted that views are not uniform and can be distinguished by different views and their quality. For example, the view of water or vegetation can range from high quality to low quality within the same neighborhood. Consequently, buyers usually consider different values for various land uses and the range of visible specific land use (full view or partial view).

Jain (2008) further explains that in property valuation, influential variables like building size, lot size, unpaved streets, street width, land use, etc., can be extracted from the remotely sensed data (high spatial resolution aerial photography). The GIS and RS data used for the property valuation analysis are often in the format of 2D. Accordingly, considering only these data in the valuation modelling cause to ignore some of the indicators that can be quantified only by using 3D data (such as the view of each story in high-rise buildings) (Ying, 2019). Hence, the GIS and RS data, which are used to visualize 2D data, cannot precisely describe the property's features for valuation in-depth in the areas with high-rise buildings.

Consequently, applying only 2D data in the house pricing models cannot represent the complexity of vertical developments in urban areas due to the need for the data in the 3rd dimension. Generally, the Hedonic Pricing Value Model (HPM) is usually used to estimate property value in relation to building surrounding land uses (accessibility to services) and structural and environmental features of the buildings (Schläpfer et al., 2015). Although the Hedonic Price Model (HPM) is a commonly used framework for the mass evaluation of indicators that influence property values, it has significant drawbacks (Helbich et al., 2013). Helbich further explains that deriving the explanatory data only based on the 2D vector or raster data is the weakness of this model. The study also states that HPM can disregard variables that substantially impact property value, and applying 3D data can strengthen the hedonic model's prediction potential. Moreover, based on the study of (Yamani et al., 2021), utilizing 3D elements in property valuation is critical since a building is made up of indoor and outdoor components that are connected to a property as a 3D object (e.g., volume, height, view, shadowing, pollution). Hence, considering the vertical 3D variables in the property valuation, which consider various elements to estimate the price of a property in the trading market, can help to reach a precise property value estimation. Another research conducted by Ying (2019) indicates that utilizing both 2D and 3D data in the HPM cause the development of the model and consequently leads to fair property taxation due to better estimation of factor that can influence the property price. It also mentions that 3D models with Higher Level Detail (LOD) can improve the process of property value estimation.

Accordingly, due to the current trend in the property valuation and the emphasis of buyers on other aspects (namely, the property's height, view, noise level, etc.), applying 3D techniques might be an effective way to describe the complex property attributes in the vertical dimension (Toppen, 2016, Zhang, 2019). For property valuation, the 3D modeling techniques can be used to combine 2D and 3D data. To be more explicit, the advantage of using 3D variables related to a building in the property valuation arises from the capability of using 3D physical modeling, which considers the building's functional features. Hence, in research done by Yamani et al. (2021), the 3D parameters that can be utilized to be integrated into the property value model were studied. The study further classifies the indicators that substantially impact the property valuation, for example, indoor variables (physical, inherent to the property unit) and outdoor variables (locational, environmental). As a result, a 3D model of a target building can be applied to reflect the relationship between the 3D data (such as sunlight analysis, landscape analysis, or noise analysis) and GIS data (2D) to quantify the 3D data for applying in the property valuation model for more accurate property value estimation (Zhang et al., 2014).

Hence, applying 2D and 3D data can benefit the property valuation process, considering the commonly neglected indicators. This relatively new approach of using 2D and 3D data and visualizing it as a 3D model can be beneficial in examining the 3D indicators that might influence the valuation of a property after the Covid-19 outbreak.

2.2.1. Common housing price attributes in the Netherland

A residential property's value is the price that a willing buyer and the seller negotiate. The value is related to the purchased building's environmental, locational, and structural characteristics. Moreover, two different values should be considered regarding the residential property value. The first one is the intrinsic value which would be determined by the objective character of the property and its location. The second value is the subjective market value, and it shows the amount of money that buyer is willing to pay to purchase a property. For example, the WOZ value, which is calculated every year for all properties by the municipalities, shows the intrinsic value of a property while it does not indicate the market price of a house, which is also influenced by speculative and emotional effects. The primary input for these models is building structural characteristics, such as size, age, and property type. The created model with the mentioned characteristics lacks comprehensive attention to the locational and environmental features of the building or any new changes in the interior of the building, such as a new kitchen. These criteria are the elements that affect the price of a property in the market.

Oud (2017) studied the property valuation needs in the Dutch context. This research shows that the Dutch property valuation model (provided by municipalities and real estate agencies) requires both information related to the building and the cadastral information. The prementioned information is needed for calculating the value for taxation and market. Besides, it further explains why the Dutch Council has provided a list of quality standards for the real estate assessments, which can be utilized for the fair valuation of a property. This list aims to consider the basic physical characteristics of the building, such as its location, building age, building size, plot size, and type of property type. Besides, the sustainability factors (roof insulation and energy-efficient glazing) can influence the increase in house prices. Table 1 illustrates the factors that usually are considered by the realtors for calculating the price of a property.

Table 2-1: NVM realtors database (Oud, 2017)

Explanatory variable			Descriptive variables	
Spatial information	**Physical information**		**Legal information**	**Administrative information**
Fine location	Category	Floors	Investment	Entry date
Heavy traffic	Property type	Inside maintenance	Leasehold	Closing date
In center	Building	Outside maintenance	Partly rented	Duration
	period	Fireplace	Buyer condition	Initial listing price
	Rooms	Parking	Sales condition	Ultimate listing Price
	Garage	Parcel size	Status	Transaction Price
	Furnished	Shed		Neighborhood
	Volume	Apartment		House number
	Inbuilt garage	Roof type		House Letter
	Isolation	Housing type		Postal code
	Basement	Heating		Street name
	Quality	Living shape		District
	Elevator	Living size		Place of residence
	Monumental	Garden size		
	Size (m2)	Basic attic		
	Balconies	Attic		
	Toilet	fix stairs		
		Garden position		

2.3. Impact of demographic shocks on the housing market

The occurrence of a pandemic such as COVID-19 is not unprecedented in human history; however, the COVID-19 pandemic seems to be more severe than the last pandemic (Spanish Flue), which occurred over a century ago (Ferguson et al., 2020). Different studies have revealed that an economic crisis inevitably would occur following all the demographic shocks due to the spread of a virus, and the real estate market is one of these economic sectors which is directly related to household wealth (Croom et al., 2020; Hu et al., 2021). According to research conducted in the United States by Wang (2021), although there was a 42 % reduction in real estate market transactions at the start of the pandemic, this trend has reversed, and transactions increased from September 2020. The research has assessed five different cities with various economic features. The result illustrates that house prices in four out of the five examined towns experienced a considerable rise in housing prices. Francke, and Korevaar (2021) also have assessed the impact of historical outbreaks on the housing market for two major cities in Europe (Amsterdam and Paris). The study further indicates that due to local features, the response of land prices to these changes differs in various locations. However, the common fact regarding the property valuation in the short-term assessment shows that the majority of these areas experience a decrease in the first six months, and then the land value starts to rise to reach its starting point. The micro-level transactions of purchased properties in the first six months of the mentioned cities indicate a 10-13 % drop in the value. De Toro et al. (2021) and Wang (2021) also studied the possible reasons for the mentioned fluctuation in the property prices. They conclude that some of the reasons for this trend are that the construction projects have slowed due to the COVID-19 outbreak, and there has also been a disruption in the property search process for purchasers. Additionally, they explain that these prices have also been impacted due to a series of events, such as interest rate cuts, stay-at-home regulations, business shutdowns, or forbearance on mortgage payments.

It seems that the changes in the land value of the residential building can be rooted in people's reaction to their new experiencing lifestyle, such as distance working. A study in the UK indicates that during the pandemic, the factors of comfort and quality of the indoor environment attract the attention of buyers more than usual since they are looking for improvement in their living conditions (De Toro et al., 2021). It further explains that better thermal insulation, acoustic insulation, visual comfort, indoor air quality, and natural light are some of these elements. Moreover, in the city of Padua in Italy, the identified pattern in the rise of the land value is related to the larger houses with additional spaces with a terrace or garden; since they work in their home, they need more spaces for their activities.

Only a few studies have looked at the micro-level transactions of real estate agencies to examine the effects of the COVID-19 outbreak on property values. One of the studies conducted in Wuhan, China, used micro-level real estate transactions in nine areas to assess buyer behavior changes during the COVID-19 pandemic (Cheung et al., 2021). Consequently, the study began evaluating real estate transactions from January 2019 to July 2020 to determine how property prices changed before and during the outbreak. The findings of the mentioned study revealed that property values fell by 4.8% at the start of the outbreak and afterward began to rise, with the exception that there was a shift in growing property value from the epicenter to the periphery (with lower density). Qian et al. (2021) assessed the average house prices in the 1319 districts in China, and the result indicates that the house prices in the areas with the higher number of infections decreased by around 2.4%. Another research conducted by Yang and Zhou (2021) evaluates the impact of COVID-19 in China by considering the average selling price of commercial housing. In this study, they consider factors like land transaction price, GDP, income and did not consider the quality of houses or their proximity to services while they have been traded. Del Giudice et al. (2020) also studied the house price dynamic in the Campania region in Italy by considering the economic indicators (namely, unemployment, personal and household income, and real estate judicial execution). The result of the research showed that the city experienced a drop of 4.16% in late 2020 and 6.49 in early 2021.

The literature review indicates that due to relatively the short-time passage from the COVID-19 outbreak, there is limited literature related to examining the influence of COVID-19 on the real estate market. Furthermore, the majority of these articles have focused on the pandemic's impact on China.

3. METHODOLOGY

This section elaborates on the quantitative methods which have been applied to address the objectives of the research. Figure 3-1 illustrates the overall research design, including the theoretical (literature review) and practical (collecting data, choosing indicators, statistical analysis, etc.). After the literature review, which provides the theoretical basis for continuing the study, data were processed. In the pre-processing section, the data were cleaned by deleting the missing value (such as null data regarding the area of the purchased property), or the errors within the dataset (such as the unbalance transaction price compared to the area of the property).
In the first part of analyzing the 2D data, multiple potential POIs were selected based on similar studies (in the literature review) to calculate the distance of each house to the closest amenities. In the second part, the data was trained for the regression model to gain insight into the potential influence of demographic shocks on the reaction of the market and buyers regarding the scope of housing before and during the outbreak.

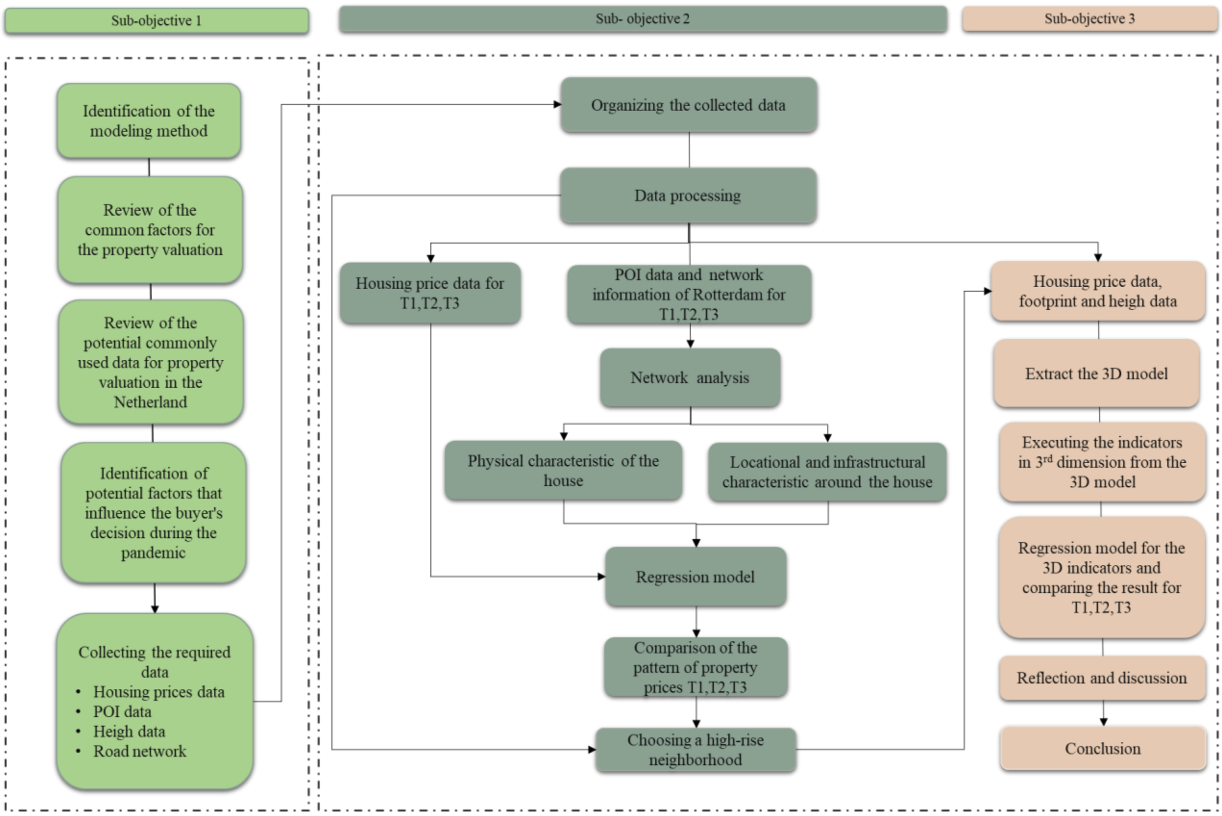

Figure 3-1:Methodology

((T1-from February 2019 to January 2020), (T2-from February 2020 to January 2021), (T3-from February 2021 to December 2021))

3.1. Study area

The study area is the city of Rotterdam (figure 3-2), the second biggest city in the Netherlands. This city, located in the south Holland province, is one of the attractions for tourists due to the city's architecture. Rotterdam consists of 14 districts, and its area is 324.14 km2.
Globally, the spread of the COVID-19 mostly started at the end of the year 2019, but the major pressure to control this virus started in March 2020, which caused the Duch government to suggest citizens stay at home in "intelligent lockdown" (Hulsen, 2020). The regulation of the Duch government gradually got more severe until staying at home (lockdown) became mandatory. Consequently, these new regulations affected various aspects of the economy (Manshanden & van Oort, 2020).

The Kadaster organization provides the data for assessing the changes in the property prices in the Netherland during the pandemic. Hence, Rotterdam has been selected for its towering residential structures to illustrate the property price differences in height (the vertical dimension). Besides, no similar research regarding the property price assessment during the pandemic has been done in this city. In Rotterdam, many high-rise neighborhoods have been built, and property values differ amongst them due to different views, levels of noise, or sunlight that they receive on each floor (Toppen, 2016). Each district has distinctive vertical features that can impact the value of its property. Consequently, the study aims to determine the change in the valuation models' feature importance and the underlying spatial pattern for property prices before and during the spread of COVID-19 across Rotterdam, emphasizing applying both 2D and 3D property valuation methods.

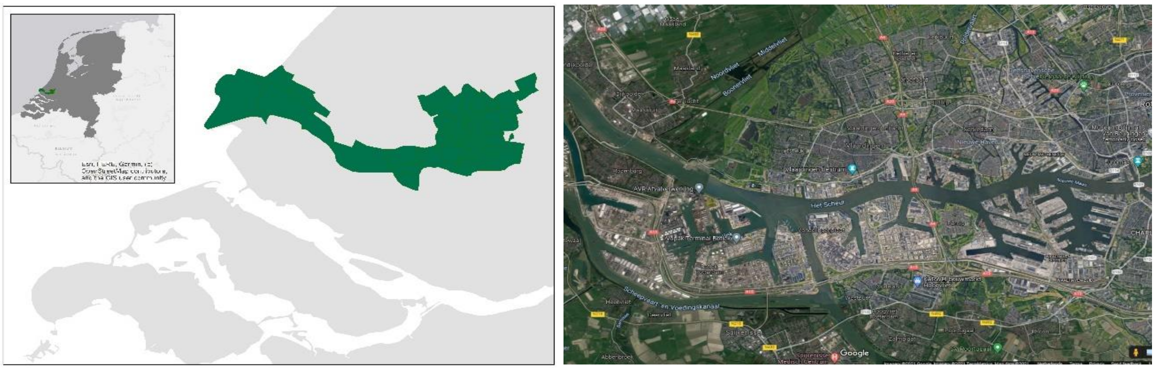

Figure 3-2: Study Area

3.2. Data description

This study uses four types of data to compare the influential factors on property prices before and during the outbreak (as shown in Table 3-1).

Table 3-1: Overview of available data

Data	Unit	Source
Housing Prices	Euro	Kadaster organization
Road Network	Line	Kadaster organization
POIs	Vector	Zuid holland website: https://opendata.zuid-holland.nl/geonetwork/srv/dut/catalog.search#/home
Height data and footprint	Vector and polygon	Pdok website: https://3d.kadaster.nl/basisvoorziening-3d/

House price data. This data (CSV format) is the price of residential properties within Rotterdam from 2019 to 2021. The data is provided by the Kadaster organization (Land registry department). The provided data about the price of the purchased property consists of information about the year and month of purchase, coordination, administrative district, name of the located neighborhood, year of construction, building area, plot size, and house type. The Land Registry registers the prices of all homes sold.

POIS. In this research, POI (point of interest) represents a feature located in a point to assess the characteristics of the area around the purchased house. The points of interest have been extracted from the Zuid holland websites. The last update of the data mostly backs to 2020.

3.3. Data pre-processing

Before training the data for the regression model, pre-data-processing is a crucial step. Cleaning the data related to the transaction of the housing prices has been started by eliminating records from the dataset that have noticeable errors, such as the low price for the purchased property (e.g., 40098 euro for a 105m^2 property), or removing records without information (Null rows) regarding the size or price of the property. Moreover, some neighborhoods have been excluded from the selected study area due to Rotterdam's east to west elongation. The eliminated neighbors (*Dorp, Strand en Duin, Rozenburg, Hoogvliet Zuid, Hoogvliet Noord, Pernis, Heijplaat*) have been surrounded by the industrial area of Rotterdam. Although the mentioned neighborhoods have been located in the CBS boundary of Rotterdam, they are closer to the smaller cities than part of Rotterdam in which most neighbors have accumulated. As a result of the data cleaning, 5045 records for T_1, 5571 records for T_2, and 4975 records for T_3 remained for further analysis.

In the following, data has been divided into three different timetables with equal intervals for further analysis regarding identifying the influential indicators on the property price (T_1-from February 2019 to January 2020), (T_2-from February 2020 to January 2021), (T_3-from February 2021 to December 2021). Then, for normalizing the purchased property price, the price of the transacted residential property has been divided by the size of the property (m^2).

In the next step, some variables have been categorized, such as the type of the building (detached house, semidetached house, corner house, terraced house, and apartments) or the level of the urbanity. Table 3-2 shows the created categorized variables for this work.

Table 3-2:Categorized variable

Variable	Category	Value
Type of the house	detached house	1
	semidetached house	2
	corner house	3
	terraced house	4
	apartments	5
Garden	Yes	1
	No	0
Level of Urbanity	Low density (rural)	4
	Medium-density	3
	High density	2
	Very High density (urban)	1

Finally, after preparing the processed dataset, the analysis of the data has begun to identify if there have been any changes in the pattern of property transactions over the previous years. The applied methods for this analysis have been clarified in the 3.4 and 3.5 sections.

3.4. The 2D methods for property price evaluation

This section introduces the 2D methods for the property price assessment. The analysis of the results will follow by comparing elements that affect the property prices before and during the pandemic.

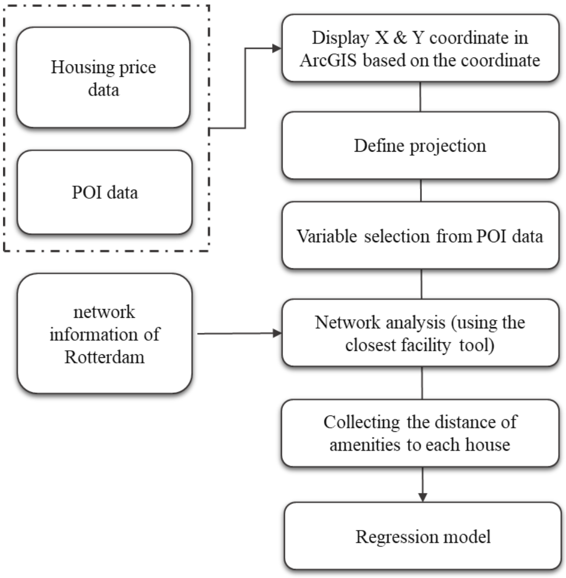

Figure 3-3:The flow diagram of 2D modeling

3.4.1. Global Moran's Index

In this study, Global Moran's I have been applied to measure spatial autocorrelation based on the samples' feature location and the price of the purchased residential property. It evaluates whether the existing pattern (relationship between the location and the housing price) is clustered, dispersed, or random.

The Moran's I statistic for spatial autocorrelation is given as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (1)$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \quad (2)$$

The z_I-score for the statistic is computed as:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}} \quad (3)$$

where:

$$\mathrm{E}[I] = -1/(n-1) \quad (4)$$

$$\mathrm{V}[I] = \mathrm{E}[I^2] - \mathrm{E}[I]^2 \quad (5)$$

Figure 3-4:Formula for calculating the Moran's I (Source: https://pro.arcgis.com)

The value of the global moran's I range from -1 to +1. The value of -1 indicates a perfect negative correlation, +1 shows the perfect positive correlation, and 0 means no correlation. The z-score and p-value evaluate the significance of this index.

3.4.2. Selection of potential indicators

This study applies structural and locational indicators for 2D methods as the potential indicators that affect housing prices. These indicators were chosen based on the availability of the data, assessment of the study area, and the literature review.

As is shown in Figure 3-5, the house price data (secondary data) and selected variables (POI data) were used to calculate the distance of each house to the nearest amenities. All the selected variables and the house price transacted data contain geospatial data, which can be used to identify how close the amenity is to the transacted house based on the available road network of the city.

3.4.3. Random forest model

Random forest is an ensemble learning method used for classification and regression analysis. The RF model constructs several decision trees by training the data and classifying the result to reach a conclusion. The RF model as a classifier combines the number of decision trees on different subsets of a dataset to predict an independent classification result. It then averages the results and votes to predict the best outcome for increasing the dataset's predicted accuracy. Since the RF model collects the forecasts based on the numerous decision trees instead of one, it predicts the final result based on the majority votes of predictions. This procedure leads to the reduction of overfitting influence, and satisfactory generalized performance is demonstrated.

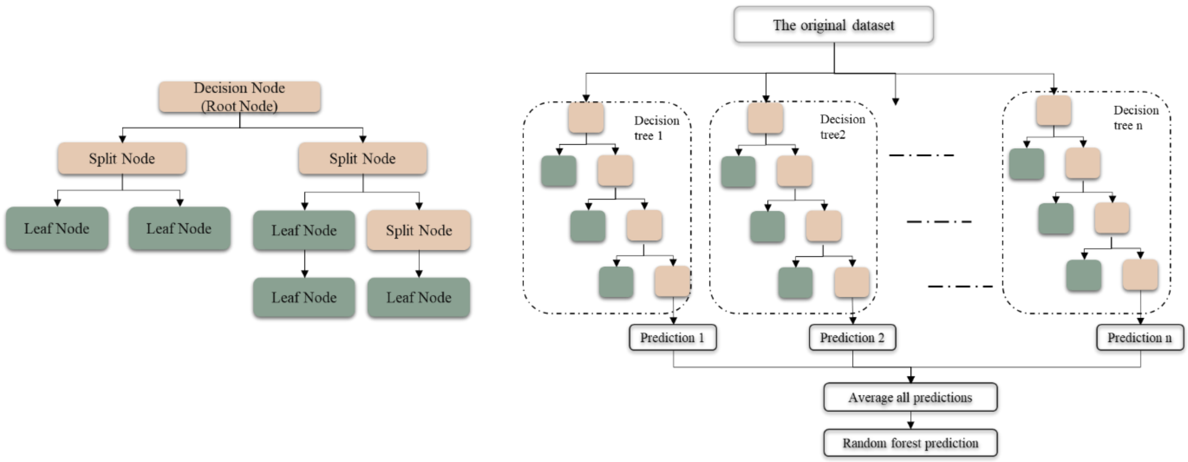

Figure 3-6: Structure of a decision tree (shown on the left) and the Random Forest model (shown on the right)

The random forest starts with the independent selection of the bootstrap sample from the original dataset, further as the input dataset of each decision tree. This model is called random forest due to two random processes, bootstrapping and random feature selection. Bootstrapping ensures that the model does not use the same data for every tree; hence, it helps the model be less sensitive to the original date training data. The random feature selection also helps reduce the correlation between the trees. Some of the trees will train on less important features, and consequently, they give bad predictions, but there will also be some trees that give bad predictions in the opposite direction, which causes them to balance out.

The decision tree consists of three sections: root node, split node, and leaf node.

The Root Node is the topmost decision node that starts the graph and evaluates which indicator splits the data better.

The Split Node is the process of splitting the nodes into sub-nodes and splitting sub-nodes into further sub-nodes based on the particular criteria (e.g., gini for the classification)

The Leaf Nodes are the tree's terminal nodes when a category's or a numerical value's predictions are produced, and there is no more split in the tree.

3.4.4. Model validation

Model evaluation is critical for determining a model's efficacy and also plays a role in model monitoring. It helps to determine how well that model performs and estimates the generalization accuracy of a model. The model evaluation assesses the model's fitness based on comparing the predicted and actual prices. In the following, the statistical metrics applied to measure the model performance are introduced.

1- R squared /adjusted R square:

R-squared (R^2) is the measure of the correlation between two variables. It indicates the proportion of the variance explained by the regression model and provides an estimate of the strength of the relationship between the regression model and the independent variable. It ranges from zero to one to show how well the independent variables explain the variation in the outcome variable (in this case, price). Hence, 0 means the model does not explain any of the variations in the outcome (no correlation), and 1 indicates that the model explains all of the variations in the outcome variable(complete correlation).

Often in models, the adjusted R-squared is added for assessing the correlation when there are a different number of variables. R-squared (R^2) increases by increasing the number of variables, while Adjusted R^2 only rises if the new variable improves the model.

2- Root Mean Squared Error (RMSE)

RMSE measures the difference between the predicted and real prices, showing how concentrated the data is around the best-fit line. Root mean squared error is the standard deviation of the residuals (prediction errors), and it is commonly used in regression analysis to verify experimental results, but the number on its own does not show anything. It will be used to find the RMSE for several different models once they have been run. The model with a lower RMSE is the one that fits the best.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$$

Where:

- n = sample size
- i=variable
- y_i= forecasts (expected values)
- x_i= observed values (known results)

3- Mean Absolute Error (MAE)

Mean Absolute Error measures the difference between the error of predicted and real prices without considering their direction.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n}$$

Where:

- n = sample size
- y_i= forecast
- x_i= true value

4- Pearson correlation coefficient

The Pearson correlation coefficient is a method to measure both the strength and direction of the relationship between two variables. Its value range from -1 to +1, where the greater the absolute value, the stronger the relationship between two variables. The value 1 indicates a complete positive correlation, -1 shows a complete negative correlation, and 0 no correlation.

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(f_i - \overline{f})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}\sqrt{\sum_{i=1}^{n}\left(f_i - \overline{f}\right)^2}}$$

Where:

- R= Pearson correlation
- f = value of the predicted prices
- $\overline{f}$ = mean value of the predicted prices
- y_i= value of the y-variable (actual price) in a sample
- $\overline{y}$= mean value of the y-variable (actual price) in a sample

3.4.5. Hedonic model

The hedonic model is often used in the housing market to explain the variation of prices in residential properties. This regression predicts the value of an outcome from other variables. In this model, the property price is an outcome dependent on the value of other factors (explanatory variable). In other words, the HPM considers the price of a residential property or other goods as a combination of internal and external attributes, so the hedonic regression is used to measure the relative importance of these attributes (explanatory' variables). As a result, to determine the property's price, considering the property's characteristics (such as the size or age of the building, etc.) and its surrounding environment is essential.

The price of a house can be summarised by applying HPM as below, where the price of a house (y) is a function of other indicators such as structural, locational, and environmental factors (X).

$$y=b_0+b_1X_1+ b_2X_2+\ldots\ldots\ldots\ldots..+ b_nX_n+\varepsilon_i$$

3.5. Methods used for inclusion of the 3rd dimension

Extensive methods and tools are used in the different studies working on 3D modeling. In the studies focusing on quantifying the impact of 3D indicators on the real-state market, different Levels of Detail (LOD) were employed based on the data's availability or the sample size. Generally, in most prior studies that focused on measuring the value of the view in real estate valuation, the LOD1 or LOD2 were applied. Hence, based on the available data and former research, this study required a model with Level of Detail 1 to conduct the analysis.

The applied data for this section includes sale price, coordinate of the transacted property, area, transaction date, and height information. The main technique that usually is used to measure and assess the influence of environmental factors is to construct a viewshed index (Lee et al., 2020, Ying, 2019, Yu et al., 2007). Hence, for quantifying the effect of environmental factors (view) on residential property price, some form of variables is needed to capture the extent and type of the visible view.

According to a study conducted by Yu et al. (2007), the view variable should reflect:

- Observer’s orientation
- Observer’s height elevation
- The height of the surrounding buildings
- The surrounding topography and,
- Type of view such as water, city, nature.

Therefore, CityEngine software (a rule-based modeling tool) was applied to analyze the effects of the three-dimensional spaces. It is widely used to represent the 3D city models by integrating the spatial information and all the relative information of the buildings, which can be used for further analysis or visualization purposes.
In this study, the view effect was split into five variables that capture the type and extent of the visible land uses. All variables are constructed with the assistance of the viewshed tool in the CityEngine software. The first step was to generate a Digital Elevation Model (DEM) of the study area. Then the buildings were generated by extruding the footprint of the buildings based on their actual height, and categorized land uses were imported into the software environment. Finally, the viewshed operation was conducted to capture the proportion of different visible land uses of each transacted high-rise building.

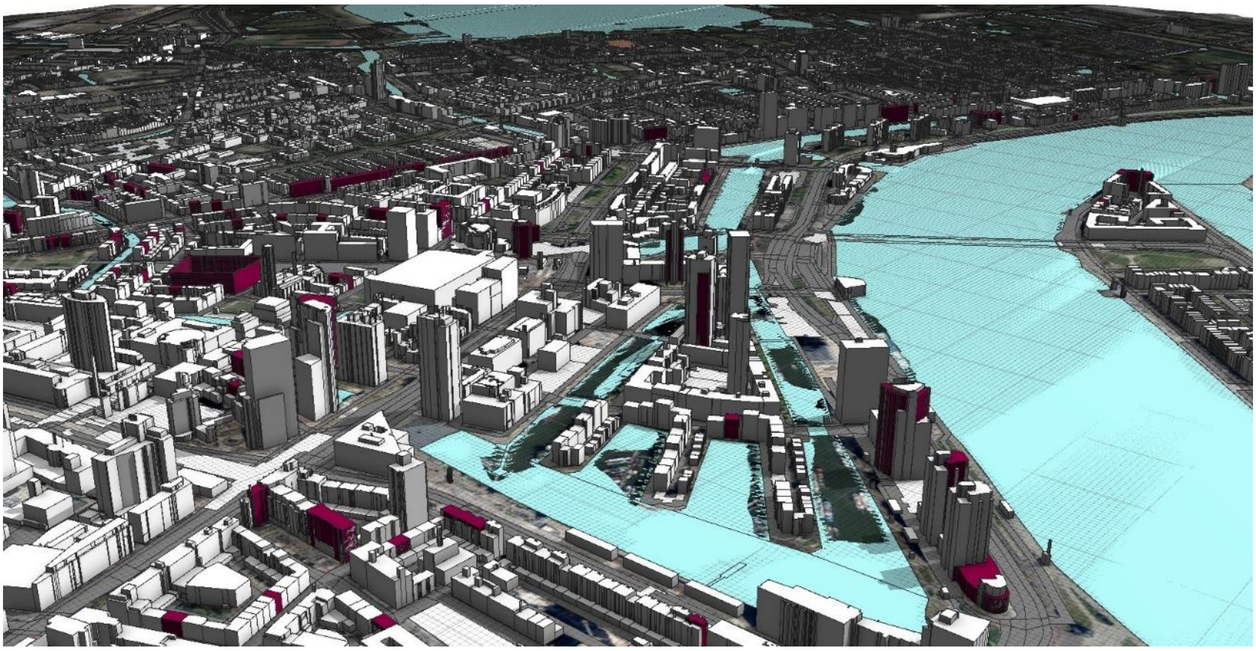

Figure 3-7: visualization of part of the study area (red color buildings belong to a selected sample of apartments)

In the process of generating the 3D model of the city, the parameters such as the angle of observers or their height can be set based on the user's needs. For example, the view distance can be set, as can be seen in Table 3-3. In this study, 500 meters has been considered as the view distance of the observers since at a distance further than 500m, people's vision starts blurry (Ying, 2019). Moreover, due to a lack of specific information about the purchased property's floor level or the building's orientation, in this study, all the observers for the viewshed analysis were considered in the middle of the buildings, and the viewshed was set based on the open visible view (either panorama view if four sides of the building were open, or two sides of the building in case the sample was a terraced house). Since this section focuses on evaluating the effects of building height on the property's price, the buildings with three or higher stories have been selected. The sky view and variation of view type are more visible in the higher buildings compared to the viewshed are located in the middle of the selected building. In this way, the viewshed of the selected buildings with lower height can have a limited view of the surrounding environment since the adjacent building cover their view.

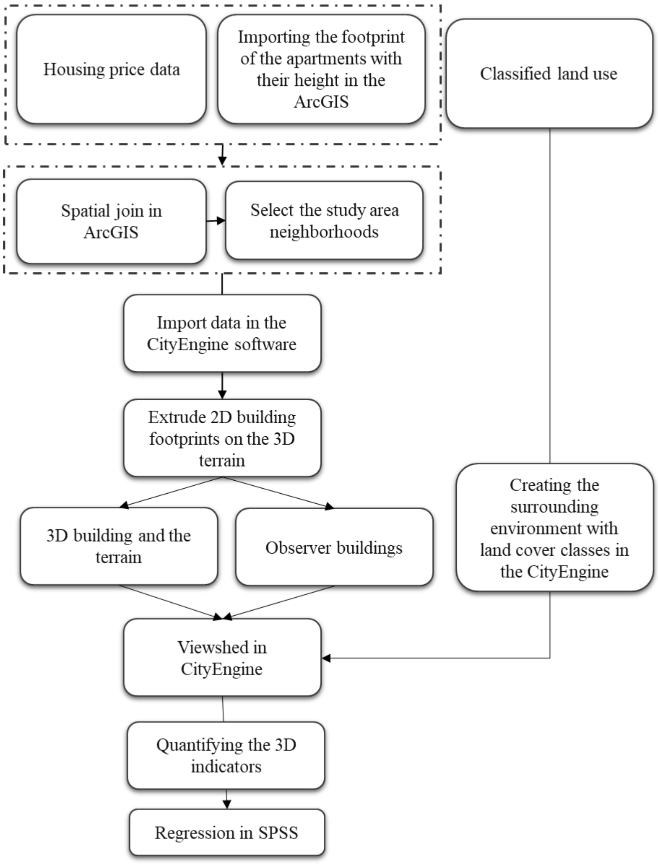

Figure 3-8: The flow diagram of 2D modeling

3.5.1. Viewshed analysis

Viewshed analysis tool in the CityEngine can visualize and quantify the 3D indicators such as sky view or the building and land cover views considering the set parameters (Table 3-3). In the created model, the categorized environmental layers consist of paved, built-up, roads, water, green, and sky view. This tool quantifies the ratio of the visible area of different view types to the total visible area. The formula is as it is shown in the following:

$$\text{Viewshed analysis} \quad \frac{\text{Area of visible view types}}{\text{The total visible area}}$$

Table 3-3: the parameter setting of the viewshed analysis (https://doc.arcgis.com/en/cityengine/latest/help/help-viewshed.htm)

Parameter	Description
Horizontal Angle of View	Horizontal angle of view, or field of view, from the observer
Vertical Angle of View	The vertical angle of view, or field of view, from the observer
Observer Point X	X-coordinate of observer
Observer Point Y	Y-coordinate of observer
Observer Point Z	Z-coordinate of observer
Tilt Angle	Camera view angle from -85 to 85 degrees
Heading Angle	Camera view angle from -360 to 360 degrees
View Distance	Distance between observer and point of interest

4. RESULTS

This chapter provides the quantitative analysis result in line with the mentioned research sub-objectives in the first chapter. Section 4.1 indicates the result of the property price assessment in Rotterdam and describes the potential indicators selected for the 2D data (structural and locational indicators). Sections 4.2 and 4.3 elaborate on the results of the influence of different indicators on the housing prices model for the time before and during the pandemic. Finally, section 4.4 shows the result of the 3D indicators analysis in the hedonic pricing model.

4.1. The general result of the property price assessment

As shown in Figure 4-1, the overview of the dataset (from 2009 to 2021) indicates that the number of transactions usually increases each December, which is the seasonal effect on the real estate market that applies to the whole of the Netherlands, and it is not specific to the Rotterdam. Then it experiences a drop in the following months. It shows that there has not been any unexpected fluctuation in the number of transactions since February 2020, when the pandemic started in the Netherlands.

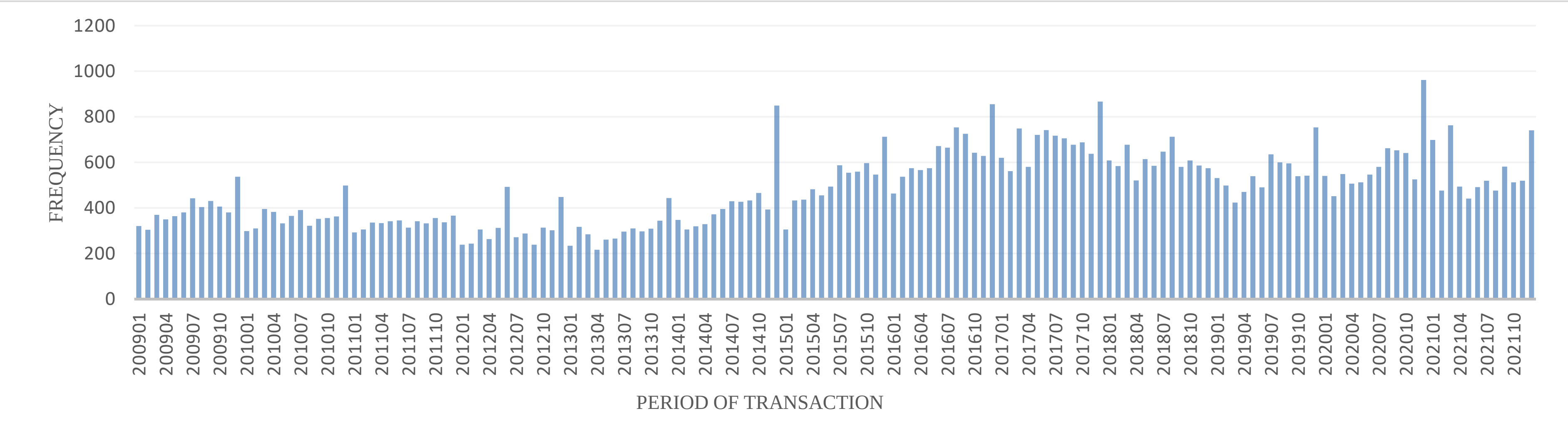

Figure 4-1:Frequency of the house transactions between 2009 to 2021

On the other hand, a deeper look at the number of residential property transactions in different districts (Figure 4-2) shows some unusual patterns. Even though there always has been a fluctuation in the number of purchased houses during different months of the year, the number of transactions in December 2020 (when the government regulation for the curfew was announced) the number of transactions dramatically rose (especially in the Charlois district). However, after the mentioned rise, the trend returned to its usual pattern and decreased again. One of the reasons for this considerable rise in the number of transactions in December, apart from the announcement of curfew, can be the new government rules regarding the taxes. In September 2020, the government announced that from the first of January 2021, taxes would increase for house buyers who purchase a house for investment. Based on this new rule, when people buy a house, not for their own use (so to rent out), they have to pay 8% instead of 2% (which it was before). This caused investors to buy a lot of houses in the last month of 2020, especially in the Carlos region, due to lower house prices.
Although the provided dataset filters out most of those buyers (as it focuses on homes bought by private individuals, it does not filter out all as there are also private individuals that buy houses as an investment (to rent). This might also explain the higher number of transactions in December 2020.

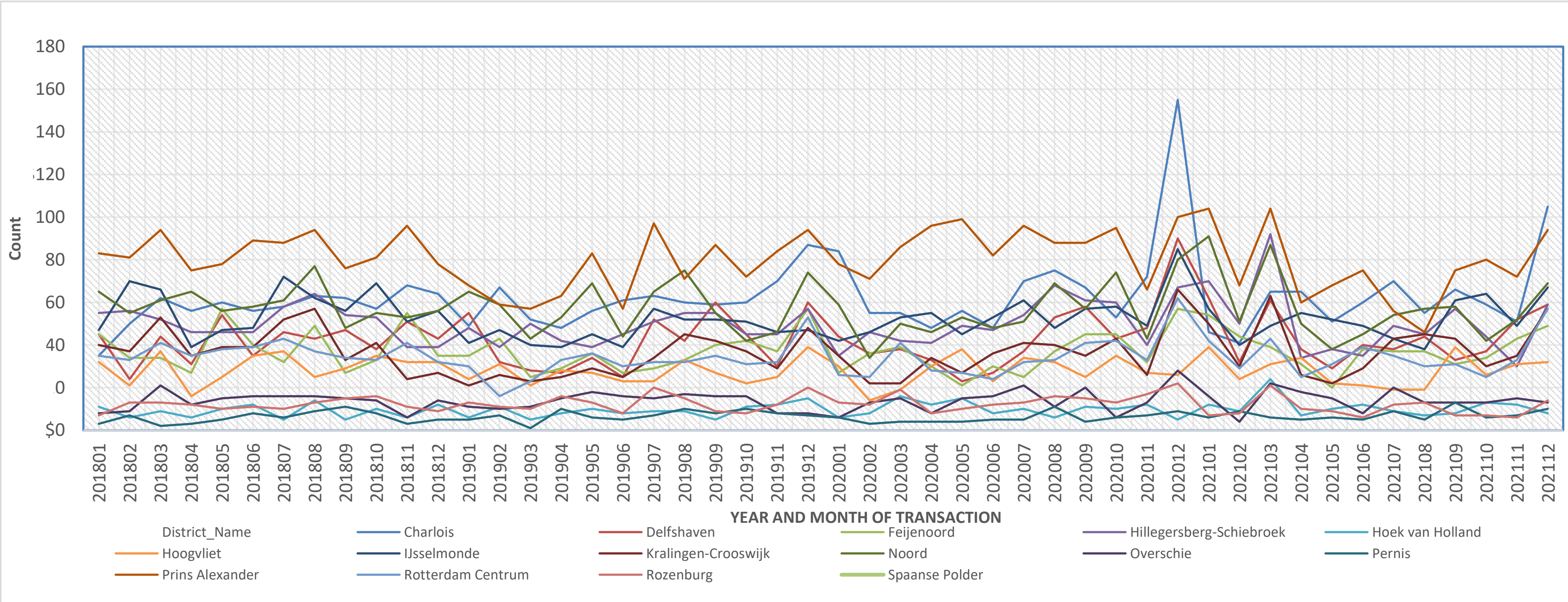

Figure 4-2: number of the house transactions in different districts within the Rotterdam (2018 to 2021)

Finally, the sale price of residential properties (euro/m2) has been applied to compare the house price variation in the different neighborhoods of Rotterdam. The percentage of house price growth (euro/m2) has been calculated to reach better insight into the comparison of prices before and during the pandemic (Figure 4-3). The result shows a considerable difference in house prices in 2021 (an increase of more than 20 percent).

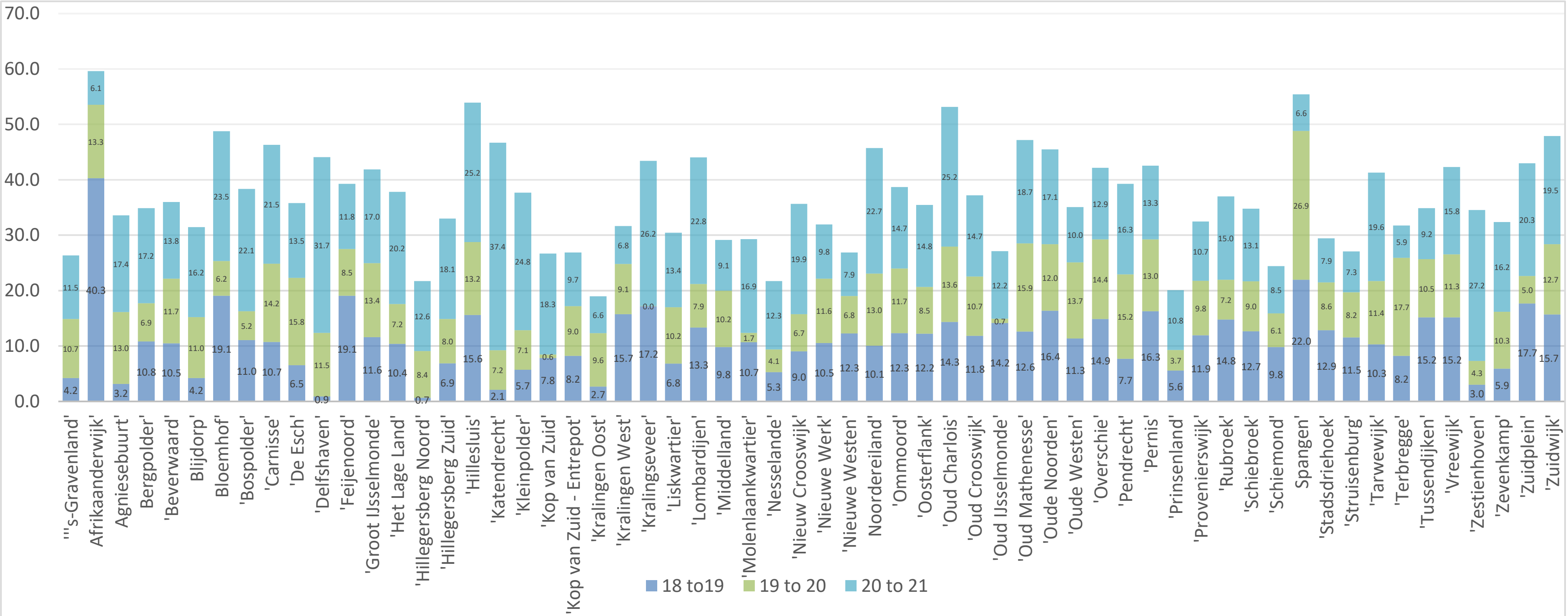

Figure 4-3: Percentage of house price increase (euro/m2)

A close look at some of these neighborhoods (Figure 4-4: Percentage of house price increase (euro/m2) from 2020 to 2021) illustrates that the areas that experienced the highest increase in 2021 can be categorized into two different groups. The first group is the areas surrounded by water and green areas or the ones that are further from the dense area of the city center. The second group is the high-density neighborhoods which have been identified as deprived neighborhoods of Rotterdam.

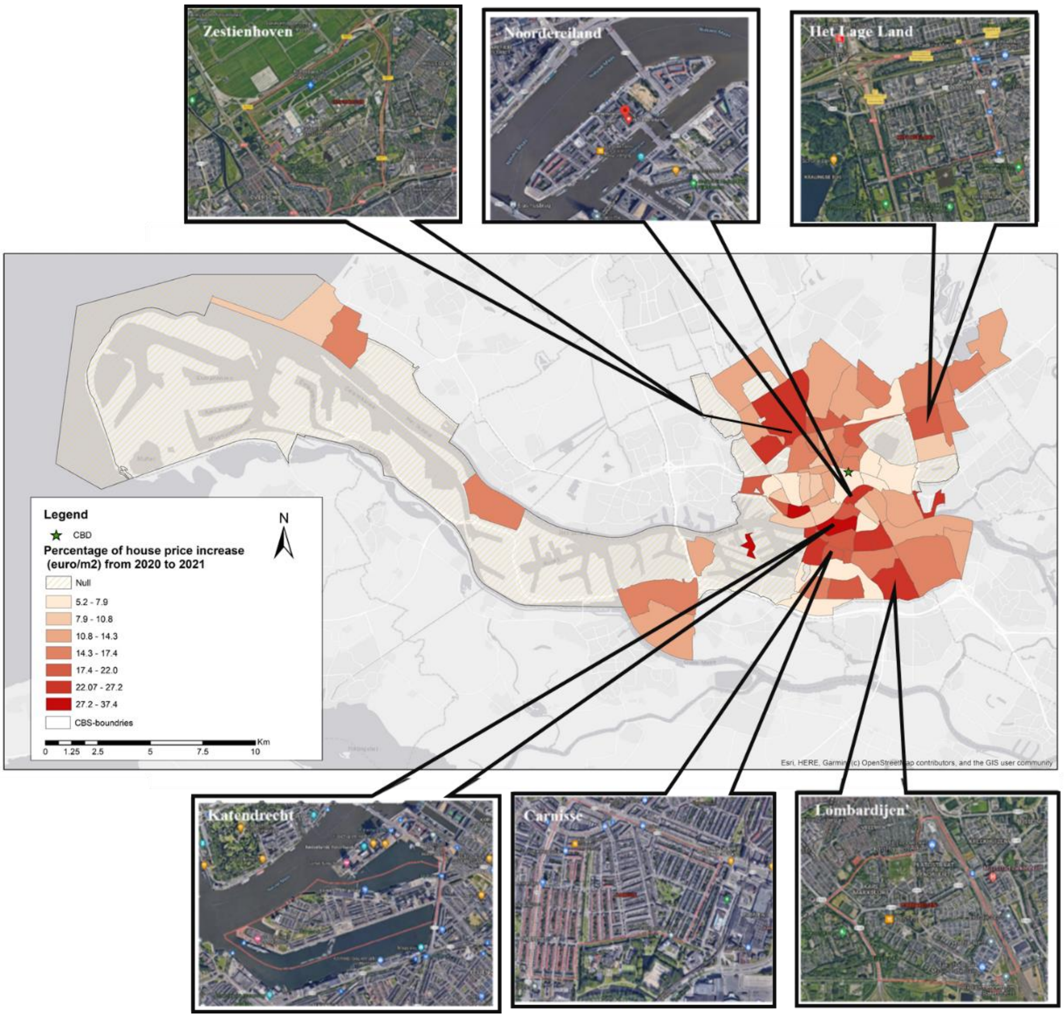

Figure 4-4: Percentage of house price increase (euro/m2) from 2020 to 2021

Based on the studies, one of the reasons for the increase in the house price in the deprived neighborhoods (in the appendix: Figure 7-5) in Rotterdam is the increase in popularity of these neighborhoods for first-time buyers and investors. Because of the tight market in Rotterdam, prices are rising rapidly, and many investors are also active in purchasing properties for rental, it is more probable that first-time buyers intend to buy their first house in the derived neighborhood due to the affordability of the housing price (*Deprived Neighborhood More Popular with First-Time Buyers: "Due to High House Prices" | RTL News*, n.d.). Hence, the increase in demand for buying a property in these areas has led to a considerable increase in price.

In the next step, hotspot analysis (Getis-Ord Gi*) was applied to identify any spatial distribution of the original house price data (euro/m^2) within the city's boundary (CBS boundary: Wijk- en buurtkaart 2020). In Figure 4-5, the red areas indicate a greater concentration of high price properties (euro/m2) in the ArcGIS. The spatial distribution of the house price from T1 to T3 illustrates that most high-priced residential areas are in the north and center of the city, while the concentration of the lower houses price is in the southern part or around the industrial area of Rotterdam. The comparison of these three maps also shows that the distribution of the property prices has been relatively constant within the city before and during the pandemic; however, there has been an increase in the price of the properties in all the neighborhoods.

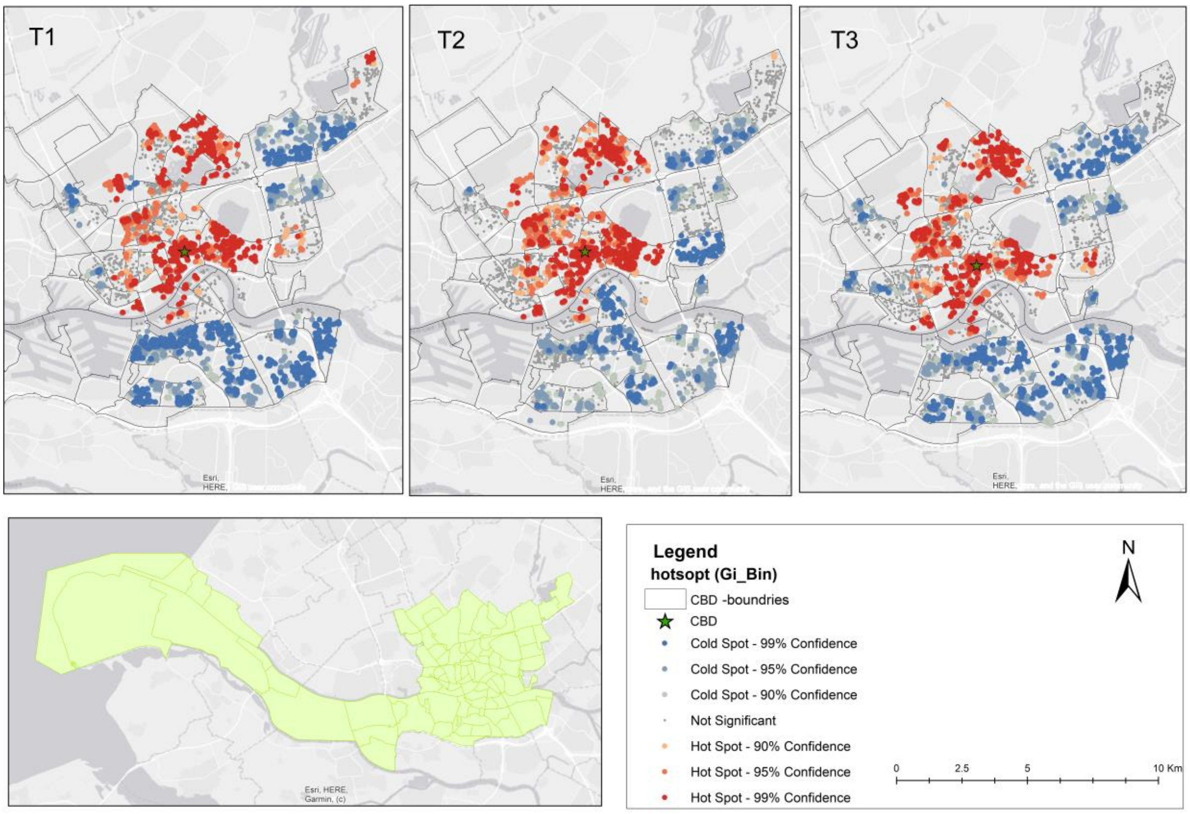

Figure 4-5: Housing prices hotspot map
(T1-from February 2019 to January 2020), (2-from February 2020 to January 2021), (3-from February 2021 to December 2021)

4.1.1. Determination of the potential indicators

This section determines the potential drivers for housing prices based on data availability, analysis of the study region, and related research.

Table 4-1:Indicators

Indicator	Attribute	Definition
Property price	Dependent variable	The price of the transacted residential areas
Area		Square meters of the living area (m2)
Age of the residential area		(Calculated by subtracting the construction year from the transaction month (in years).
House Type	Structural	Detached house (value1), semidetached house (value2), terraced house (value 3), corner house (value4), apartment (value5)
Presence of garden		Dummy variable
Distance to park		The distance to the closest public parks
Distance to business		The distance to the closest industrial and commercial areas
Distance to food		Distance to the closest cafes, restaurants, etc.
Distance to University facility		Distance to the closest colleges and libraries
Distance to Educational centers		Distance to the closest kindergartens and schools
Distance to the sports facility		The distance to the closest sports centers, tennis courts or gyms, etc.
Distance to cultural facilities	Locational	Distance to the closest cinema, theater, museum, galleries, etc.
Distance to medical care		Distance to the closest hospital and small medical cares
Distance to CBD		Distance to the Central Business District (CBD)
Distance to supermarket		Distance to the closes hypermarkets
Distance to public transport stations		Distance to the closest public transport stations
Distance to road		Distance to the closest primary or secondary roads
The density of the district		The degree to show the level of urbanity

4.2. Result of random forest

This model applies locational elements (geospatial data) and structural elements to explore the extent to which the influential variables on the property price have changed before and during the pandemic. By considering the correlation between the indicators in the Pearson's correlation (appendix: figure7-2), two variables were deleted after the assessment of the correlation analysis. In the Pearson's correlation, the distance to cultural facilities with the distance to the central business district (CBD), and the house type 5 with garden 0 were highly correlated, so these variables were omitted.

Data in different variation intervals can adversely affect each other and the algorithm. Hence, the data should be in an equal range relative to each other; for example, each should be in the same range from 0 to 1. Hence, in this way, the x values were normalized. In addition, the Y values (transacted property price (euro/m^2)) were replaced with the logarithm of base 10 to reduce the dispersion and normalize the data for investigation of changes. In the following, the data is divided into two parts of training and testing in the ratio of 80 to 20 (Empirical studies

demonstrate that using 20-30% of the data for testing produces the best outcomes). Then, by using the cross-validation method, we will look for the appropriate values for the parameters of the random forest model. In this method, to calculate the value of n_estimators, we run the range of 100 to 500 with step 50. Moreover, for finding the optimal value of the max_depth parameter, we go from 50 to 130 with step 10. According to the optimal obtained values, the training data were fit on the random forest model to predict the y values based on the data test.
Table 4-2 indicates the quality of the used criteria in the RF model. The result of the adjusted R square shows a relatively good performance on the test data set with an Adjusted R Square of about 0.68, 0.65, and 0.57 for the T_1, $T_{2,}$ and $T_{3,}$ respectively. As a clarification, it indicates that for the $T_{1,}$ about 68% variation in the changes of the property prices (euro/m^2) can be explained by the selected variables. It also shows that the effect of the chosen variables decreases in the following years; R^2_{adj} for the T_3 is around 10% lower than the R^2_{adj} for the T_1. Moreover, the correlation (Pearson R) between the predicted price and the actual price (test and trained data) is about 0.82, 0.8, and 0.75 for the T_1, $T_{2,}$ and $T_{3,}$ respectively. These numbers illustrate that there is a strong correlation between the test and trained data.

Table 4-2: Result of the model performance

	Results（test data） T_1	**Results（test data）T_2**	**Results（test data）T_3**
R^2	0.6779	0.649	0.57
R^2_{adj}	0.669	0.64	0.558
RMSE	0.0809	0.0765	0.082
RSE	0.322	0.350	0.429
MAE	0.056	0.052	0.059
MSE	0.0065	0.0058	0.006
Pearson R	0.824	0.807	0.759

The scatter plots have been used to identify the association between the predicted value and the actual price in the validation data for the mentioned three years (Figure 4-6). The scatter plots show a moderate association between the mentioned variables since the presented points are relatively fit with the identified shape.

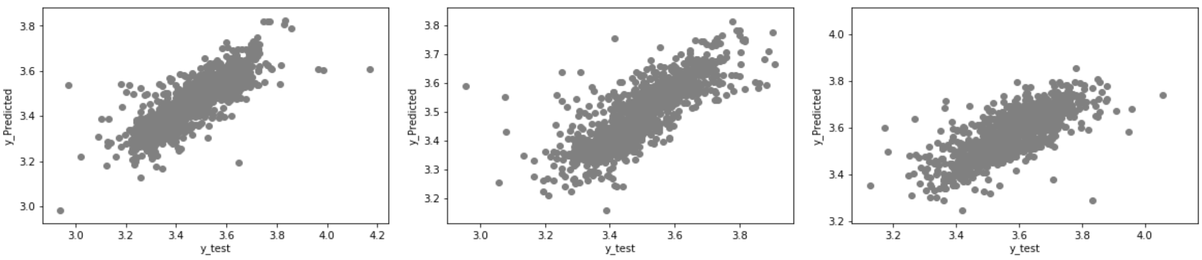

Figure 4-6: Scatter plot of the predicted value (logarithm of base 10) vs. real price for validation data (logarithm of base 10), picture from left T1,T2,T3

In the next section, the importance of each variable based on the Mean Decrease in Impurity (MDI) and permutation importance were examined. It shows how important is the variable for the model. In this process of MDI, a relative decrease in the Gini index is measured. For example, in each decision tree, one independent variable was taken out to measure the decrease in the Gini index (impurity) based on the omitted variable; For the perm_importance procedure, this method will shuffle each feature randomly and calculate the difference in the model's performance. Then, the most important features are those that have the greatest influence on performance. The following Table 4-3 shows the result of the feature importance based on the MDI and permutation.

The result illustrates the most important factors affecting residential property before and during the pandemic. Among the mentioned indicators, the size of the building, proximity to the CBD, average heigh of the building in the 200 m around the sold property, and being in the low-density neighborhood has the highest rank within the mentioned three years. The noticeable difference in the result is that before the outbreak, the distance of the property and its size had the highest rank, while during the outbreak, the rank is related to the neighborhood's density.

Table 4-3: Result of feature importance based on *Mean Decrease in Impurity* (MDI) and *perm_importance*

	MDI 2019	MDI 2020	MDI 2021	PERM_IMPORTANCE 19	PERM_IMPORTANCE 20	PERM_IMPORTANCE 21
AREA OF THE PURCHASED HOUSE (M^2)	0.165	0.079	0.102	0.184	0.338	0.327
BUILDING AGE	0.084	0.055	0.066	0.074	0.058	0.047
DIS TO CLOSEST PARK	0.018	0.019	0.025	-0.001	-0.001	-0.006
DIS TO CLOSEST BUSSINES DISTRICT	0.026	0.025	0.032	0.018	0.011	0.011
DIS TO TO CLOSEST SPORT FACILITIES	0.021	0.047	0.091	-0.002	0.042	0.123
DIS TO CLOSEST ROAD	0.023	0.059	0.035	0.004	0.094	0.018
DIS TO CLOSEST HOSPITAL	0.045	0.029	0.034	0.015	0.016	0.015
DIS TO CLOSEST FOOD	0.019	0.021	0.020	-0.002	0.003	0.000
DIS TO CLOSEST UNIVERSITY	0.023	0.023	0.030	0.005	0.003	0.007
DIS TO CLOSEST EDUCATION	0.019	0.022	0.028	0.004	0.002	0.000
DIS TO CLOSEST MEDICAL CENTERS	0.019	0.021	0.022	0.000	0.002	-0.002
DIS TO CBD	0.292	0.072	0.103	0.861	0.085	0.263
DIS_SUPERMARKET	0.018	0.024	0.024	-0.004	0.003	-0.001
DIS TO CLOSEST SHOPPING	0.034	0.026	0.033	0.009	0.007	0.008
DIS TO CLOSEST PUBLIC TRANSPORTAION STATION	0.020	0.024	0.026	0.001	0.001	-0.004
MEAN OF THE BUILDING HEIGHT	0.062	0.044	0.023	0.086	0.059	-0.003
DENSITY_NE (VERY HIGH DENSITY)	0.058	0.353	0.241	0.078	0.965	0.518
DENSITY_NE (HIGH DENSITY)	0.003	0.003	0.003	0.002	0.001	0.000
DENSITY_NE (MEDIUM-DENSITY)	0.000	0.000	0.002	0.000	0.000	-0.011
DENSITY_NE (LOW DENSITY)	0.000	0.000	0.000	0.000	0.000	0.000
HOUSETYPE (DETACHED HOUSE)	0.007	0.007	0.008	0.004	0.002	0.002
HOUSETYPE (SEMIDETACHED HOUSE)	0.001	0.001	0.007	0.000	0.000	0.005
HOUSETYPE (CORNER HOUSE)	0.005	0.006	0.008	0.000	0.009	0.002
HOUSETYPE (TERRACED HOUSE)	0.002	0.002	0.004	0.001	0.000	0.000
GARDEN_0(NO)	0.017	0.013	0.020	0.011	0.006	0.009
GARDEN_1(YES)	0.019	0.024	0.014	0.021	0.040	0.005

Since the previous result does not explain the nonlinear relationship between the price and the variable, the partial dependence plot was used to interpret the changes precisely. The variables that significantly influence the Gini index (MDI) within the mentioned three years were chosen for further analysis.
The partial dependence plot indicates the interactions between variables and housing prices. As shown In the figures below, the Y-axis is related to the predicted house price, and the X-axis is related to the variables while

holding all other variables constant. The following five common high-rank variables were used to interpret the bivariate relationship between each variable and housing prices.

The first plot (Figure 4-7) shows the relation between the house price and the size of the purchased property (Area (m^2)). The nonlinear relationship between the area of the house and house price demonstrates that once the area reaches the size of 100 m^2, the property's price drops considerably, and once it reaches 200 m^2, the price does not vary in relation to the area. Although the trend for all three years seems similar, the result of the partial dependence plot for 2019 shows a sharper decrease compared to 2020 and 2021. Besides, the comparison of the plot for the three timetables(T_1, T_2, and T_3) shows that after reaching the size of 200 m^2, there is no relationship between the two factors.

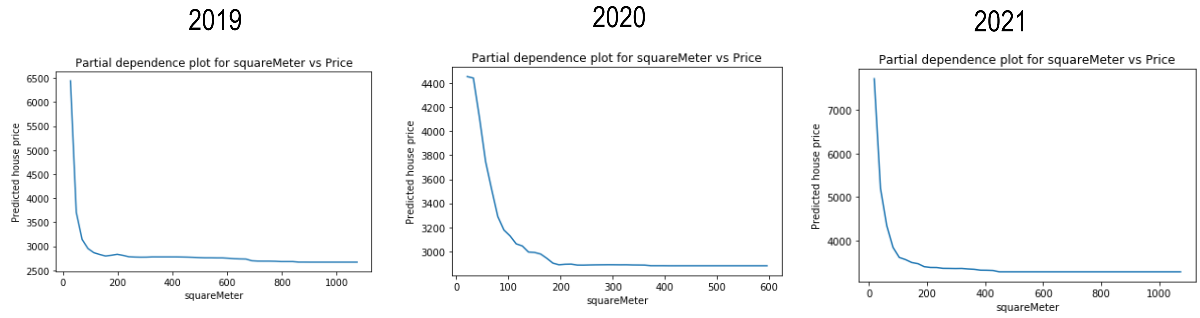

Figure 4-7: The partial dependence plots (relation between the house price and the size of the purchased property (m^2))

The second variable is the relation between the house price and the average height of the buildings around the purchased residential property. The height of surrounding buildings with a height lower than 7m refers to the neighborhoods with less than three floors. This height is usually related to a 2-story Detached or semi-detached house, which is more expansive than other residential buildings. Hence, the price drops when it reaches the mentioned height and rises again (the trend is the same for all the three mentioned years (T_1, T_2, and T_3)). The first timetable shows a relative pause in the house price changes when it reaches the height of 8 to 18 m (3 stories to 6 stories), and then the price increases. Compared to the first graph, this pause in the second timetable is shorter and in the third graph does not exist.

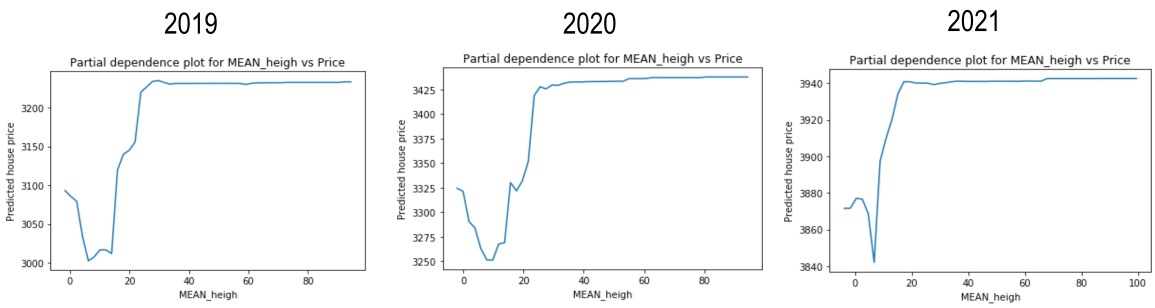

Figure 4-8: The partial dependence plots(relation between the house price and the average height of the buildings around the purchased residential property)

From the third plot, it is apparent that the relationship between the natural logarithm of house price (euro/m^2) and the different types of neighborhood density was relatively similar before the strike of the pandemic; for example, the natural logarithm of the all the neighborhoods with *high, medium and low density* was nearly 8 for the year 2019. However, during the outbreak, the price of residential properties in low-density areas increased compared to the medium-density area. The result of the natural logarithm in the *high* and *low-density* neighborhoods is around 8.3, while in the *very high* and *medium density* is nearly 8.1 for 2020 and 2021.

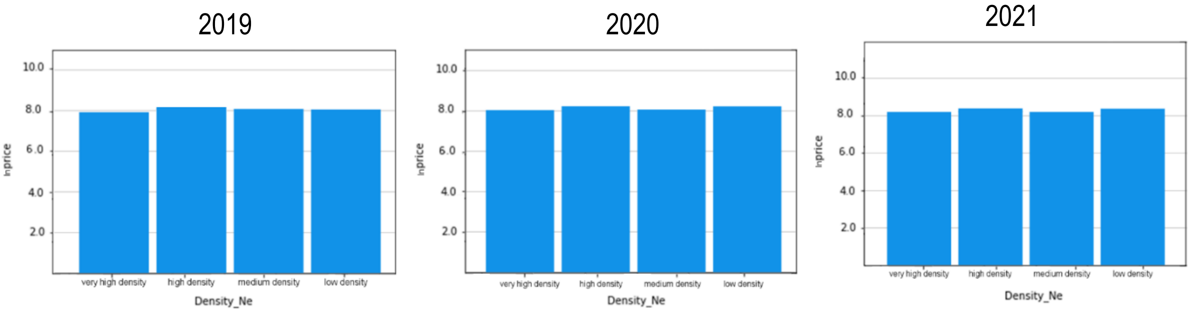

Figure 4-9: The partial dependence plots (relation between the natural logarithm of house price per square meter and the different types of neighborhood density)

The fourth plot (Figure 4-10) shows the partial dependence of the proximity to CBD (Central Business district). As it can be seen in the figure, with the increase of the distance to the CBD from 500 to about 1000 m, the housing price decreased by around 200 euros/m^2 for 2019 and 2020, but the price for the year 2021 relatively remained constant until the distance 2000m from the CBD. The housing prices usually decrease with the increase of the distance since many amenities, businesses, and city attractions are located close to the CBD, which attracts the attention of house buyers. This trend has probably changed in the last-mentioned year (2021) due to the new circumstance that forced many businesses to close.

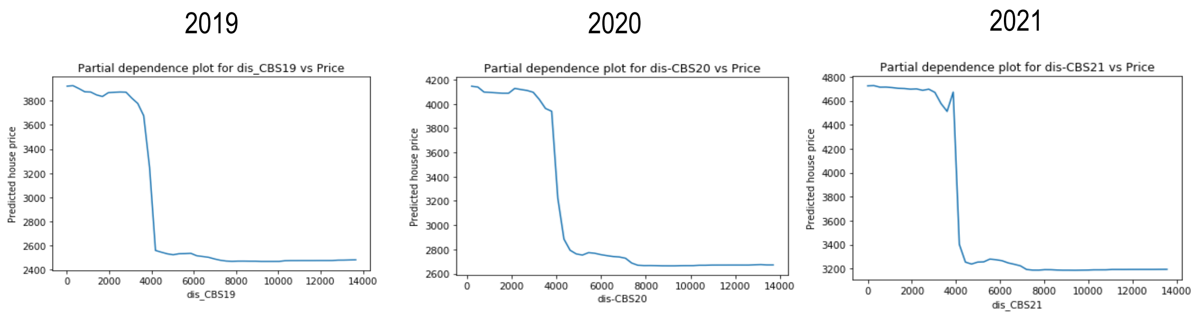

Figure 4-10: The partial dependence plots(the partial dependence of the house price and the proximity to CBD)

The last plot shows partial dependence on the proximity to the open sports fields (football, tennis, golf courts). The 2019 and 2020 show that the housing prices significantly dropped by around 100 euro/m2 when the distance to sports fields increased from 0 to about 1500 m, and housing prices experienced a rise as the distance continued to increase. Compared to the two previous years, the plots for 2021 have a different pattern. Apart from the small fluctuations in the price regarding the distance to the sports fields, the figure shows that the housing price rises as the distance to sports fields increases. As a result, the comparison of all the three timetables illustrates that in the year 2021, after one year of lockdown, being close to the city's sports facilities does not significantly affect the housing prices.

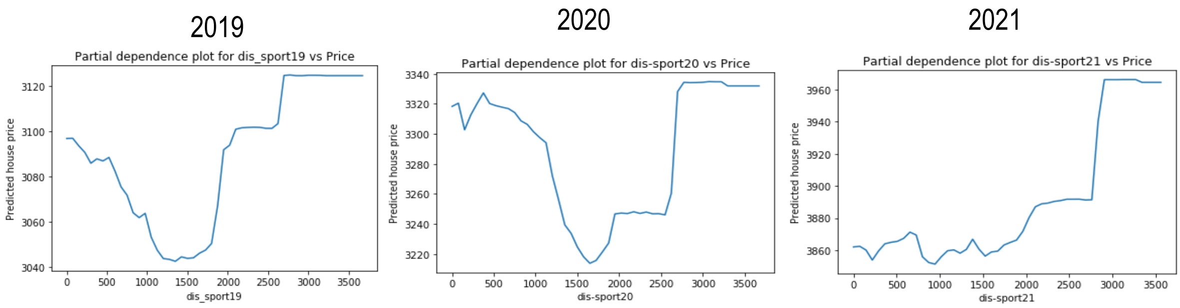

Figure 4-11: The partial dependence plots (partial dependence on the proximity to the open sports fields)

4.3. Hedonic model

In this section, the hedonic pricing model is applied for better interpretation and visualization of the changes in the variables that affect the price of the residential properties within the beforementioned three years. Several ways can be used to get better performance from the data with a nonlinear relationship in linear regression (HPM). For example, one way is to get a natural logarithm from the continuous data such as distance to make it normal or linearize the relationship between two variables. The other way is to break the data and categorize it into several groups. Consequently, the table below shows the relationship between the natural logarithm of the price (euro/m2) and the locational variables used in the previous section. It can be seen in Table 4-4 that the result of the coefficient in the HPM shows that the distance to the CBD, business areas, hospitals, and shopping malls are the top four important variables affecting the price of the residential properties.

In this HPM, the percentage of effectiveness of most of the applied variables is close to zero. Therefore, only the result of the most influential factors will be assessed in the following.

The result of the coefficient related to the **Area** of the residential properties reveals that in the year before the pandemic, a 1 % increase in the housing area led to the decrease of the price by 0.03%, on average, by holding other variables constant. While this trend changed in the coming year, it reached from 0.03% to 0.09% and then to 0.11%. It means the interest of buyers in purchasing smaller size houses has increased.

In this research, the used points for the **business centers** are related to the industrial areas located in the west of the city and commercial areas which are mainly situated close to the city center. The sign of this coefficient is positive, which means that the farther from the business centers, the higher the property price. Generally, apart from the slight decrease in the effectiveness of this element in the year 2020, the influence of this variable on the price of a property has been relatively steady.

The coefficient value for the **closest distance to the primary and the secondary roads** shows that its importance in the first year after the pandemic strike increased slightly and then backed to the initial value in the coming year. The sign of this variable is positive, which means that the farther from the road infrastructure, the higher the property price. Hence, the result indicates that buyers preferred to get further from the road when the pandemic started.

After the distance to CBD (central businesses district), the **distance to the hospital** is the most influential factor on the price of a property based on Table 4-4. The fluctuation of the result for the three mentioned years is the same as the trend for the distance to the roads. It first experienced a rise in the value, and then it decreased. In the year before the pandemic (2019), the value of this coefficient indicates that a 1% increase in the distance to the location of the hospitals leads to a 0.12 % increase in property price, on average, holding the other variables constant. This value increased by 0.03% in the first year of the pandemic, and then it decreased to around 0.05%. Apart from the observed changes within time, it can be seen that the difference in the value of the coefficient is not considerable.

Finally, the most important variable in the executed result of HPM is the **distance to CBD**. The negative value indicated that the farther from the CBD, the lower the property price. In the T1, the influence of distance to CBD on the property price was around - 0.303%, while the trend reached nearly half of its value compared. This coefficient again increased and relatively reached its initial value before the pandemic.

Table 4-4: the result of the hedonic model (detailed tables in the appendix)

	Coefficient T1	**Coefficient T2**	**Coefficient T3**
(Constant)	8.854	8.349	9.312
Ln-Area (euro/m2)	-0.034	-0.090	-0.106
Ln-dis to park	-0.026	-0.032	-0.020
Ln-dis to business	0.061	0.046	0.063
Ln-dis to sport	0.007	-0.001	0.006
Ln-dis to road	0.008	0.020	0.014
Ln-dis to hospital	0.120	0.147	0.105
Ln-dis to food	-0.021	0.006	-0.003
Ln-dis to university facility	-0.004	-0.007	-0.004
Ln-dis to educational centers	0.007	0.003	0.007
Ln-dis to medical centers	-0.003	-0.002	-0.022
Ln-CBD	-0.303	-0.155	-0.269
Ln-dis to supermarket	0.026	0.000	0.022
Ln-dis to shopping mall	0.057	0.046	0.047
Ln-dis to public transport station	0.007	-0.003	0.003
Ln- average height in surrounding area	0.017	0.001	0.013

After getting the result of the hedonic price model, the coefficient of each model was applied for visualization of the land price prediction within the three mentioned years (T1, T2, and T3).

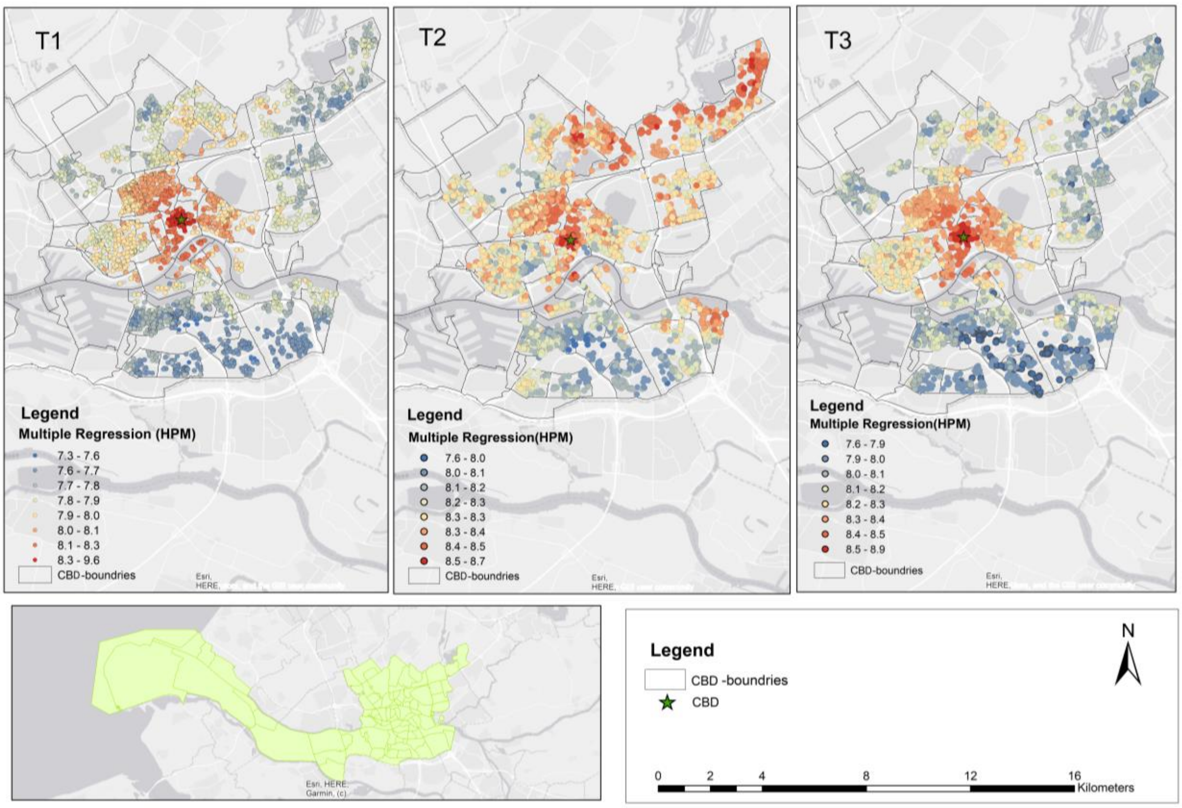

Figure 4-12: distribution of the housing prices based on the applied coefficient in the Hedonic Price Model (HPM)

Figure 4-12 illustrates that during the first year of the pandemic strike, the variables affecting house prices experience a change. As can be seen in the figure above, in the T2, in addition to the concentration of house prices in the center, the pattern of high price property also spread in the city's northern, east-northern, and part of east-southern parts of the Rotterdam. Besides, the dispersion in the pattern of the housing prices can be seen throughout the whole city compared to the T1 and T3. For the T1 and T3, a specific housing price pattern can be detected within the city. The mentioned dispersion in T2 was temporary, returning to its previous pattern before the pandemic.

4.4. The analysis of 3D indicators

Based on the literature review and the previous sections' results, five neighbourhoods with high-rise buildings have been selected for analysis of the 3D indicators. Since the majority of the high-rise building has been located close to the city centre of Rotterdam, five neighbourhoods that had the most transaction related to high-rise building were selected to quantify the influence of the visible proportion of land use (road infrastructure, green area, and water), and sky view.

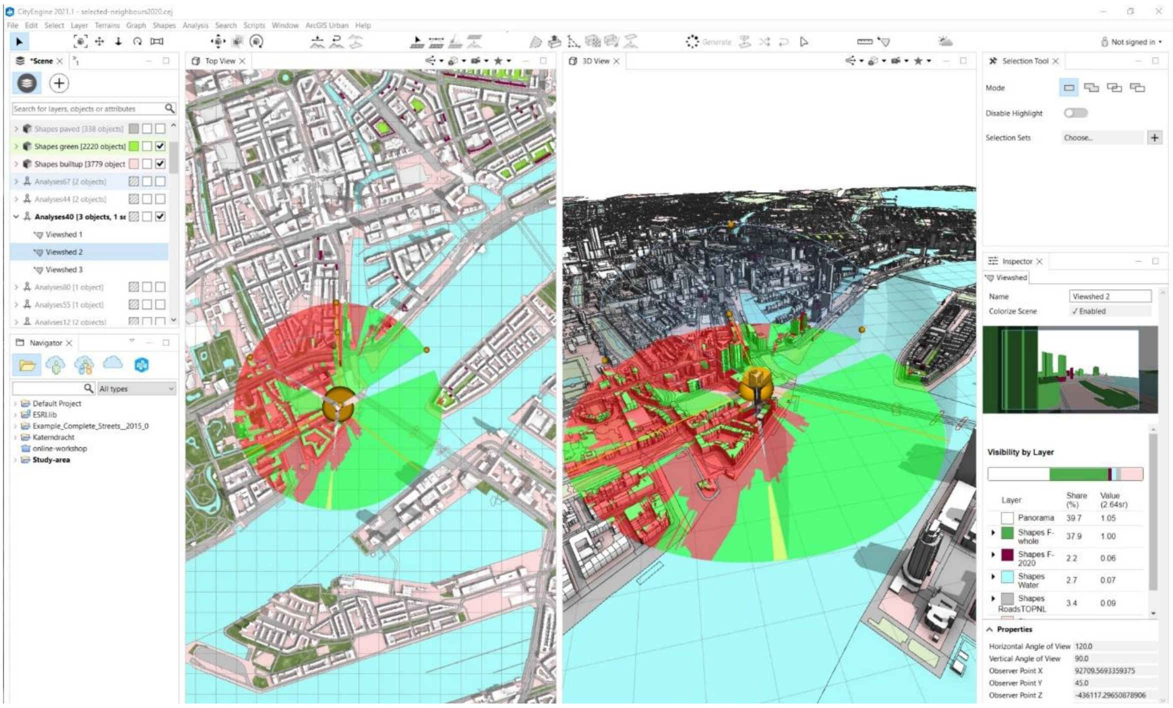

Figure 4-13: Viewshed analysis with the view distance of 500m (the green section illustrates the visible view while the red part shows the views that have been blocked by other buildings (link to the CityEngine WebScene)

Figure 4-14: Viewshed analysis of buildings with different heights with a view distance of 500m

It also should mention that despite the previous section that RF and OLS (hedonic model) regression has been used, in this section, the only hedonic model has been applied due to the limited number of data. For applying the RF model, a vast number of data is needed to be trained by the model and tested, but the used data in this part for all three timetables is nearly 150.

The table below shows the overall result of the model performance for all three years.

Table 4-5: Model performance

	T1	T2	T3
R Square*	0.591	0.459	0.470
Adjusted R Square*	0.574	0.440	0.448
Durbin Watson**	0.922	1.821	1.908

* One of the aspects that should be checked regarding the generalizability is R Square and Adjusted R Square scores in the multiple regression. When values of these elements are very close, it shows that the model can be generalized.

** Durbin-Watson: This element shows the independence of error, and errors should not have autocorrelation (values range 0-4, not below1 and above 3); the model can be considered more generalized by choosing the variables which the result of their Durbin-Watson is more close to 2.

Table 4-6 shows the statistical result of the hedonic model for the 3D indicators for years before the outbreak and the first and the second year after the strike of the pandemic. The screenshots in SPSS are shown in the appendix. As it is shown in Table 4-5, the result of the adjusted R square is lower than in the RF model and higher than the adjusted R square in the hedonic model created with the 2D indicators. The statistical result of the VIF and Tolerance also shows the positive autocorrelation in the applied data. Since the VIF is far less than 10 and Tolerance is higher than 0.2, it indicates no collinearity exists among the data.

Table 4-6:The comparison of the result of the 3D variables

Variables	T1				T2				T3			
	Standardized Coefficients	Sig.	Collinearity Statistics		Standardized Coefficients	Sig.	Collinearity Statistics		Standardized Coefficients	Sig.	Collinearity Statistics	
			Tolerance	VIF			Tolerance	VIF			Tolerance	VIF
Floor area(m^2)	0.53	0.376	0.800	1.249	-0.126	0.034	0.932	1.073	-0.323	<0.001	0.711	1.407
Ln-building height	0.12	0.843	0.752	1.329	-0.133	0.057	0.673	1.486	0.035	0.596	0.856	1.168
Sky	0.298	0.001	0.600	1.668	0.231	<0.001	0.782	1.278	0.103	0.248	0.478	2.093
Road	-0.116	0.086	0.631	1.584	-0.197	0.002	0.807	1.239	-.272	<0.001	0.752	1.330
Water	0.326	0.001	0.721	1.386	0.234	<0.001	0.546	1.831	0.216	0.002	0.830	1.204
Green	0.335	0.001	0.723	1.383	0.253	<0.001	.672	1.487	0.201	0.009	0.643	1.556

For comparison of the result in tables 4-6, changes in the coefficient values were assessed. In this way, the extent of alteration for the time before and during the pandemic was analyzed by quantifying the interaction between each variable for the mentioned regressions (T1, T2, or T3).

The result in the table above indicates that an increase in the view of the road infrastructure has a negative impact on the property price, and this negative impact remained constant during the time of the pandemic. Apart from the fact that the result of the p-value for the road indicator in T1 is insignificant, the result illustrates that the interaction between the road variable and other variables is relatively constant. For example, the difference between the road coefficient and green variable coefficient is around 0.45 for the three mentioned years. At the same time, the influences of other view variables are positive. While the difference between the green and water view coefficients was constant in all three years (nearly 0.01), the difference between the coefficient of the green and sky view experienced an increase of nearly 0.06 in the T3.

Moreover, the standardized coefficients for the floor area variable for the year before the pandemic (T1) show that a “higher area” leads to a higher price per square meter, while this trend changed during the pandemic, and this coefficient shows a negative sign. The sign of the coefficient for the height of the building in the first and third timetables (T1 and T3) is positive, but in the first year of the pandemic strike, it gets negative. It means that in the first year of the pandemic strike, people's interest in the high buildings decreased (it should be mentioned that the result of the p-value for the height variable was not significant for all three mentioned years). The comparison of the results for the three consequent years (2019, 2020, 2021) shows that the proportion of these effects on the price before and during the Covid-19 pandemic has remained relatively constant for the positive views (sky, water, and green area). In this model, the variable related to the view of the built-up area has been removed from the model due to the shown insignificant result and having a negative impact on the result of R square.

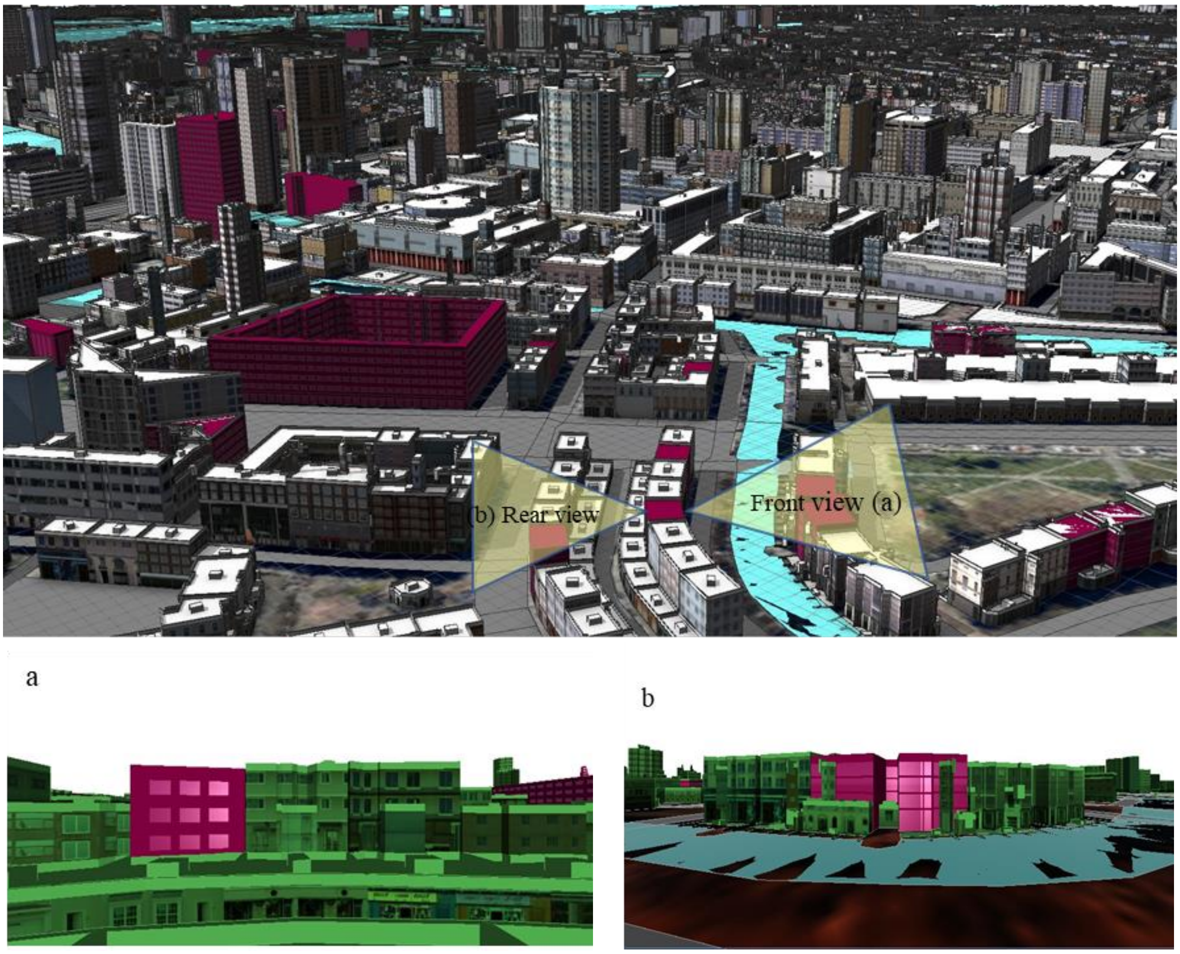

Figure 4-15: Front and rear views of an apartment in Rotterdam, (a) Part of the front view (b) Part of the rear view

5. DISCUSSION

The main object of this research was to detect the potential changes in the price of residential areas and factors that affect the housing prices due to the short-term result of the COVID-19 outbreak. In this section, the study results (from chapter 4) are discussed in line with the mentioned objective and sub-objectives in the first chapter, and its focus is on explaining the findings related to the current literature. Sections 5.1 and 5.2 discuss and summarise the result of the property price assessment in section 4.1 and the regression for the 2D indicators in sections 4.2 and 4.3 and compare the result with the related literature. Section 5.3 explains the result of the regression created by the 3D indicators, and the existing limitation of this study has been discussed in the end.

5.1. Reflection on the result of the property price

Generally, most of the conducted studies that examined the impact of Covid-19 on the housing market showed that significant alterations have occurred in the price and the influential factors that explain the property prices. They also have mentioned that the property's price and the buyers' interest in the suburban areas have increased due to new circumstances resulting from the pandemic (Cheung et al., 2021, Francke & Korevaar, 2021). In contrast, the result of assessing the property prices in Rotterdam and visualizing the concentration of the high-price properties Figure 4-5 is different from the result of other studies. The map in shown in Figure 4-5 indicates that the location of the high property prices pattern has remained constant after the pandemic. Moreover, the assessment of the transaction frequency Figure 4-1 & Figure 4-2 and neighborhoods that experienced the highest price increase (Figure 4-3) illustrate that the fluctuations in the results are not entirely related to the pandemic. One of the reasons that some neighborhoods increased during the previous years in the Rotterdam is due to new tax regulations of the government for the investors; hence it led to the considerable growth of house prices in the southern part of the city due to lower initial price in these areas.

5.2. Reflection on the result of the 2D indicators

Adjusted R^2 in the random forest model and the scatter plots (with the 2D indicators) indicate that the model can be generalized, and the 2D variables can simulate the property price variation in this study. Compared to the RF model, the result of Adjusted R^2 and Durbin Watson (autocorrelation) in the hedonic model was considerably low. For example, the Adjusted R^2 in the RF model is 0.66 and 0.64 and 0.55 for T1, T2, and T3, respectively, while this element (Adjusted R^2) is around 0.32 for all the years in the Hedonic model. The discrepancy in model performance between the two mentioned models might be due to the fact that most of the variables in the models are nonlinear. Although in the hedonic model, the natural logarithm of the variables has been used to reduce the effects of applying nonlinear data in the linear model, the result of the model does not show good performance (Adjusted R^2 of 0.32 and Durbin Watson of nearly 1.1) is. In the other studies in which the hedonic model has been used, the outcome of model performance is usually higher (Oud, 2017, Wittowsky et al., 2020). It can be due to variants of nonlinear indicators such as indicators related to the physical characteristics of the building (number of rooms or bedrooms) or density of amenities at a certain distance from the house instead of the closest distance.

The outcome of the feature importance in the RF model specifies several variables as the most influential factors in the price model. Hence based on this result, the partial dependent plot has been executed to identify any alteration in the variable that influences the house price. The observed alterations in the behaviour of the indicators have been mostly minor since the start of the pandemic. But the plots related to the relationship between the price and sports facilities indicate a considerable change in the second year after the pandemic strike. Moreover, the result related to the changes in the price base on the size of the residential property was against the initial hypothesis since many studies have illustrated that the interest of buyers is towards the houses with the bigger area and more bedrooms (Toro et al., 2021).

It also can be seen in both models (RF and HPM) that the negative impact of being further from the city center (CBD) reduced in the first year of the pandemic (T2). This trend is because buyers get interested in low-density areas to reduce the risk of getting exposed to the covid virus. For example, Cheung et al. (2021) showed that the house price in the epicenters (high-density areas) reduced during the time of the pandemic. At the same time, the house prices in the peripherals (low-density areas) were flattered in the context of Wuhan city in China.
This difference in the results of this study with others can be due to differences in the studied countries and rules conducted by different governments. According to (Dalen & de Vries, 2015), modeling the Dutch housing market in the short-term and during the crisis period does not accurately predict the influence of changes in the explanatory factors. This study further explains that the created model during a crisis based on the transacted prices usually ignores the important variables and provides a poor result during an unstable housing market.

The result for the hedonic model is relatively the same as the result of the RF model. It shows that the coefficient of the variables does not change considerably before and during the pandemic (except for the distance to CBD, the distance to the roads in the HPM, and the distance to sports facilities in the RF model). The only noticeable difference occurs in the distance to sports amenities variable trend. This may be because, during the pandemic, all these facilities were closed for about the total duration after the start of the pandemic; hence this variable lost its importance in the pricing model.

5.3. Reflection on the result of the 3D indicators

As shown in section 4.4, the evaluation of the 3D coefficient for each timetable compared with the coefficient of other timetables reveals that the trend for the different view types remained constant after the pandemic strike. The result illustrates that the view of the road has a negative impact on the property price and the view of the sky, water, and green areas has a positive effect on the property price. Based on the other studies conducted in other countries, such as Italy (Toro et al., 2021), it has been proved that the value of view to the green area in the high-rise buildings in the high-density areas experienced a rise during the pandemic. This rise in the mentioned factors might be because people had to spend most of their time in their houses during the pandemic. During these circumstances, It was predicted that the demand for a better view (such as green areas) experienced an increase during the pandemic. Since sunlight and view quality of floors in the high-rise buildings do not block with other properties, it is predicted that the price of flats in higher levels will rise.
The result of Adjusted R^2 in this section for the 3D variables is higher than Adjusted R^2 for the hedonic model for the 2D variables (Adjusted R^2 for 2D variables=nearly 0.32 and Adjusted R^2 for 3D variables= T1:0.59, T2:0.45 and T3:0.47). This can be due to the fact that the 2D variables are nonlinear, so the result of the model for the 3D data (linear) shows better performance. On the other hand, the model performance of the study conducted by Oud (2017), which applies relatively the same variables in the context of the Netherland, is higher due to the more accurate location of the buildings and the orientation of the transacted floors compared to this research. In the mentioned study, only two-story family houses were applied, which have access to the orientation of installed windows in the house, providing a more accurate view of the outside. Another explanation for the poor model performance in this study and an insignificant result of the p-value for the height variable was the lack of accurate data regarding the height where the observer is located. In this study, only the height of the building was used for analysis instead of the real height where the flat was located.

5.4. Limitations

First, in the process of preparing the 2D data for the regression, some practical steps for preparing the data were skipped due to the time limit. For example, many studies use the number of amenities in a certain buffer around the purchased property instead of considering the closest distance to amenities. But in Rotterdam, due to the existence of several water channels and lakes, the buffer tools could not be used. While for certain amenities such as accessibility to food, the number of facilities that have been located in close proximity to the house is more important than the closest facility.

As mentioned before in section 3.5, in the process of this study, there was a lack of detailed information per property transaction. Hence, to overcome this limitation, we considered the observer in the middle of the apartment's height, and all the possible views were quantified. This way does not genuinely represent the buyer's visible view of the existing surrounded land use by the building. This can be one of the reasons that the result for the adjusted R square is lower than the adjusted R square in the 2D model (RF).

Finally, since the data are not allowed to be shared due to ethical considerations, it can be considered as a limitation that limits further analysis regarding this scope in the future.

6. CONCLUSION AND RECOMMENDATIONS

The previous chapter summarises the main findings and limitations of this study. This chapter presents a conclusion on the main objective and sub-objectives of this research and, in the end, provides recommendations for future works.

6.1. Conclusion

6.1.1. Research sub-objective one

The first sub-objective was to identify the impacts of COVID-19 on property prices through the relevant previous studies. Hence, in the first step, the methods that can be applied to model the residential properties were investigated. The literature review illustrated that the hedonic model is a common model that has been applied for analyzing property prices, but in recent years, new machine learning methods such as Random Forest (RF) are also commonly used due to higher accuracy and handling the nonlinear data compared to the hedonic model.

The factors considered influential on the price of a property are the property's environmental, locational, and physical characteristics, and the concentration of most of these created models are on the 2D data. In the context of the Netherlands, for the prices that are calculated for the taxation, mostly environmental factors would be ignored, but in the transacted price provided by the real estate markets, all the three pre-mentioned factors will be considered. Finally, the previous literature investigating the impacts of the *natural crisis (such as Covid-19)* on property prices and the reaction of buyers indicate that the demand for the residential properties in the periphery area usually rises since people want to get further from the epicenter. These studies also investigate buyers' behavior during the pandemic, and the result indicates that they care more about environmental factors compared to the past due to the new circumstances.

6.1.2. Research sub-objective two

The second sub-objective was to analyze the property prices in 2D within Rotterdam city before and during the pandemic. The assessment of the residential property prices in Rotterdam illustrates that although the percentage growth of house prices has increased significantly in the year 2021 compared to previous years, the concentration of high-price residential properties remained constant before and during the pandemic (central and northern part of the city). Besides, the assessment of the fluctuation in the house transactions cannot directly prove that Covid-19 affected the annual transaction trend in Rotterdam.

The analysis of the influential indicators within three years (one year before the pandemic and the first and second year after the start of the pandemic) illustrates that despite other countries, there are not any significant changes in the relationship of indicators with the house price. The feature importance in the RF shows that the most important indicators over these three years remained constant. According to the HPM results, except for the indicator related to "distance to CBD" and "distance to the roads," the outcome of the feature importance for the applied indicators in the time before and during the pandemic is relatively the same. As a result of the change in the importance of the two mentioned indicators in the first year of the pandemic (T2), the housing price pattern indicates buyers interested in going to lower density areas by purchasing the periphery residential properties. This trend came back to its previous pattern in the second year of the pandemic.

Generally, the result of residential property transactions and the two quantified different models (random forest and hedonic model) indicate that changes in the Dutch housing market are slow, and predicting the effects of a short-term crisis does not reflect the changes accurately. As mentioned above, based on an analysis of micro-level transactions, the change in the spatial pattern of the city was related to the year 2020 (T2), while the growth in the percentage of house prices occurred in the year 2021(T3). Apart from the change in the importance of distance to

CBD and roads, which is most probably due to the spread of the covid-19 disease, there is no proof that COVID-19 is the main reason that affects house prices in Rotterdam.

6.1.3. Research sub-objective three

The third sub-objective was to compare the result of property prices in high-rise buildings by applying the data in the 3rd dimension in the selected neighborhood for the time before and during the pandemic. The visualization and quantifying of the 3D indicators were achieved in the Cityengin software. The results are against the initial hypothesis that in the high-density area in Rotterdam (with mostly apartment house types), the water or green area value will increase due to lower accessibility to open natural areas, just like in suburban regions. The result of the height coefficient in the first year of the pandemic turns negative, which means the higher the building leads to lower the property price. It can be considered as an alignment result with the previous section that distance to CBD lost its importance in the first year of the pandemic since most of the high-rise buildings are located close to the city center.

As a result, the final outcome reveals that the value of high-quality views does not change, but after the pandemic strike, the residential property prices decrease by increasing the height of the building.

6.2. Ethical considerations

All the data required for this study will be provided by the Kadaster organization. However, since the data includes the detail related to the residential buildings, such as microtransaction, size, or the address, there is a concern regarding the privacy and misuse of the data. This situation will be dealt with by making responsible use of the given data for the sole purpose of this research. It will not be shared with anyone without prior written permission from the Kadaster organization, and only the outcome will be presented in the research result.

6.3. Recommendations

The information related to the physical characteristics of the purchased property should be developed further. Physical characteristics of a flat, such as the number of rooms and bedrooms, exitance of the balcony, and the degree of inside maintenance, can more accurately explain the housing market model. In this case that the research tries to investigate the changes in the short-term crisis of the pandemic, this information is crucial since the lifestyle of people and the time that they spend in their house increased compared to the past.

In the analysis of the viewshed, the quantification of the 3D data can be improved by using a higher level of details (LOD) for the buildings. Having the information about the floor that the purchased building has been located and the orientation of the flat can provide the opportunities for the sunlight analysis and identifying the exact view direction of the building. This led to reaching a more accurate result. Hence, by having the orientation of the flat in the building, we can calculate the influence of particular land uses, such as a green area in the different proximity to the building. Also, the information that shows the level at which a house has been purchased can explain the relationship between the price and the height.

Furthermore, introducing more land-use sub-groups to differentiate among the different types of green, agricultural land, green belt, etc., can be beneficial for improving the model. This can provide better information regarding the value of the indicators since, for the buyers, the value of the green area in a public park is higher than the value of the green area in the agricultural land or a green belt.

Finally, other machine learning techniques can be examined in future studies to provide interpretable feature importance. It can provide a better result since the feature importance in the RF model was not interpretable, and the reliability of the HPM model's feature importance was low due to using non-linear data. Also, the machine learning methods can be applied for the 3D modeling and extracting the 3D indicators since the methods used in this research contained manual work, leading to error and lower accuracy.

LIST OF REFERENCES

Adair, A., McGreal, S., Smyth, A., Cooper, J., & Ryley, T. (2010). House Prices and Accessibility: The Testing of Relationships within the Belfast Urban Area. *Http://Dx.Doi.Org.Ezproxy2.Utwente.Nl/10.1080/02673030050134565*, *15*(5), 699–716. https://doi.org/10.1080/02673030050134565

Balemi, N., Füss, R., & Weigand, A. (2021). COVID-19's impact on real estate markets: review and outlook. *Financial Markets and Portfolio Management*. https://doi.org/10.1007/s11408-021-00384-6

Benson, E. D., Hansen, J. L., Schwartz, A. L., & Smersh, G. T. (1998). Pricing Residential Amenities: The Value of a View. *Journal of Real Estate Finance and Economics*, *16*(1), 55–73. https://doi.org/10.1023/A:1007785315925

Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., & Çöltekin, A. (2015). Applications of 3D City Models: State of the Art Review. *ISPRS International Journal of Geo-Information*, *4*(4), 2842–2889. https://doi.org/10.3390/ijgi4042842

Bryson, J. R., & Vanchan, V. (2020). COVID-19 and Alternative Conceptualisations of Value and Risk in GPN Research. *Tijdschrift Voor Economische En Sociale Geografie*, *111*(3), 530–542. https://doi.org/10.1111/tesg.12425

Carroll, T. M., Clauretie, T. M., & Jensen, J. (1996). Living next to godliness: Residential property values and churches. *The Journal of Real Estate Finance and Economics*, *12*(3), 319–330. https://doi.org/10.1007/BF00127540

Chen, L., Ng, E., An, X., Ren, C., Lee, M., Wang, U., & He, Z. (2012). Sky view factor analysis of street canyons and its implications for daytime intra-urban air temperature differentials in high-rise, high-density urban areas of Hong Kong: a GIS-based simulation approach. *International Journal of Climatology*, *32*(1), 121–136. https://doi.org/10.1002/joc.2243

Cheung, K. S., Yiu, C. Y., & Xiong, C. (2021). Housing Market in the Time of Pandemic: A Price Gradient Analysis from the COVID-19 Epicentre in China. *Journal of Risk and Financial Management*, *14*(3), 108. https://doi.org/10.3390/jrfm14030108

Chin, T. L., & Chau, K. W. (2003). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications*, *27*(2), 145–165.

Clapp, J. M., & Giaccotto, C. (1998). Residential Hedonic Models: A Rational Expectations Approach to Age Effects. *Journal of Urban Economics*, *44*(3), 415–437. https://doi.org/10.1006/juec.1997.2076

Croom, B., Kennedy, S., Ojha, S., Sparks, J., Croom, B. ;, Kennedy, S. ;, & Ojha, S. ; (2020). Analysis of the Commercial Real Estate Market in a post COVID-19 World. *SMU Data Science Review*, *3*(3), 5. https://scholar.smu.edu/datasciencereview/vol3/iss3/5

Czembrowski, P., & Kronenberg, J. (2016). Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. *Landscape and Urban Planning*, *146*, 11–19. https://doi.org/10.1016/j.landurbplan.2015.10.005

Dalen, P. Van, & de Vries, P. (2015). *Huizenprijzen vooral bepaald door inkomen en rente Special Inleiding en conclusies*. 1–9. https://economie.rabobank.com/publicaties/2015/augustus/huizenprijzen-vooral-bepaald-door-inkomen-en-rente/

De Toro, P., Nocca, F., & Buglione, F. (2021). Real Estate Market Responses to the COVID-19 Crisis: Which Prospects for the Metropolitan Area of Naples (Italy)? *Urban Science*, *5*(1), 23. https://doi.org/10.3390/urbansci5010023

Del Giudice, V., De Paola, P., & Del Giudice, F. P. (2020). COVID-19 Infects Real Estate Markets: Short and Mid-Run Effects on Housing Prices in Campania Region (Italy). *Social Sciences*, *9*(7), 114. https://doi.org/10.3390/socsci9070114

Deprived neighborhood more popular with first-time buyers: "Due to high house prices" | RTL News. (n.d.). Retrieved June 6, 2022, from https://www.rtlnieuws.nl/editienl/artikel/5267236/achterstandswijk-populair-hoogopgeleiden-gentrificatie-woningnood

Fan, G.-Z., Ong, S. E., & Koh, H. C. (2006). Determinants of House Price: A Decision Tree Approach. *Urban Studies*, *43*(12), 2301–2315. https://doi.org/10.1080/00420980600990928

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Perez, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green, W., Hamlet, A., Hinsley, W., Okell, L., Van Elsland, S., … Ghani, A. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. *Imperial College COVID-19 Response Team*, *March*, 1–20. https://doi.org/10.25561/77482.

Foye, C. (2017). The Relationship Between Size of Living Space and Subjective Well-Being. *Journal of Happiness Studies*, *18*(2), 427–461. https://doi.org/10.1007/s10902-016-9732-2

Francke, M., & Korevaar, M. (2021). Housing markets in a pandemic: Evidence from historical outbreaks. *Journal of Urban Economics*, *123*(February), 103333. https://doi.org/10.1016/j.jue.2021.103333

Garrod, G. D., & Willis, K. G. (1992). Journal of Environmental Management (1992) 34, 59-76 Valuing Goods' Characteristics: an Application of the Hedonic Price Method to Environmental Attributes G. D. Garrod and K. G. *Journal of Environmental Management*, *34*, 59–76.

Helbich, M., Jochem, A., Mücke, W., & Höfle, B. (2013). Boosting the predictive accuracy of urban hedonic house price models through airborne laser scanning. *Computers, Environment and Urban Systems*, *39*, 81–92. https://doi.org/10.1016/j.compenvurbsys.2013.01.001

Herwany, A., Febrian, E., Anwar, M., & Gunardi, A. (2021). The Influence of the COVID-19 Pandemic on Stock Market Returns in Indonesia Stock Exchange. *Journal of Asian Finance, Economics and Business*, *8*(3), 39–47. https://doi.org/10.13106/jafeb.2021.vol8.no3.0039

Hu, L., He, S., Han, Z., Xiao, H., Su, S., Weng, M., & Cai, Z. (2019). Monitoring housing rental prices based on social media:An integrated approach of machine-learning algorithms and hedonic modeling to inform equitable housing policies. *Land Use Policy*, *82*, 657–673. https://doi.org/10.1016/j.landusepol.2018.12.030

Hu, M. R., Lee, A. D., & Zou, D. (2021). COVID-19 and Housing Prices: Australian Evidence with Daily Hedonic Returns. *Finance Research Letters*, *September 2020*, 101960. https://doi.org/10.1016/j.frl.2021.101960

Hulsen, M. Van. (2020). *Het nederlandse coronabeleid als sociaal dilemma*. 17–19. file:///C:/Users/User/Downloads/VGEbulletin_november_2020-vanHulsen-Rohde-Van-Exel.pdf

Jain, S. (2008). Remote sensing application for property tax evaluation. *International Journal of Applied Earth Observation and Geoinformation*, *10*(1), 109–121. https://doi.org/10.1016/j.jag.2007.10.008

Jim, C. Y., & Chen, W. Y. (2010). External effects of neighbourhood parks and landscape elements on high-rise residential value. *Land Use Policy*, *27*(2), 662–670. https://doi.org/10.1016/j.landusepol.2009.08.027

Kim, I. (2021). *Has the COVID-19 Pandemic Changed People's Attitude about Where to Live? Some Preliminary Answers from a Study of the Atlanta Housing Market*. https://smartech.gatech.edu/handle/1853/64677

Kohlhase, J. E. (1991). The impact of toxic waste sites on housing values. *Journal of Urban Economics*, *30*(1), 1–26. https://doi.org/10.1016/0094-1190(91)90042-6

Lee, H., Lee, B., & Lee, S. (2020). The Unequal Impact of Natural Landscape Views on Housing Prices: Applying Visual Perception Model and Quantile Regression to Apartments in Seoul. *Sustainability*, *12*(19), 8275. https://doi.org/10.3390/su12198275

Leech, D., & Campos, E. (2003). Is comprehensive education really free?: A case-study of the effects of secondary school admissions policies on house prices in one local area. *Journal of the Royal Statistical Society. Series A: Statistics in Society*, *166*(1), 135–154. https://doi.org/10.1111/1467-985X.00263

Li, W. E. I. (2020). *The Relationship Between Street Visual Features and Property Value Using Deep Learning*. *March*.

Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the Netherlands. *Landscape and Urban Planning*, *48*(3–4), 161–167. https://doi.org/10.1016/S0169-2046(00)00039-6

Manshanden, W. J. J., & van Oort, F. (2020). *Impact van de corona-epidemie op de economie van Rijnmond, Metropoolregio Rotterdam Den Haag en Zuid-Holland*. 1–55.

Nijskens, R., Lohuis, M., Hilbers, P., & Willem, H. (2019). Hot Property: The Housing Market in Major Cities. In *Springer* (Vol. 206, Issue 3). https://link.springer.com/content/pdf/10.1007%2F978-3-030-11674-3.pdf

Oud, D. A. J. (2017). *GIS based property valuation Objectifying the value of view*.

Qian, X., Qiu, S., & Zhang, G. (2021). The impact of COVID-19 on housing price: Evidence from China. *Finance Research Letters*, *December 2020*, 101944. https://doi.org/10.1016/j.frl.2021.101944

RICS. (2012). Global Comparable evidence in property valuation. *RICS Professional Information Paper, 1st Edition (Part of the RICS Valuation Professional Standards -IP 26/2012)*, 22. www.ricsbooks.com

Schläpfer, F., Waltert, F., Segura, L., & Kienast, F. (2015). Valuation of landscape amenities: A hedonic pricing analysis of housing rents in urban, suburban and periurban Switzerland. *Landscape and Urban Planning*, *141*, 24–40. https://doi.org/10.1016/j.landurbplan.2015.04.007

Toppen, T. P. (2016). *The use of 3D city models in real estate valuation and transactions defining and developing a use case requiring 3D city models in real estate valuation and transaction applications*. https://cesiumjs.org/NewYork/index.html

Toro, P. De, Nocca, F., & Buglione, F. (2021). Real Estate Market Responses to the COVID-19 Crisis: Which Prospects for the Metropolitan Area of Naples (Italy)? *Urban Science 2021, Vol. 5, Page 23*, *5*(1), 23. https://doi.org/10.3390/URBANSCI5010023

Wang, B. (2021). How Does COVID-19 Affect House Prices? A Cross-City Analysis. *Journal of Risk and Financial Management*, *14*(2), 47. https://doi.org/10.3390/jrfm14020047

Williams, A. W. (1991). A guide to valuing transport externalities by hedonic means. *Transport Reviews*, *11*(4), 311–324. https://doi.org/10.1080/01441649108716793

Wittowsky, D., Hoekveld, J., Welsch, J., & Steier, M. (2020). Residential housing prices: impact of housing characteristics, accessibility and neighbouring apartments – a case study of Dortmund, Germany. *Urban, Planning and Transport Research*, *8*(1), 44–70. https://doi.org/10.1080/21650020.2019.1704429

Yamani, S. El, Hajji, R., Nys, G. A., Ettarid, M., & Billen, R. (2021). 3D Variables Requirements for Property Valuation Modeling Based on the Integration of Bim and Cim. *Sustainability (Switzerland)*, *13*(5), 1–22. https://doi.org/10.3390/su13052814

Yang, M., & Zhou, J. (2021). The impact of COVID-19 on the housing market: evidence from the Yangtze river delta region in

China. *Applied Economics Letters*, *00*(00), 1–4. https://doi.org/10.1080/13504851.2020.1869159
Ying, Y. (2019). *Assessment of 2D and 3D Methods for Property Valuation Using Remote Sensing Data At the Neighbourhood Scale in Xi'an, China*. 89. http://essay.utwente.nl/83578/1/ying.pdf
Yoo, S., Im., J., & Wagner, J. E. (2012). Variable selection for hedonic model using machine learning approaches: A case study in Onondaga County, NY. *Landscape and Urban Planning*, *107*(3), 293–306. https://doi.org/10.1016/j.landurbplan.2012.06.009
Yoruk, B. (2020). Early Effects of the COVID-19 Pandemic on Housing Market in the United States. *SSRN Electronic Journal*, *May 2020*. https://doi.org/10.2139/ssrn.3607265
Yu, S.-M., Han, S.-S., & Chai, C.-H. (2007). Modeling the value of view in high-rise apartments: a 3D GIS approach. *Environment and Planning B: Planning and Design*, *34*(1), 139–153. https://doi.org/10.1068/b32116
Zhang, H., Li, Y., Liu, B., & Liu, C. (2014). The application of GIS 3D modeling and analysis technology in real estate mass appraisal - Taking landscape and sunlight factors as the example. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(4), 363–367. https://doi.org/10.5194/isprsarchives-XL-4-363-2014
ZHANG, J. (2019). Developing a comprehensive framework for property valuation using 3D and remote sensing techniques in China. *Library.Itc.Utwente.Nl*, *March*. https://library.itc.utwente.nl/papers_2019/msc/upm/zhang.pdf
Zhao, Y. (2020). US Housing Market during COVID-19: Aggregate and Distributional Evidence. *IMF Working Paper No. 2020/212*, *47*. https://doi.org/https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3744679
Zheng, S., Xu, Y., Zhang, X., & Wang, R. (2016). Transit development, consumer amenities and home values: Evidence from Beijing's subway neighborhoods. *Journal of Housing Economics*, *33*, 22–33. https://doi.org/10.1016/j.jhe.2016.05.003

7. APPENDIX

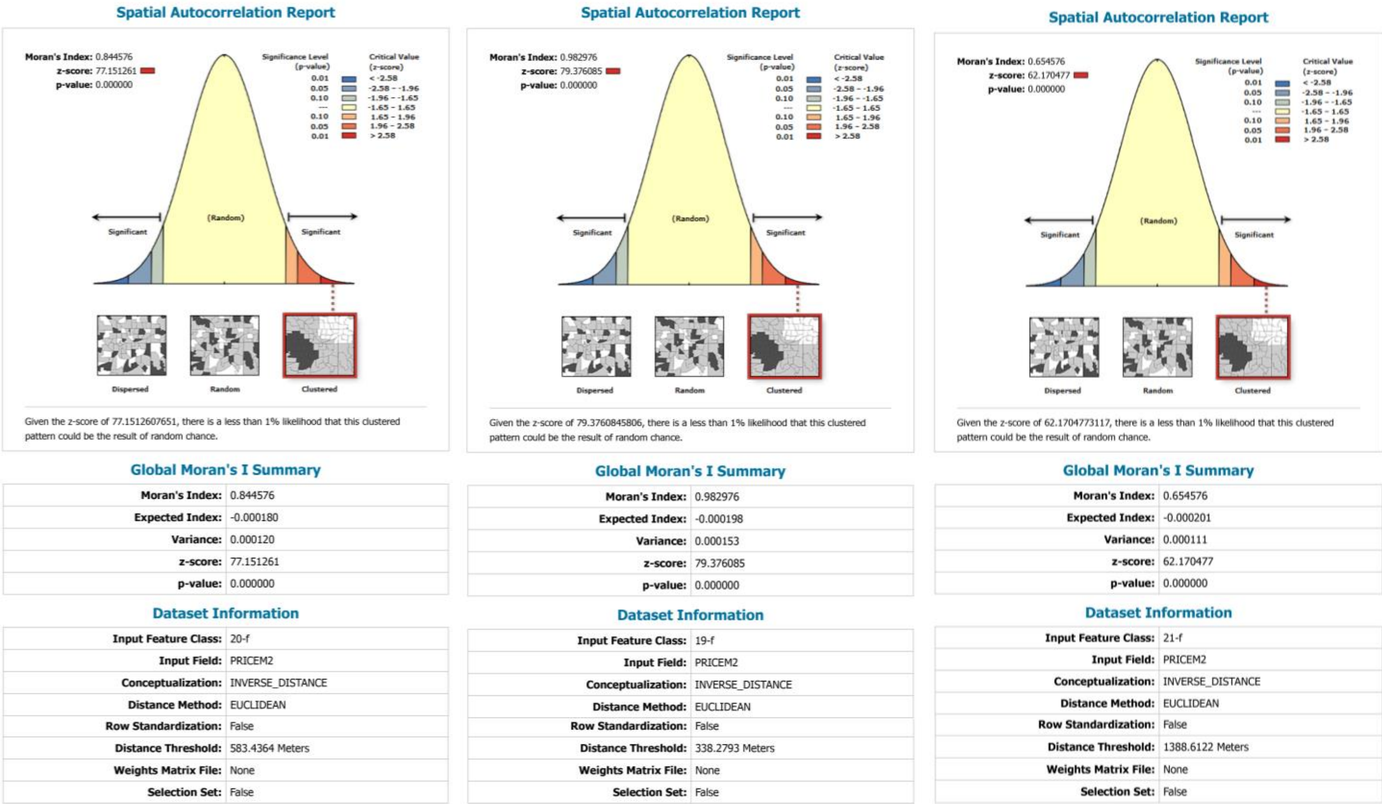

Figure 7-1: The Global Moran's Index report

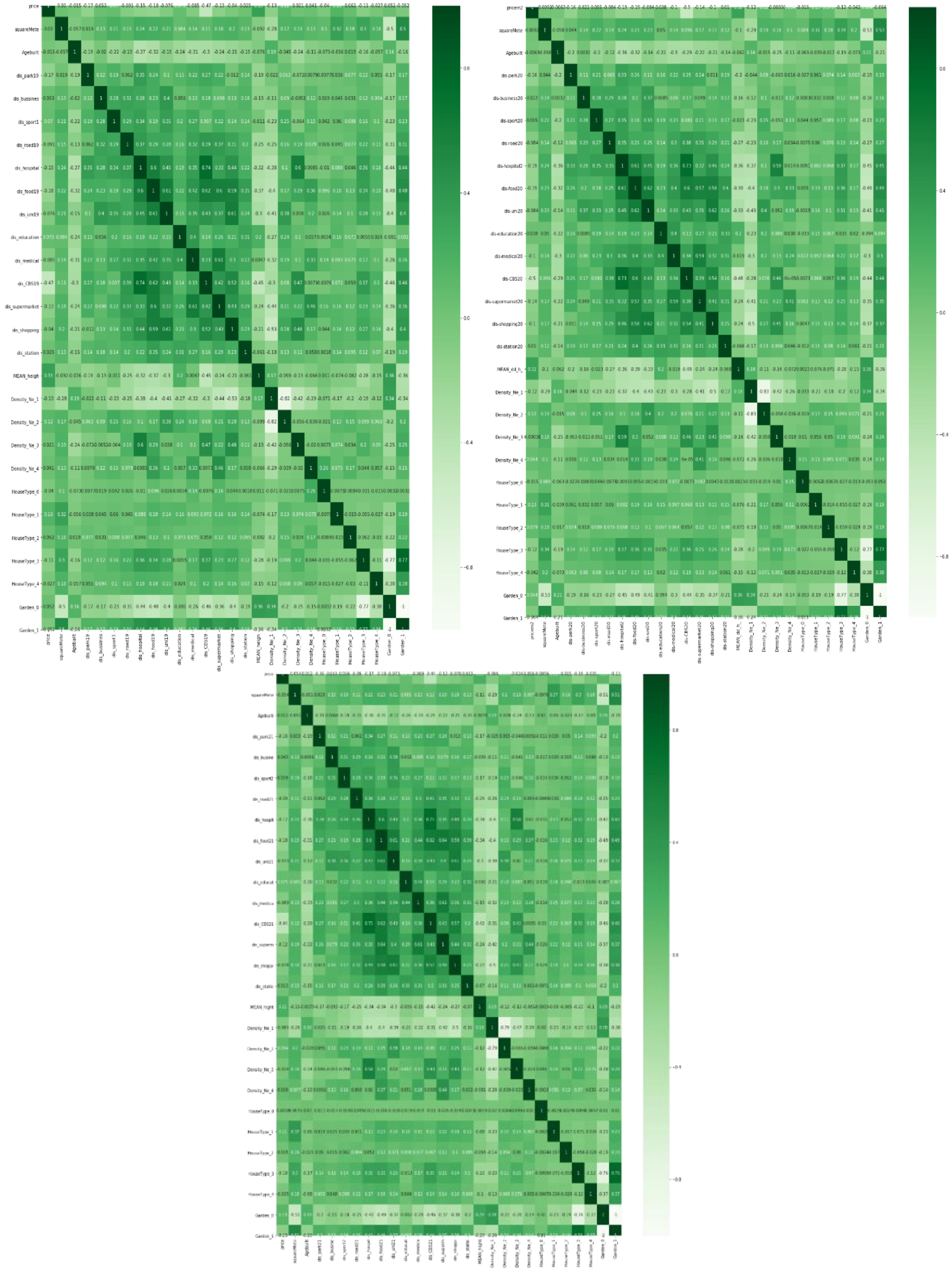

Figure 7-2: Pearson's correlation (left top picture :T1 , and right top picture :T2, and below picture: T3

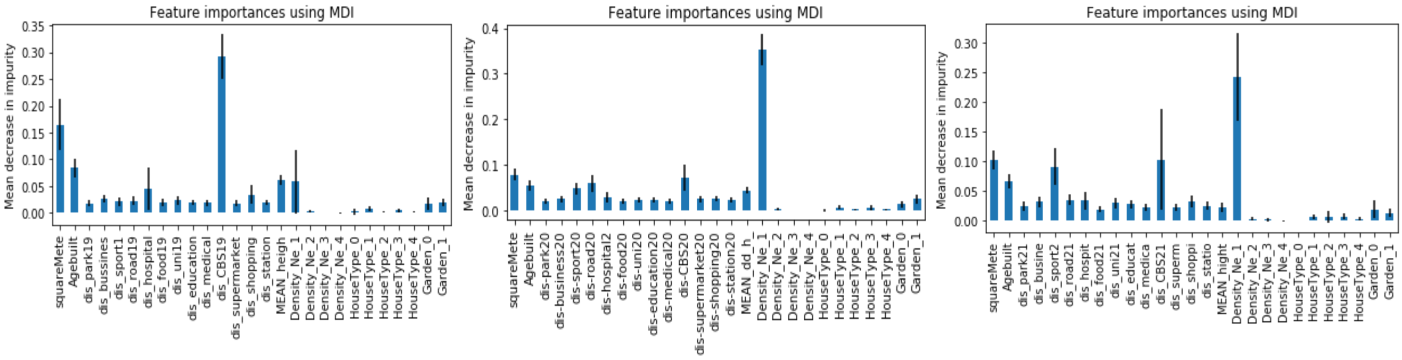

Figure 7-3: Feature importance (MDI) (T1, T2, and T3 from left to right, respectively)

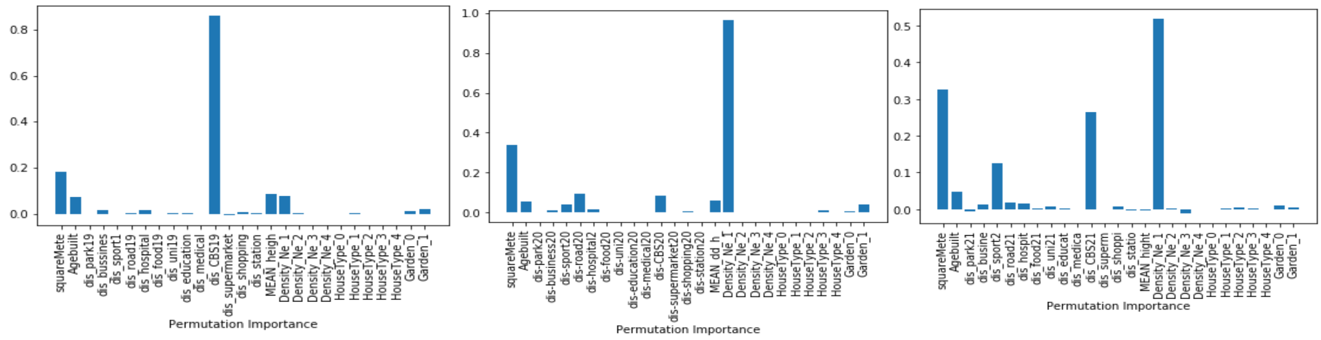

Figure 7-4: Feature importance(permutation importance)(T1, T2, and T3 from left to right, respectively)

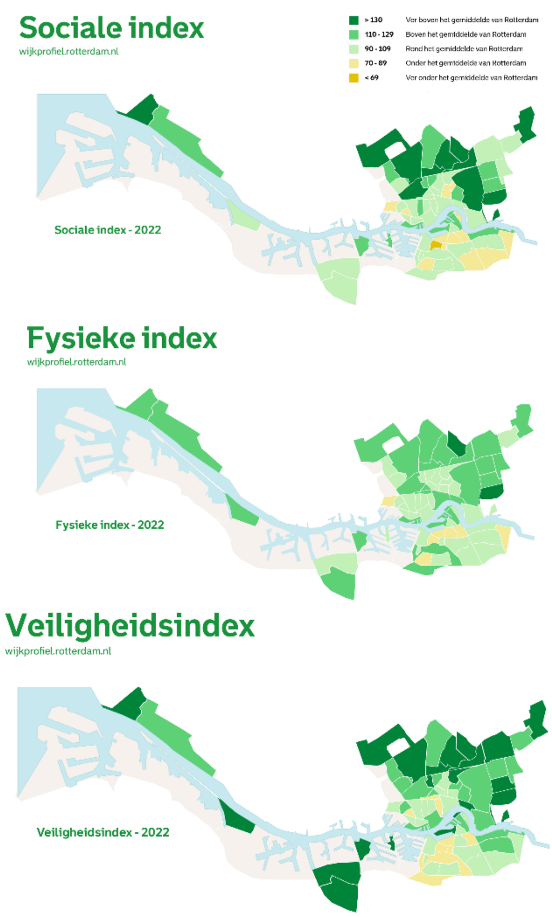

Figure 7-5: Social, physical and safety index in the Rotterdam.
(source : https://wijkprofiel.rotterdam.nl/nl/2022/rotterdam)

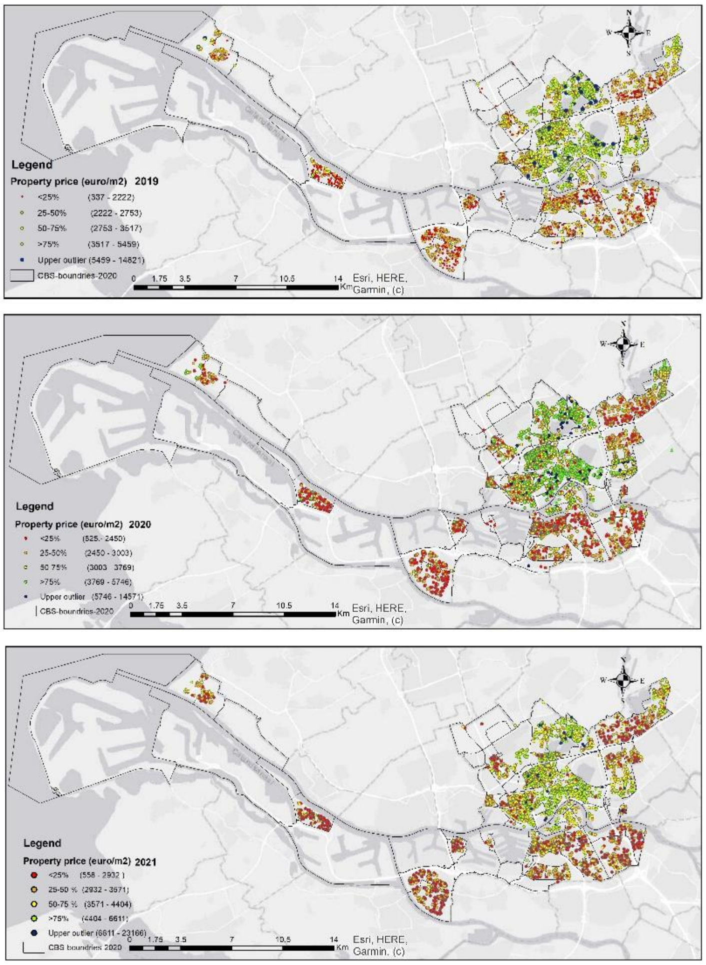

Figure 7-6: Distribution of property prices (euro/m^2)
(years 2019,2020,2021)

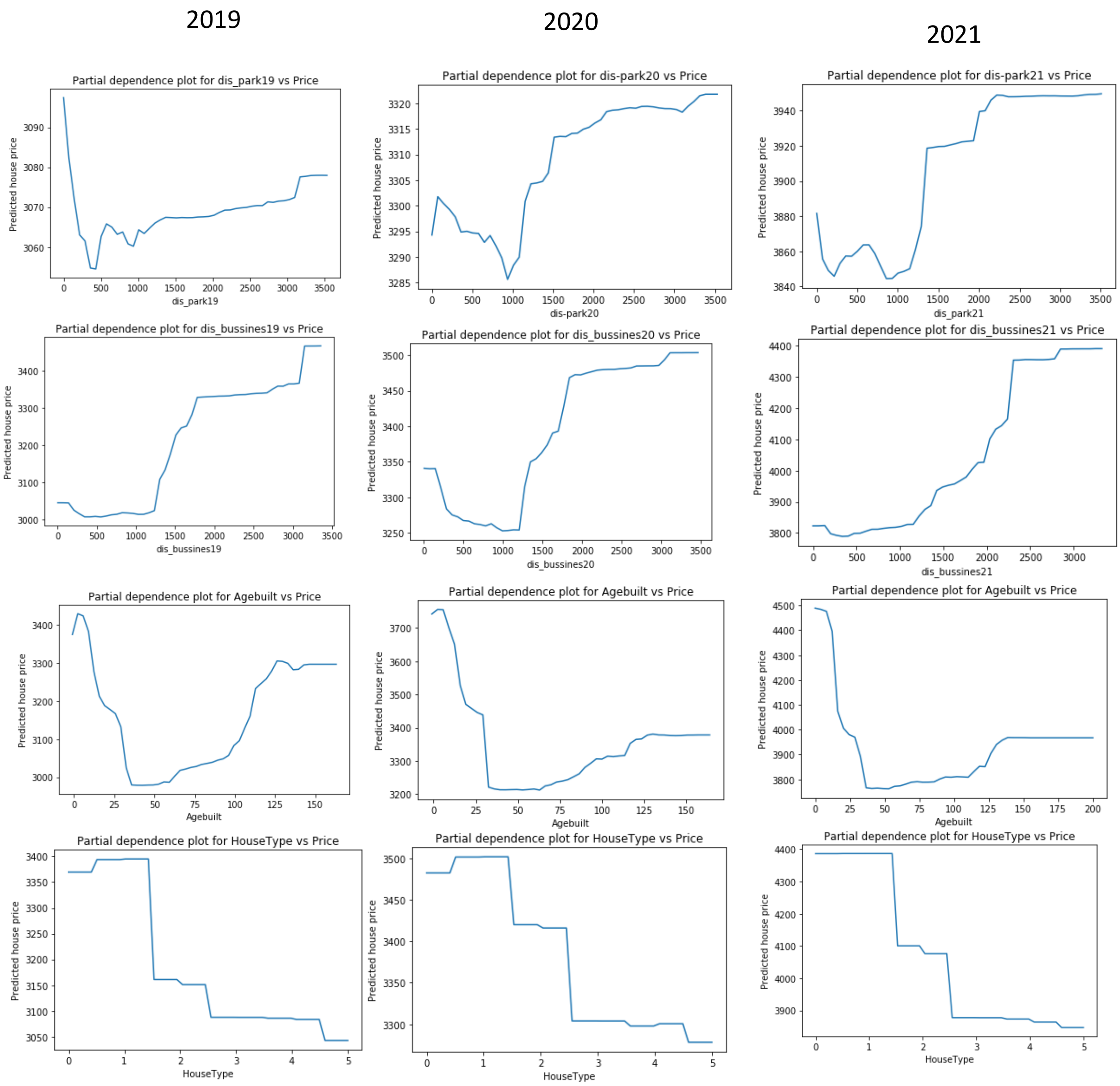

Figure 7-7: The partial dependence plots`

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.580[a]	0.336	0.334	0.26175	0.336	165.476	15	4907	0.000	1.069

a. Predictors: (Constant), lnheigh, lneducation, lnstation, lnbusiness, lnsport, lnshopping, lnpark, lnArea, lnmedical, lnroad, lnsuper, lnuni,

b. Dependent Variable: lnprice

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	170.061	15	11.337	165.476	.000[b]
	Residual	336.196	4907	0.069		
	Total	506.257	4922			

a. Dependent Variable: lnprice

b. Predictors: (Constant), lnheigh, lneducation, lnstation, lnbusiness, lnsport, lnshopping, lnpark,

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	8.854	0.105		84.368	0.000	8.648	9.060					
	lnArea	-0.034	0.011	-0.040	-3.179	0.001	-0.054	-0.013	-0.029	-0.045	-0.037	0.861	1.161
	lnpark	-0.026	0.006	-0.058	-4.652	0.000	-0.036	-0.015	-0.156	-0.066	-0.054	0.860	1.163
	lnbusiness	0.061	0.007	0.107	8.521	0.000	0.047	0.076	0.049	0.121	0.099	0.854	1.170
	lnsport	0.007	0.007	0.013	0.979	0.327	-0.007	0.021	0.089	0.014	0.011	0.725	1.379
	lnroad	0.008	0.004	0.026	1.961	0.050	0.000	0.017	-0.091	0.028	0.023	0.786	1.273
	lnhospital	0.120	0.008	0.260	14.332	0.000	0.104	0.136	-0.134	0.200	0.167	0.412	2.430
	lnfood	-0.021	0.005	-0.077	-4.336	0.000	-0.030	-0.011	-0.261	-0.062	-0.050	0.433	2.309
	lnuni	-0.004	0.007	-0.010	-0.629	0.529	-0.018	0.009	-0.133	-0.009	-0.007	0.563	1.778
	lneducation	0.007	0.004	0.020	1.650	0.099	-0.001	0.016	0.000	0.024	0.019	0.889	1.125
	lnmedical	-0.003	0.005	-0.007	-0.528	0.598	-0.013	0.007	-0.078	-0.008	-0.006	0.796	1.256
	lnCBD	-0.303	0.008	-0.663	-37.326	0.000	-0.319	-0.287	-0.508	-0.470	-0.434	0.429	2.333
	lnsuper	0.026	0.006	0.066	4.417	0.000	0.015	0.038	-0.174	0.063	0.051	0.615	1.627
	lnshopping	0.057	0.006	0.132	9.225	0.000	0.045	0.069	-0.026	0.131	0.107	0.662	1.512
	lnstation	0.007	0.005	0.017	1.343	0.179	-0.003	0.017	0.035	0.019	0.016	0.857	1.167
	lnheigh	0.017	0.006	0.049	3.036	0.002	0.006	0.028	0.248	0.043	0.035	0.521	1.920

Figure 7-8:Result of the hedonic pricing Model for 2019

Model Summary[b]										
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.622[a]	0.387	0.385	0.24083	0.387	205.085	15	4883	0.000	1.170

a. Predictors: (Constant), lnheight, lneducation, lnstation, lndis_bussines, lndis_sport2, lnpark, lnshopping, lnarea, lnmedical, lndis_road20,

b. Dependent Variable: lnpricem2

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	178.427	15	11.895	205.085	.000[b]
	Residual	283.219	4883	0.058		
	Total	461.647	4898			

a. Dependent Variable: lnpricem2

b. Predictors: (Constant), lnheight, lneducation, lnstation, lndis_bussines, lndis_sport2, lnpark,

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	8.349	0.126		66.115	0.000					
	lnarea	-0.090	0.010	-0.111	-9.161	0.000	-0.081	-0.130	-0.103	0.863	1.159
	lnpark	-0.032	0.005	-0.073	-6.130	0.000	-0.164	-0.087	-0.069	0.884	1.131
	lndis_bussines	0.046	0.006	0.087	7.203	0.000	0.038	0.103	0.081	0.860	1.163
	lndis_sport	-0.001	0.006	-0.001	-0.079	0.937	0.080	-0.001	-0.001	0.702	1.424
	lndis_road	0.020	0.004	0.062	4.846	0.000	-0.105	0.069	0.054	0.776	1.288
	lndis_hospital	0.147	0.009	0.323	16.738	0.000	-0.181	0.233	0.188	0.337	2.965
	lnfood	0.006	0.004	0.024	1.442	0.149	-0.268	0.021	0.016	0.467	2.140
	lnuni	-0.007	0.006	-0.017	-1.130	0.258	-0.152	-0.016	-0.013	0.585	1.711
	lneducation	0.003	0.004	0.009	0.798	0.425	-0.051	0.011	0.009	0.918	1.090
	lnmedical	-0.002	0.005	-0.006	-0.470	0.639	-0.136	-0.007	-0.005	0.821	1.219
	lnsuper	-0.155	0.013	-0.359	-12.218	0.000	-0.544	-0.172	-0.137	0.145	6.881
	dis_CBD	-5.579E-05	0.000	-0.471	-14.242	0.000	-0.522	-0.200	-0.160	0.115	8.699
	lnshopping	0.046	0.006	0.114	8.361	0.000	-0.095	0.119	0.094	0.673	1.485
	lnstation	-0.003	0.005	-0.008	-0.661	0.509	0.011	-0.009	-0.007	0.859	1.164
	lnheight	0.001	0.005	0.002	0.126	0.900	0.245	0.002	0.001	0.533	1.877

a. Dependent Variable: lnpricem2

Figure 7-9: Result of the hedonic pricing Model for 2020

Model Summary[b]										
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.562[a]	0.316	0.314	0.24320	0.316	134.846	15	4374	0.000	1.180

a. Predictors: (Constant), lnheigh, lnstation, lneducatin, lnbusiness, lnspor, lnpark, lnarea, lnshopping, lnmedical, lnroad, lnsuper,
b. Dependent Variable: lnprice

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	119.637	15	7.976	134.846	.000[b]
	Residual	258.711	4374	0.059		
	Total	378.348	4389			

a. Dependent Variable: lnprice
b. Predictors: (Constant), lnheigh, lnstation, lneducatin, lnbusiness, lnspor, lnpark,

Coefficients[a]											
		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant	9.312	0.101		92.555	0.000					
	lnarea	-0.106	0.010	-0.139	-10.380	0.000	-0.130	-0.155	-0.130	0.876	1.141
	lnpark	-0.020	0.006	-0.047	-3.567	0.000	-0.126	-0.054	-0.045	0.883	1.132
	lnbusines	0.063	0.007	0.118	8.866	0.000	0.066	0.133	0.111	0.882	1.133
	lnspor	0.006	0.007	0.013	0.870	0.384	0.065	0.013	0.011	0.751	1.332
	lnroad	0.014	0.004	0.046	3.295	0.001	-0.086	0.050	0.041	0.785	1.274
	lnhospital	0.105	0.008	0.244	12.813	0.000	-0.147	0.190	0.160	0.431	2.321
	lnfood	-0.003	0.005	-0.011	-0.597	0.551	-0.246	-0.009	-0.007	0.439	2.277
	lnuni	-0.004	0.007	-0.009	-0.550	0.582	-0.133	-0.008	-0.007	0.606	1.650
	lneducati	0.007	0.004	0.023	1.793	0.073	0.010	0.027	0.022	0.923	1.083
	lnmedical	-0.022	0.005	-0.059	-4.166	0.000	-0.135	-0.063	-0.052	0.786	1.273
	lnCBD	-0.269	0.008	-0.660	-34.604	0.000	-0.487	-0.464	-0.433	0.430	2.326
	lnsuper	0.022	0.006	0.061	3.861	0.000	-0.174	0.058	0.048	0.623	1.605
	lnshoppin	0.047	0.006	0.119	7.761	0.000	-0.078	0.117	0.097	0.662	1.510
	lnstation	0.003	0.005	0.009	0.667	0.505	0.035	0.010	0.008	0.859	1.165
	lnheigh	0.013	0.005	0.043	2.610	0.009	0.230	0.039	0.033	0.566	1.768

a. Dependent Variable: lnprice

Figure 7-10: Result of the hedonic pricing Model for 2021

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.769[a]	.591	.574	.098319896	.591	34.681	6	144	<.001	.922

a. Predictors: (Constant), gree, squareMete, logheight, water, road, sky

b. Dependent Variable: logprice

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.012	6	.335	34.681	<.001[b]
	Residual	1.392	144	.010		
	Total	3.404	150			

a. Dependent Variable: logprice

b. Predictors: (Constant), gree, squareMete, logheight, water, road, sky

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Partial	Part	Collinearity Statistics Tolerance	VIF
1	(Constant)	7.901	.084		94.452	<.001					
	squareMete	.000	.000	.053	.888	.376	-.190	.074	.047	.800	1.249
	logheight	.004	.023	.012	.198	.843	.329	.017	.011	.752	1.329
	sky	.006	.001	.298	4.328	<.001	.561	.339	.231	.600	1.668
	road	-.002	.001	-.116	-1.729	.086	-.516	-.143	-.092	.631	1.584
	water	.005	.001	.326	5.198	<.001	.541	.397	.277	.721	1.386
	gree	.007	.001	.335	5.352	<.001	.577	.407	.285	.723	1.383

a. Dependent Variable: logprice

Figure 7-11:The statistical result of the hedonic model for the 3D variables (T1)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.678[a]	.459	.440	.13375	.459	23.617	6	167	<.001	1.821

a. Predictors: (Constant), green, squareMete, road, logheight, sky, water

b. Dependent Variable: logpricem2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.535	6	.422	23.617	<.001[b]
	Residual	2.987	167	.018		
	Total	5.522	173			

a. Dependent Variable: logpricem2

b. Predictors: (Constant), green, squareMete, road, logheight, sky, water

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound	Correlations Zero-order	Partial	Part	Collinearity Statistics Tolerance	VIF
1	(Constant)	8.347	.093		89.316	<.001	8.162	8.531					
	squareMete	-.001	.000	-.126	-2.135	.034	-.002	.000	-.059	-.163	-.122	.932	1.073
	logheight	-.041	.021	-.133	-1.916	.057	-.083	.001	.181	-.147	-.109	.673	1.486
	sky	.006	.002	.231	3.584	<.001	.002	.009	.464	.267	.204	.782	1.278
	road	-.004	.001	-.197	-3.113	.002	-.007	-.002	-.353	-.234	-.177	.807	1.239
	water	.004	.001	.324	4.206	<.001	.002	.006	.511	.310	.239	.546	1.831
	green	.005	.001	.253	3.646	<.001	.002	.007	.527	.272	.207	.672	1.487

a. Dependent Variable: logpricem2

Figure 7-12: The statistic result of the hedonic model for the 3D variables (T2)

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.686[a]	.470	.448	.11787	.470	20.994	6	142	<.001	1.908

a. Predictors: (Constant), green_1, logheight, road_1, water_1, squareMete, sky_1

b. Dependent Variable: logpricem2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.750	6	.292	20.994	<.001[b]
	Residual	1.973	142	.014		
	Total	3.723	148			

a. Dependent Variable: logpricem2

b. Predictors: (Constant), green_1, logheight, road_1, water_1, squareMete, sky_1

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Partial	Part	Collinearity Statistics Tolerance	VIF
1	(Constant)	8.578	.111		77.227	<.001					
	squareMete	-.002	.000	-.323	-4.464	<.001	-.429	-.351	-.273	.711	1.407
	logheight	.009	.016	.035	.531	.596	-.019	.045	.032	.856	1.168
	sky_1	.002	.002	.103	1.160	.248	.522	.097	.071	.478	2.093
	road_1	-.007	.002	-.272	-3.855	<.001	-.361	-.308	-.236	.752	1.330
	water_1	.005	.001	.216	3.226	.002	.400	.261	.197	.830	1.204
	green_1	.005	.002	.201	2.635	.009	.467	.216	.161	.643	1.556

a. Dependent Variable: logpricem2

Figure 7-13: The statistic result of the hedonic model for the 3D variables (T3)