ASSESSMENT OF 2D AND 3D METHODS FOR PROPERTY VALUATION USING REMOTE SENSING DATA AT THE NEIGHBOURHOOD SCALE IN XI'AN, CHINA

YUE YING
February, 2019

SUPERVISORS:

Dr. M.N. Koeva

Dr. M. Kuffer

Dr. X. Li

ADVISOR:

K. O. Asiama MSc.

ASSESSMENT OF 2D AND 3D METHODS FOR PROPERTY VALUATION USING REMOTE SENSING DATA AT THE NEIGHBOURHOOD SCALE IN XI'AN, CHINA

YUE YING
Enschede, The Netherlands, February, 2019

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.

Specialisation: Land Administration

SUPERVISORS:
Dr. M.N. Koeva
Dr. M. Kuffer
Dr. X. Li

ADVISOR:
K. O. Asiama MSc.

THESIS ASSESSMENT BOARD:
Prof. dr. K. Pfeffer (Chair)
Dr. M.N. Koeva
Dr. M. Kuffer
Dr. B. A. Ricker (External Examiner, University of Twente)

DISCLAIMER

This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author and do not necessarily represent those of the Faculty.

ABSTRACT

The Chinese property market has kept flourishing in the past decades due to fast urbanisation. Xi'an, the capital city of Shaanxi Province, also has become one of the cities with a fast-growing property market. The high-rise apartments dominate the property market to meet the demands of the growing urban population. The continuous construction of the neighbourhoods has led to significant spatial changes in the vertical dimension. However, the change of the geographical information in the vertical dimension cannot be represented by the current 2D-based property valuation methods. Therefore, it is important to introduce 3D indicators and 3D modeling into the property valuation.

In this research, a mixed qualitative-quantitative methodology was issued to assess 2D and 3D methods for property valuation using remote sensing data at the neighbourhood scale. The author employed semi-structured expert interview, focus group and questionnaire in understanding the pricing policy, identify the current situation of 3D modeling in China, and buyers' preferences for high-rise apartments. The government adopts the market comparison method and the real estate developers adopt the cost method at present. 3D modeling needs to be further developed in Xi'an. The different aspects of buyers' preferences were analysed and taken as selection criteria of 2D and 3D indicators for property valuation.

The 2D methods applied both ordinary least squares (OLS) and geographically weighted regression (GWR) to run the model of 2D indicators. The results showed that GWR performed better than OLS, so GWR was chosen for detailed analysis. It also revealed that density of factory, normalised difference vegetation index (NDVI), distance to Central Business District (CBD), distance to food and distance to subway were the five significant indicators influencing property price. However, unlike other studies, it could not generalise the model for they both had low R^2. The fixed-price and purchase-restriction policy established by the Xi'an municipal government may influence the results.

The 3D method included four indicators, view quality, sky view factor (SVF), sunlight and property orientation and executed model of 3D indicators. SVF, sunlight and property orientation were the three significant indicators. Leave-one-out cross-validation (LOOCV) was carried out based on local knowledge. The error percentage between the predicted price and the real price was 9.76%. In conclusion, it was proved by the comparison results that 3D method could better explain the property price variation at the neighbourhood scale than 2D methods. The R^2 in 3D method was 0.451 while R^2 in GWR of 2D methods was 0.217. 3D indicators were successfully analysed and quantified in CityEngine. They were also effectively visualised via graphs and videos to show the geographical information change in the vertical dimension.

This research contributes to the existing literature related to property valuation and 3D modeling by showing the importance of 3D indicators in influencing the property prices of the high-rise apartments and the possibility of applying 3D modeling in property valuation. Future research opportunities were identified such as machine learning on predicting the property price and developing suitable 3D software for buyers.

ACKNOWLEDGEMENTS

First and foremost, I want to thank ITC, The University of Twente for providing financial support for the fieldwork in China of my thesis, without which this thesis would never have been done.

I would like to express the deepest gratitude to my first and second supervisors, Dr. Mila Koeva, Dr. Monika Kuffer for their great patience, the strong sense of responsibility, and providing me with valuable guidance in every stage of my thesis writing. I was motivated to continue with my research and develop the essential academic competence with your support. I have to say it is so lucky and happy to have you as my supervisors.

A very special altitude goes to Mr Kwabena Obeng Asiama, who participated in the supervision meeting from the proposal stage to the very end, and your discussions and valuable comments helped me develop better research ideas and thesis structure. It is so nice to have you

I am also grateful to my third supervisor Dr. Li who gave me warm help and specific guide during the fieldwork in Xi'an. Thanks for your care even when you were very busy at work.

I would also like to thank my tutor Dr. Xuefeng Yuan at Chang'an University who encouraged me to study at ITC.

Thanks also go to all the research respondents during the fieldwork in Xi'an for kindly answering my questions, devoting their time, providing valuable and advanced information, and helping me understand the complex knowledge that I did not know before. This research could not be accomplished without your devoted effort and time.

I would like to thank Alfred, my dear classmate, for giving me valuable comments for proof-reading.

Finally, last but by no means least, I want to thank my mother for giving birth to me and her selfless love.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

AICc	Akaike Information Criterion
CAD	Computer-Aided Design
CBD	Central Business District
CGA	Computer Generated Architecture
DEM	Digital Elevation Model
GIS	Geographical Information System
GTWR	Geographically Temporal Weighted Regression
GWR	Geographically Weighted Regression
HPM	Hedonic Price Model
IP	Internet Protocol
LiDAR	Laser Imaging Detection and Ranging
LoD	Level of Detail
ML	Maximum Likelihood
NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared
OLS	Ordinal Least Squares
SS_R	Residual Sum of Square
SVF	Sky View Indicator
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UML	Unified Modeling Language
UHI	Urban Heat Island
VIF	Variance Inflation Factor
VR	Virtual Reality

GLOSSARY

3D indicator: it refers to the indicator influencing the property price in terms of the geographical information in the vertical dimension.

Land transfer fee: a transaction fee happens when the government transfer the land use rights to the land users in China.

Neighbourhood: a community of several residential buildings with a relatively independent living environment in the urban area. It is always equipped with living service facilities, such as shops, restaurants, and schools. Only residents can be permitted to enter the neighbourhoods. Real estate developer buys the land parcel from the local government and constructs buildings or houses on the land. The coverage area of one neighbourhood can vary significantly.

Property: it refers to an apartment in one building, but the land where it builds on does not include in. According to the China Land Management Law, urban land belongs to the state and cannot be owned by private.

Property price: In this research, this refers to the first-hand transaction price of one apartment in one building which is registered at the Price Bureau of Xi'an. The unit is yuan/m^2.

APPENDICES

1. INTRODUCTION

In the last decades, the rapid population growth and increasing urbanisation rates have led to the fast vertical developments in urban areas besides a horizontal urban sprawl in China. It seems inevitable to construct high-rise buildings in the urban area due to limited land (Tavernor, 2007). The geographical information of these high-rise buildings in the vertical dimension has experienced significant changes in terms of view types, vision scope and daylight. Therefore, the need to accurately define these property characteristics increased dramatically in the perspectives of the government, real estate developers and buyers. It puts forward the necessity to include 3D indicators in property valuation. However, these indicators did not receive enough attention in current 2D property valuation methods (Jim & Chen, 2006). With 3D modeling and 3D geographical data, complex property characteristics in the vertical direction can be identified in high-rise and highly-density areas, which is hard to be achieved by conventional 2D-based property valuation methods.

Furthermore, the current public awareness of the possibilities provided by 3D modeling is low (Isikdag, Horhammer, Zlatanova, Kathmann, & van Oosterom, 2015). Although 3D modeling has not been used today for property valuation, it might be used in the future. This research aims to narrow the gap by assessing 2D and 3D methods for property valuation at the neighbourhood scale and comparing the results.

This chapter provides the background and justification with supporting literature, the research problem, research objectives and research questions. It ends with a summary.

1.1. Background and justification

The accelerating urbanisation has put great pressure on land, posing a challenge on how to accurately define property characteristics and value. Given its abundant spatial information and robust image processing capability, Geographical Information System (GIS) and remote sensing data have been widely used for property valuation (Wyatt, 1997; Zhang, Li, Liu, & Liu, 2014). However, the integration of GIS and property valuation are mainly 2D-based. When it comes to handling the complexity of vertical developments in urban areas, these methods are incapable of describing 3D characteristics of the property in details and providing the precise difference between properties regarding the spatial changes. With the considerable increase in property price and the technical development in GIS, 3D modeling for property valuation can better describe the complex property characteristics, especially in the vertical dimension, in the urban area. It has been implemented in a multitude of domains for solving problems such as making 3D noise maps and reconstructing sunlight direction (Biljecki, Stoter, Ledoux, Zlatanova, & Çöltekin, 2015).

Generally, the property price is determined by different spatial, physical, legal and economic indicators within the framework of hedonic price model (HPM) (Tomić, Roić, & Ivić, 2012), among which the 3D indicators in the vertical dimension were difficult to quantify, such as the view on different storeys and the sky view factor (SVF) (Wen, Xiao, & Zhang, 2017; Yu, Han, & Chai, 2007). Besides, it is hard to represent the spatial heterogeneity in the vertical dimension in high-rise buildings with 2D-based techniques. In contrast, 3D modeling can reflect the spatial relationships between different geographical information in the vertical direction clearly with its 3D visualisation. It is more intuitive and accurate compared to traditional 2D-based methods (Zhang et al., 2014).

As an effective technical approach, 3D modeling also has the advantage of better interactivity with users. 3D visualisation can offer people a better understanding of spatial relationships by realistic animations (van Lammeren, Houtkamp, Colijn, Hilferink, & Bouwman, 2010). With the help of 3D modeling software and web technology, public participation can improve. In general, people do not have to get information at specific times or locations. Instead, they can have more options of when and how they participate, and what they want to see (Onyimbi, Koeva, & Flacke, 2017). For instance, the real estate developers can show the 3D model of the properties on tablets to their customers according to people's visual habits. The customers can get a comprehensive view of the property structures and the surrounding environment. Similarly, the integration of other applications (e.g., BIM) can conveniently improve the user experience for their customised purposes (Biljecki et al., 2015).

Apart from 3D modeling, the use of remote sensing data can also complement conventional property valuation approaches[1]. Traditionally, the property price always refers to another property with similar characteristics. The vertical spatial changes between different neighbourhoods were inadequately considered, and spatial data is also hard to acquire from manual fieldwork. However, remote sensing data can offer rich geographical information in different domains with enough coverage without time-consuming fieldwork (Yu et al., 2007). Lake, Lovett, Bateman, and Langford (1998) were one of the early applications to combine GIS and large-scale digital data into property valuation. They used the Viewshed function in ArcGIS to evaluate the visibility of properties, and their results indicated that the views of road, railways, and industry had a negative impact on property prices. Their findings disclosed that the 3D GIS technology could describe the geographical information of the high-rise buildings in the vertical dimension and has the potential to quantify complex 3D indicators.

3D modeling is the key method for many types of research and applications. Although there have been empirical studies related to 3D modeling, only one article reported the integration of 3D modeling with property valuation (Tomić et al., 2012). They mainly discussed how to develop property valuation in urban areas with the use of 3D cadastre data and built a test example of a 3D Vector Terrain Model. It was a test model and did not include the visualisation of 3D indicators. It is important to develop an understanding of how 3D indicators influence the property price and show the application potential of remote sensing.

From a macro perspective, China still takes the real estate industry as its pillar at present, and the property price in big cities has kept booming in the last decades. Xi'an, the capital city of Shaanxi Province, was chosen as the study area because of its particularly prosperous property market. The rapid urbanisation and the opening of the "Hukou" policy[2] have led to a large influx of population. The demand for residential housing thus looms, and the property price has increased significantly. Many high-rise neighbourhoods have been constructed, and the property prices between different neighbourhoods vary greatly. These neighbourhoods have formed the unique vertical characteristics in space, and it keeps changing during the continuing construction, but the impact from these vertical changes remains unknown. Many studies have applied the HPM to identify the effects of the surrounding environment on property price. However, no study has ever investigated what role the 3D indicators play in the property price and the methods of how to quantify and visualise them.

In conclusion, the conventional property valuation approaches lack the description of the vertical spatial heterogeneity, while the 3D modeling can fill in this gap by including 3D indicators and visualising their effects. The result can serve as a reference for developing a 3D method for residential property valuation in China.

[1] The conventional property valuation approaches include cost approach, sales comparison approach, and income approach.

[2] It is a nationwide household registration system in mainland China. "Hukou" records official identification of an individual as a resident of a specific area and related identifiable information such as the name, age, educational background and address. If people migrate to a new city without local Hukou, they cannot settle down with enough support of medical care, education and other public services from local government (Wu, Gyourko, & Deng, 2012).

1.2. Research problem

China, with its flourishing property market, has attracted huge attention from academia because of its rapidly rising property prices (Feng & Wu, 2015). Among the world's 50 cities with the most significant housing price rise, in the last year, 24 were Chinese. It is notable that Xi' an, as a new entrant, ranked 29th with an increase of 12.3% ("Hurun Global House Price Index 2017," 2018).

Although several case studies of HPM have been conducted for property valuation in different cities of China, their purposes were mainly to identify the external effect of specific issues in public goods, such as parks (Jim & Chen, 2010) and educational facilities (Wen, Zhang, & Zhang, 2014). These indicators were all 2D-based and little is known about the effects of 3D indicators. There is no such study in Xi'an city exploring the effect of 3D indicators (e.g., building height, view and vision scope) on the property price within one specific neighbourhood, either. Furthermore, no case of applying a 3D method for residential property valuation with the usage of remote sensing data has been established yet. Adding 3D indicators, applying a 3D method and assessing the performances of 2D and 3D methods can provide a reference for property valuation to clarify the property price variation of the high-rise apartments in Xi'an, a city with dense high-rise neighbourhoods.

1.3. Research objectives and research questions

1.3.1. General objective

To assess 2D and 3D methods for property valuation using remote sensing data at the neighbourhood scale in Xi'an, China.

1.3.2. Sub-objectives and the corresponding research questions

Sub-objective 1: To identify the existing property valuation methods relevant to the study area.

a) What are the current commonly-used property valuation methods in China?

b) What are the 2D indicators considered in the property valuation in general?

Sub-objective 2: To identify and calculate 2D and 3D indicators which influence the property price in the study area.

a) What is the current situation of 3D modeling for property valuation in China?

b) What are the relevant 2D and 3D indicators that influence property prices in the study area?

Sub-objective 3: To analyse, visualise and validate 2D and 3D methods for property valuation.

a) What method can be taken to analyse and visualise 2D indicators?

b) What is a suitable 3D modeling method to visualise and quantify 3D indicators for property valuation?

c) How to validate the 3D modeling method?

Sub-objective 4: To assess the added value and effect of 3D indicators for property valuation.

a) Can 3D method better describe property prices in the study area than 2D methods?

b) What is the added value of 3D indicators to explain the property price variation in the study area?

c) What will be the potential for practical utilisation of 3D method?

1.4. Conceptual framework

The conceptual framework is illustrated below (Figure 1-1). The main concepts in the research were 3D modeling, remote sensing data, and property valuation. Acquiring people's opinions consist of the buyers' preferences for the high-rise apartments and the ideas from different stakeholders. In this way, it adds people's opinions into 2D and 3D methods for property valuation. According to the existing property valuation studies, current 2D indicators influencing the property price are determined. The remote sensing data helps 3D modeling. The assessment evaluates the results of 2D and 3D methods for property valuation.

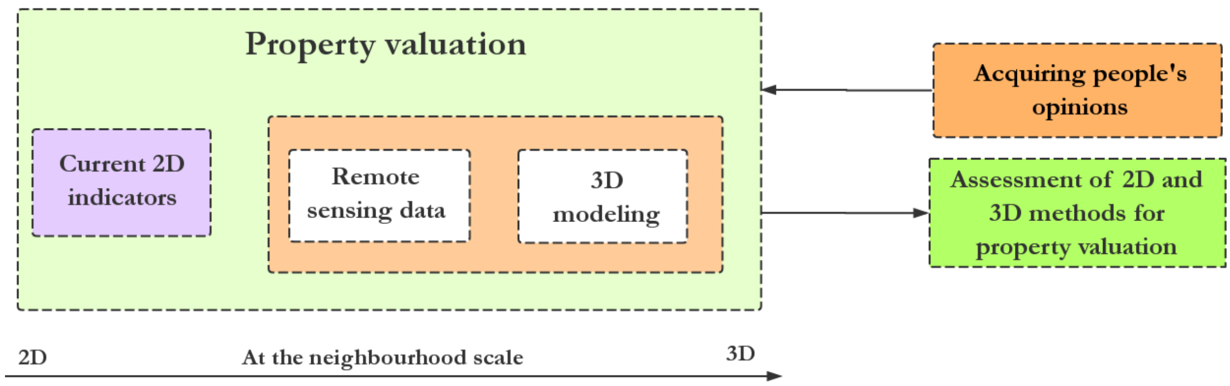


Figure 1-1 Conceptual framework

1.5. Thesis structure

Chapter 1: Introduction

The background introduction of the relevant concepts and justification of the significance of this research are provided in this chapter. As such, it includes the research questions, research objectives, conceptual framework and the thesis structure.

Chapter 2: Literature review

It reviews literature related to the HPM in property valuation, 3D modeling and visualisation for buildings, geographical information in the vertical dimension, and the remote sensing for 3D. It ends with a summary.

Chapter 3: Research methodology

The overview of the study area and the selection criteria are provided. Overall research methodology and the detailed workflows according to each research sub-objective are discussed. It ends with a summary.

Chapter 4: Results

It represents the results and the detailed interpretations in line with the research sub-objectives.

Chapter 5: Discussions

It discusses and summarises the results in Chapter 4. It highlights the important findings and links them with the existing literature.

Chapter 6: Conclusions and Recommendations

It draws conclusions based on the findings according to the research sub-objectives and reflects the research limitations. Recommendations are issued toward future research directions.

2. LITERATURE REVIEW

This chapter reviews the literature on the related research concepts to answer the research sub-objective 1. The commonly-used property valuation methods and the 2D indicators generally included are clarified by literature review. Section 2.1 introduces the hedonic price model (HPM) in property valuation. Section 2.2 presents the applications of 3D modeling and the background information on building visualisation. Section 2.3 provides an overview of the geographical information in the vertical dimension. Section 2.4 explores the possibility of combining 3D modeling, remote sensing and Geographical Information System (GIS). This chapter ends with a summary of the current research drawbacks in section 2.5.

2.1. HPM in property valuation

Property valuation is a process of establishing an opinion of the market value of the properties at a specific time point by professional valuers (the Royal Institution of Chartered Surveyors (RICS), 2012). There have been many different property valuation methods, among which the HPM has been adopted most frequently (McMillen, 2004; Rosen, 1974). It has been widely recognised as a powerful and appropriate tool to value the property by deconstructing its attributes in different categories (Czembrowski & Kronenberg, 2016). The theory of HPM was proposed by Lancaster (1966) and Rosen (1974). The fundamental concept is that the property is made up of a complex variety of attributes (e.g., structural, physical, and locational attributes). Each attribute contributes to the total price. The property price serves as the dependent variable, and the values of different attributes serve as explanatory variables. Besides, it also can assign economic value to the non-market components such as environmental amenities (Schläpfer, Waltert, Segura, & Kienast, 2015).

There has been voluminous research focusing on the economic valuation of public goods using HPM. Jim and Chen (2010) assessed the effects of neighbourhood parks and landscape elements on the prices of the high-rise apartments. The results revealed that neighbourhood parks could lift the price by 16.88% and different landscape elements had different impacts on the prices. The educational facilities were found to have a positive capitalisation effect on property price in Hangzhou, China. Besides, people were willing to pay extra for good education quality and accessibility (Wen, Xiao, Hui, & Zhang, 2018). Panduro and Veie (2013) categorised eight types of urban green spaces and applied a generalised additive model to estimate the hedonic price for each type. Wen, Xiao, and Zhang (2017) took the Grand Canal in Hangzhou, China as the study object to evaluate the effect of river landscape on property price. The results indicated that there existed a positive relationship, especially for high-rise apartments. Similar studies can also be found focusing on the effects of different types of open spaces and urban green spaces (Czembrowski & Kronenberg, 2016; Fernandez, Mukherjee, & Scott, 2018; Jiao & Liu, 2010; Sander & Polasky, 2009). Hui, Chau, Pun, and Law (2007) included various attributes (e.g., noise level and air quality) to measure the neighbourhood quality and environmental effects on property price in Hong Kong. Wu, Song, Liang, Wang, and Lin (2018) analysed the effect of the mixed land use on the property price in Beijing and found that the price increased with daily commercial land use and open spaces but decreased with the land use for hospitals.

Traditional statistical methods of executing HPM has shortcomings. Taking ordinary least squares (OLS) as an example, it has multicollinearity issues and suffers from omitted variables (Schläpfer et al., 2015). Some recent studies have proposed improvements of the statistical methods based on the traditional methods, such as geographically weighted regression (GWR) (Lu, Charlton, & Fotheringham, 2011), geographically temporal weighted regression (GTWR) (Liu et al., 2016), and several spatial econometric models (Hui et al., 2007; Wen et al., 2017).

Within the scope of this research, GWR is an appropriate statistical alternative of HPM to measure the spatial heterogeneity among different properties. It allows the variables to vary across space and offers a spatial context localised within the study area (Huang, Chen, Xu, & Zhou, 2017). Growing literature have explored the application of GWR in different domains. Dziauddin and Idris (2017) and Dziauddin et al. (2015) revealed that the proximity to location attributes and the improved accessibility provided by a light rail transit system both contributed to the property price. Huang et al. (2017) categorised structural, neighbourhood and accessibility attributes to calculate the price in Shanghai using GWR. These studies above concluded that GWR could reasonably explain the influence of spatial heterogeneity on the property price.

Majority of the HPM studies were at the city or provincial scale, i.e., the property price data varied across the city or the province. Many of them took houses, not high-rise apartments as research objects. Compared to the developed countries, many highly urbanised Asian countries have much higher demands for the high-rise buildings to supply the large population with housing in limited available urban space. Especially for China, in dense urban areas, the current predominant residence type is the high-rise apartment. It is surprising that relatively little research focused on the high-rise apartments in the dense urban environment.

2.2. 3D modeling and the visualisation of buildings

The HPM literature mentioned above were 2D-based and did not include 3D indicators in the vertical dimension. They lacked the interpretation of how vertical spatial heterogeneity influenced property price. However, 3D indicators have been found to have a substantial influence on property price, such as the sea view (Yu et al., 2007). Therefore, 3D modeling can be introduced as an advanced method for visualisation, object reconstruction and environmental simulation, particularly suitable for urban environment comprising numerous of buildings (Biljecki et al., 2015; Xie, Zhang, Li, Wang, & Yang, 2012). It describes the process starting from requiring data, data processing to building a visualised 3D model. The data acquisition is mainly through non-contact methods, such as satellite and Unmanned Aerial Vehicle (UAV).

There have been numerous case studies on 3D modeling. For example, Zhang et al. (2014) generated 3D external building models by CityEngine based on pre-provided 2D GIS data of Shenzhen, a megacity of China. They concluded that the 3D model could quantify the landscape and sunshine indexes more accurately compared to the traditional manual modeling. Han, Zhang, and Liang (2015) also proposed a conceptualised monitoring platform of the house price index based on 3D GIS in Shenzhen. Yu et al. (2007) used the ArcGIS 3D Analyst to build a 3D model and ArcView to carry out the visibility analysis. They focused on the value of the sea view, which was proven to promote the property price by an average of 15%. In conclusion, there has been no answer for choosing the best method for 3D modeling (Gimenez, Robert, Suard, & Zreik, 2016).

3D modeling can offer vivid visualisation to enhance people's understanding of reality, as well. Van Lammeren et al. (2010) experimented with 45 participants, and the researchers evaluated the affective responses to land use classes visualised by colour raster cells, 2D-icons and 3D-icons. The results demonstrated a high appreciation of 3D-icons. In the study of Lin, Homma, and Iki (2018), the virtual reality (VR) environment with different lake widths and building heights were created by 3D modeling, which was used in the experiments for finding out public preferences for the two indicators. Herbert and Chen (2015) created a shadow representation in a 3D environment and surveyed urban planners on the visualisation quality. It revealed that 3D representation could deal with more complex tasks, such as accessing shadows and recession planes.

More recently, Rau and Cheng (2013) proposed a cost-effective building modeling strategy and realised its application through a web-based 3D GIS platform. The conventional 2D-based spatial analysis preserved, and 3D modeling was extended to the original scheme. For example, the calculation of living function facilities proximity could be a part of 3D property valuation. Buyukdemircioglu et al. (2018) proposed the procedure of building 3D city models from aerial photogrammetry without additional data acquisition. Although there still existed problems, it was promising to combine the remote sensing data, GIS and 3D modeling to automatically produce the 3D model of the buildings with texture.

The value of 3D visualisation and the demands for visual analytic software have increased recently. Some software tools (e.g., CityEngine and SketchUp) have been proposed for the 3D visualisation of buildings for different purposes. They lower the technical threshold for the majority of the users and enable the creations of different 3D designs. There are two main aspects in the 3D visualisation for buildings, the information content in the model, and the type and source of building data (Gimenez, Hippolyte, Robert, Suard, & Zreik, 2015).

There are standards for generating 3D models in different levels of information content. CityGML is an Open Geospatial Consortium (OGC) standard for different hierarchies of geographical, topological and semantic information representations in 3D modeling. It has five levels of details (LoD), from LoD0 to LoD4 (Biljecki, Ledoux, & Stoter, 2016). LoD0 represents a 2.5D terrain model. LoD1 indicates building in simple extruded blocks. LoD2 adds textured roofs based on LoD1. LoD3 defines a true architectural building with the exteriors only. LoD4 describes the interior structure of the building model, such as furniture and rooms. The LoD can be set differently to serve the research scales and purposes. For example, the low LoD can fit for a large-scale 3D demonstration while the high LoD can be implemented in the fine scale (e.g., solar potential analysis) (Biljecki et al., 2015). Similar to CityGML, the Computer Generated Architecture (CGA) shape grammar of CityEngine is also a programming language dedicated to generating architectural 3D content. It can generate unique 3D models for various scenarios by assigning different rule files.

Regarding the type and source of building data, the building construction generally starts either with on-site data acquisition or documentation. On-site data acquisition includes aerial photographs, city building images, laser imaging detection and ranging (LiDAR) data, and mobile applications. Documentation includes building architecture sketches, 2D scanned floor plans and Computer-Aided Design (CAD) plans (Gimenez et al., 2015).

Nevertheless, an accurate 3D building construction in details is a difficult task. The common problems contain the computational cost and the complexity for users to learn (Zhang et al., 2014), and the difficulty in obtaining enough data to support the 3D data structure (Ohori, Ledoux, Biljecki, & Stoter, 2015). Some scholars also pointed out that the 3D model validation is generally not possible currently and will remain an issue (El-Mekawy, Östman, & Hijazi, 2012).

2.3. Geographical information in the vertical dimension

Although the view does not serve as a functional facility, it has been considered to influence the property price and people's housing selection significantly (Yamagata, Murakami, Yoshida, Seya, & Kuroda, 2016). It is vital for living environments and urban scenery for humans. A good view can add the aesthetic value to the property while a bad one can reduce the price. However, it is very hard to quantify the view or the value of the view. Dummy variables and fieldwork are two frequently used approaches to evaluate the view, but they both have limitations. The former approach may suffer from subjective decisions, and the latter one needs enormous implementation costs (e.g., time, human resource, instrument). Some researchers have attempted to include the view into the HPM to investigate its effect. Yamagata et al. (2016) evaluated the value of urban views based on very high-resolution remote sensing data in Yokohama, Japan. Sander and Polasky (2009) created a complex set of variables to calculate the viewshed area, the view quality and the standard deviation of elevations within a viewshed. Hamilton and Morgan (2010) provided a continuous and objective measure of viewshed in the urban coastal property market using GIS and LiDAR.

The different floors have different living experience and view out of the window. Hui et al. (2012) investigated the impact of story level on property price in several housing submarkets of Hong Kong. They divided the levels into three, under 10^{th}, between 11^{th} to 20^{th}, and above 20^{th}. Their findings indicated that the properties on a higher storey level (above 20^{th}) were more popular than those on a lower storey level (under 10^{th}).

Another common indicator to describe the urban geometry is the sky view factor (SVF), which has been widely used for studying the relationship between urban geometry and urban heat island (UHI) (Chen et al., 2012; Ha, Lee, & Park, 2016). It measures the sky openness and is mainly determined by the height and the density of buildings in the urban area. It could measure residents' living experience to some extent. With the technical support of GIS, satellite images and 3D modeling, it opened new possibilities to simulate SVF in software (Unger, 2009).

Shadow and sunlight also play important roles in practice, such as solar radiation estimation, energy saving strategy and thermal comfort (Biljecki, Ledoux, & Stoter, 2017a; Fleming, Grimes, Lebreton, Maré, & Nunns, 2018). Although they both have a significant influence on living comfort, they are barely considered in property valuation. Shadow can estimate the influence of existing buildings on each other (Biljecki, Ledoux, & Stoter, 2017b; Herbert & Chen, 2015). It is an important indicator influencing people's housing choice because it matters with daylight availability, temperature, and humidity. Regarding sunlight, a good sunlight condition means more daylight hours, less energy consumption and more comfortable living experience for human (Yu & Su, 2015). Jim and Chen (2006) coded the window orientation as a dummy variable according to people's preferences to represent the sunlight, but the study did not directly study the effect of sunlight on property price. Computational simulation is an alternative to investigate sunshine instead of the resource intensive and time-consuming fieldwork.

Finally, it is integral to mention Fengshui in the Chinese property market. It is known as Chinese geomancy, which helps find the suitable orientation and surrounding environment of the buildings, dwellings and other structures. For example, it is widely believed that the property with water and open spaces means prestigious social status. In traditional Chinese belief, water means wealth will come continuously, and open spaces mean there is no block for the wealth.

2.4. Remote sensing for 3D

Remote sensing can obtain a wide range of geographical data in a short time period. With the development in remote sensing and GIS, the potential of 3D modeling mentioned above can be greatly broadened in different aspects, such as sunlight direction estimation (Liu, Gevers, & Li, 2015), sunshine evaluation (Fleming et al., 2018), and urban planning management (Biljecki et al., 2015; Xu & Coors, 2012). The major data sources of remote sensing include satellite, LiDAR, and UAV. The satellite image has a very high resolution and a large coverage area. It also provides easy access to sufficient geographical information about the landscape and buildings (Liasis & Stavrou, 2016). Currently, high-resolution satellite images with a resolution smaller than 5m are becoming increasingly available (Kocaman, Zhang, Gruen, & Poli, 2006), which makes the application range even larger.

In property valuation, remote sensing data were used to calculate the distance between two specific locations, the geographical coordinates of one specific object, and attributes of one specific location (Hamilton & Morgan, 2010; Wen et al., 2014). De Nadai and Lepri (2018) used OpenStreetMap and Google Street View images to extract geographical information and predict the urban property price in Italy. Fleming et al. (2018) used a digital elevation model (DEM) to incorporate building shapes and natural topography to value the role of sunshine in property price and saw it with a 2.6% increase. In terms of 3D data structure, the high-resolution satellite data showed great availability for describing building shape, defining boundary location, and spatial analysis (Jazayeri, Rajabifard, & Kalantari, 2014; Kocaman et al., 2006).

There are also some studies combining remote sensing and GIS with other applications. Xu and Coors (2012) combined a dynamic system model, 3D visualisation and GIS to assess the urban residential development. The 2D density maps were displayed in ArcGIS, and the 3D visualisation maps were produced in CityEngine. Escobedo, Adams, and Timilsina (2015) used remotely sensed vegetation cover data and HPM to investigate the effect of urban forest structure on property price. These applications demonstrate the feasibility and efficiency of applying GIS and remote sensing data in different disciplines.

2.5. Summary

As can be concluded from the literature, there have been several studies that combine 3D modeling with remote sensing data, and property valuation with remote sensing data, separately.

On the one hand, some cases combined 3D modeling and remote sensing data to investigate urban development and UHI (Ha et al., 2016; Xu & Coors, 2012). Their focuses were on improving the technical 3D modeling and proposing a generalised workflow. On the other hand, the present studies of HPM mainly focus on the effect on the property price of one specific issue, in which the function of 3D modeling are barely used. Also, the data collection did not involve acquiring people's opinions towards 3D visualisation and housing preferences, thus lacked public participation (Huang et al., 2017; Jim & Chen, 2009, 2010; Yamagata et al., 2016).

Few cases have brought the three concepts together. Liu and Jakus (2015) proposed a 3D spatial weights matrix to study whether there existed a spatial correlation among the properties on different stories. The credibility of their results was not high due to lack of data.

3. RESEARCH METHODOLOGY

In this research, a mixed qualitative-quantitative method was applied to explore the general research objective. Figure 3-1 explains the overall research design regarding the four research sub-objectives. Literature review finished before fieldwork to achieve sub-objective 1, thus could provide the theoretical basis for the whole research. Several data collection methods were implemented during the fieldwork to finish sub-objective 2. After that, the specific 2D and 3D indicators involved in this research were clarified. Then in the post-fieldwork stage, they were split into two models of 2D and 3D indicators. The 2D model included the statistical methods of ordinary least squares (OLS) and geographically weighted regression (GWR). The 3D method executed OLS of 3D indicators, which were quantified and analysed by 3D modeling. Model validation was executed only for the 3D method to check the model robustness. There have been abundant studies using OLS and GWR in property valuation which did not have model validation. Then the sub-objective 3 was achieved. After that, it assessed the results of 2D and 3D methods and summarised the added value of 3D indicators, which was intended to achieve the sub-objective 4.

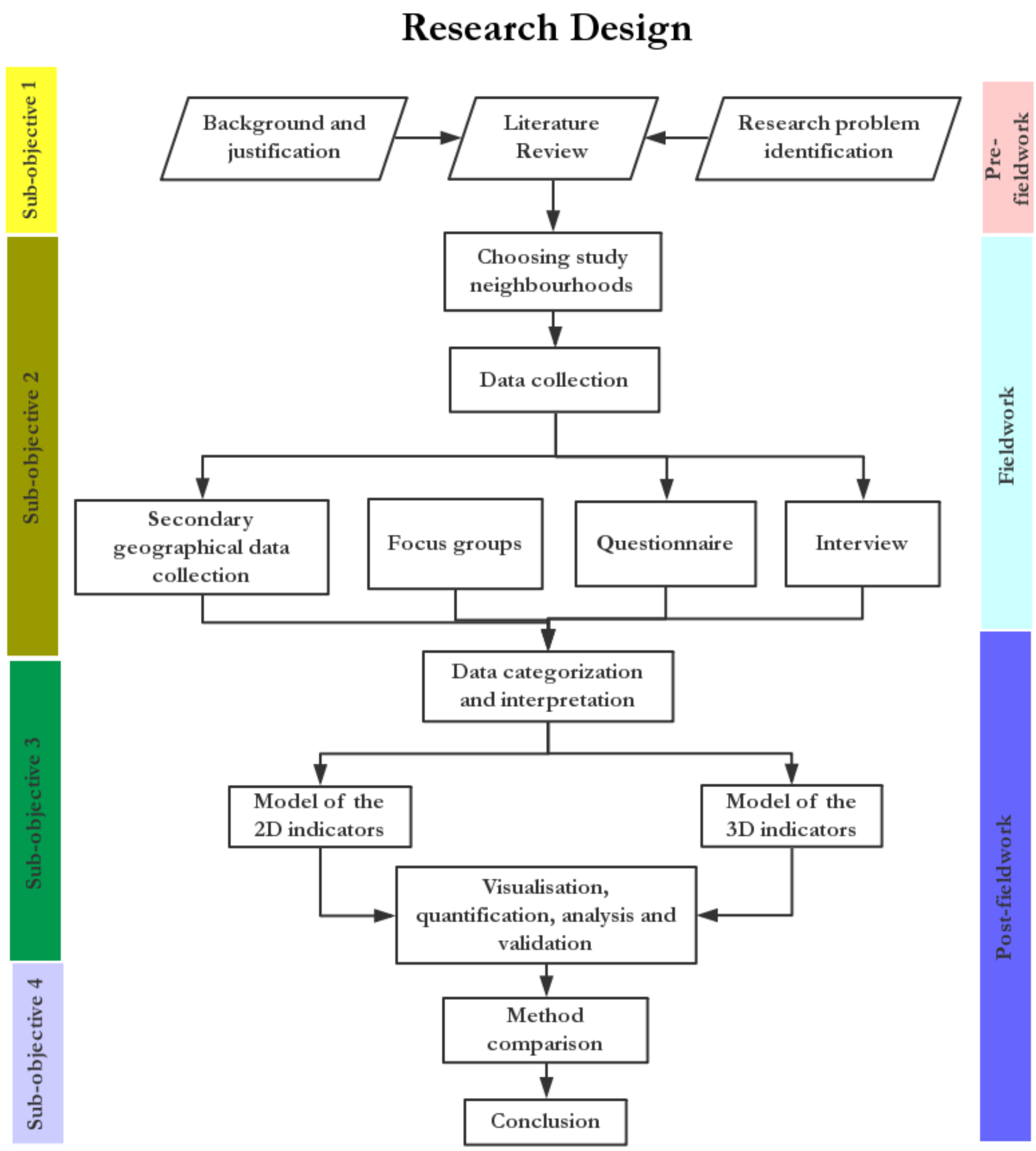


Figure 3-1 Overall methodology

3.1. Study area

The study area was Xi'an, the capital of Shaanxi Province. It locates in central China. Xi'an serves as the educational, political and economic centre of Shaanxi Province and even the centre of Northwest China. It is also known to be a famous tourist city worldwide. It covers the total area of 10,752 km² with 11 administrative districts and two counties. It was chosen as the study area based on data availability and access to local connections. Moreover, no similar research has ever been done so far in Xi'an. Investigating the effect of 3D indicators are both costly and time-consuming, and the anticipated results at the neighbourhood scale can be useful for the buyers to estimate the property price in one specific neighbourhood faster and make the study feasible in terms of computation and data collection, as well. Therefore, the neighbourhood scale was selected.

Figure 3-2 The study area map

The study neighbourhoods in this research are "Yujincheng" and "Ziranjie", both located in the administrative Baqiao District, the north-eastern part in Xi'an, as illustrated in Figure 3-3. They were abbreviated as "Y" and "Z" respectively in the following chapters.

The selection was motivated by the fact that both areas only contained high-rise apartments in roughcast conditions, thus avoided the influence of pre-decoration level on property price. This research focused on the first-handed property market, so the first-hand prices registered at the Price Bureau of Xi'an were used in 2D and 3D methods. There were accessible and enough price samples inside both neighbourhoods and they were fully covered in the provided remote sensing data.

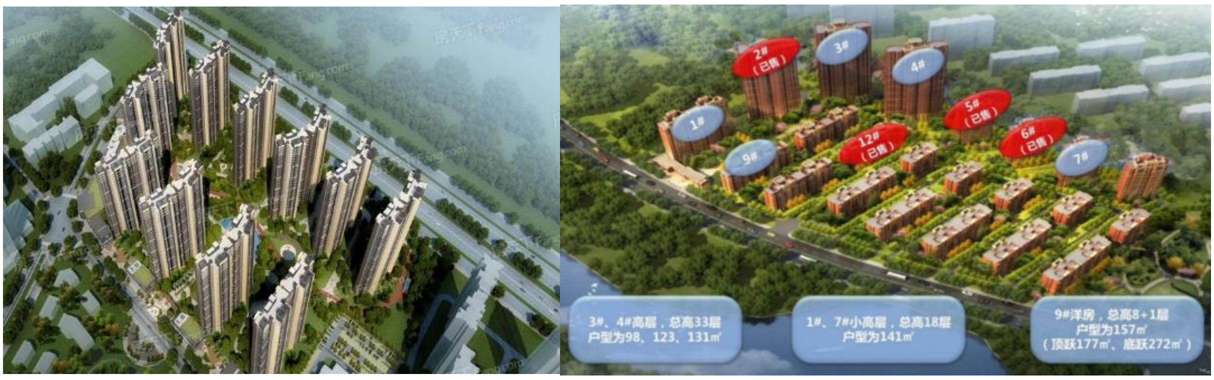


Figure 3-3 Schematic maps of the neighbourhood "Y" (left) and "Z" (right) (source: Internet)

3.2. Qualitative Analysis of pricing policy and the current situation of 3D modeling in China

The qualitative analysis was applied to achieve the research sub-objective 2 to identify the relevant 2D and 3D indicators influencing property price in the perspectives of different stakeholders and reveal the current situation of 3D modeling in China. It was done via semi-structured expert interviews and the focus groups. ATLAS.ti 8 was used to identify keywords as codes for interpretation purpose. Coding helps find the inner connections between different indicators and identify the patterns and categories from the subjective transcripts in a rigorous way (Nicholas Clifford, Cope, French, & Valentine, 2010).

3.2.1. Semi-structured expert interview

The expert interviews were all conducted in semi-structured form during the fieldwork. It is flexible and appropriate to investigate people's opinions and can ensure the interviewees can make the best use of their professional knowledge (Nicholas Clifford et al., 2010). The key questions were pre-determined, but the orders and contexts might be modified according to the responses of the interviewees. The interviewees were experts in their respective domains. All interviews were recorded in audio for subsequent interpretations. An interview scenario is shown in Figure 3-4. The interview guides are illustrated in Appendix 1. The overview of the semi-structured expert interviews can be seen in Appendix 2.

Figure 3-4 Interview with an engineer in the Xi'an Survey and Mapping Institute

3.2.2. Focus group

Focus groups can provide abundant information on diverse perspectives and feelings from the respondents towards one specific issue via group interaction in a relatively short time range (Rabiee, 2004). Two focus groups were organised during the fieldwork in Xi'an. The respondents had already known each other, and the place was cosy to make sure they feel comfortable. Both were recorded in audio. The contexts involved different aspects of their preferences for high-rise apartments. It helped to explore the necessity of a 3D method for property valuation. A focus group discussion scenario is shown in Figure 3-5. The interview guide is in Appendix 3. The overview of the focus groups can be seen in Appendix 4.

Figure 3-5 The focus group discussion

3.3. Quantitative analysis of questionnaire on buyers' preference

The questionnaire was set up to achieve part of the research sub-objective 2, investigating the 2D and 3D indicators the buyers valued. Buyers' preferences and the indicators included in 2D and 3D methods were determined through quantitative analysis of the questionnaire.

It was pre-designed specifically for the residents in the study neighbourhood to know their preferences and updated according to the knowledge acquired during the fieldwork. After choosing the study neighbourhoods, since they were still under construction and no one lived there, the target group was redirected to the residents in Xi'an. The sampling design principle was a simple random sampling because it was relatively easy to access different populations.

The online questionnaire was issued by Wenjuanxing[3], a Chinese online survey software. It could automatically filter the respondents whose Internet Protocol (IP) addresses were in Xi'an. The paper-based questionnaire was distributed randomly to the residents in Xi'an. The numbers of the responses of the questions may differ because it was not mandatory to answer every question. The example of the questionnaire in Chinese is shown in Appendix 5, and the template in English is shown in Appendix 6.

3.4. The 2D methods for property valuation

This section introduces the required data in 2D methods for property valuation and the model formulas of 2D methods. The visualisation and analysis of 2D indicators were executed by ArcGIS and SPSS. It aims to finish the 2D part of the research sub-objective 3. The results serve as a basis for comparison between 2D and 3D methods to accomplish the research sub-objective 4.

3.4.1. Data collection

The data used in 2D methods were all secondary data, which included the Sentinel-2 satellite image, the point of interest (POI) of Xi'an and the database of the first-hand price of Xi'an in 2018 (Table 3-1). According to the statistical results of the questionnaire, 2D indicators were determined. Then POI was checked for its accuracy and re-categorised. The database of the first-hand property price of Xi'an in 2018 was directly linked with the POI in ArcGIS. Each property sample located at the centre of the neighbourhood.

Table 3-1 The overview of the secondary data for 2D methods

Data	Unit	Source	Purpose
Sentinel-2 satellite image	Tiff	Copernicus Open Access Hub, 10-meter resolution, date 26-10-2018	For calculating the normalised difference vegetation index (NDVI).
POI of Xi'an	Point	Chinese E-business platform ALIBABA	For creating 2D indicators.
Database of the first-hand property price of Xi'an in 2018	Yuan/m^2	China Index Academy	For creating the dependent variable of the regression models.

3.4.2. Global Moran's Index

It has been widely applied to estimate whether there exists spatial autocorrelation based on both values and locations of the variables (Song, Wang, Wu, & Yang, 2011). In this research, it was applied to measure the spatial autocorrelation in the property samples in ArcGIS. The formula is given as:

[3] The statistical analysis in Chinese could be accessed via link https://www.wjx.cn/report/29009738.aspx.

$$\mathrm{I} = \frac{n}{S_0} * \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

Where z_i is the deviation of an attribute from an variable from its mean value, $\omega_{i,j}$ is the spatial weights between the variable i and j, n is the total number of the variables, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{i,j}$$

Global Moran's Index ranges from -1 and +1. -1 indicates a perfectly negative correlation, +1 indicates a perfectly positive correlation, and 0 meant uncorrelated. The significance of the index is generally evaluated by the z-score and p-value.

3.4.3. NDVI

It was used to extract the green rate sample inside the neighbourhood, and the result was input the model as a 2D indicator. The Sentinel-2 image used for NDVI calculation was taken on 26h October 2018. The cloud coverage was 0.015. It quantifies vegetation by measuring the difference between near-infrared (NIR) band, which is reflected strongly by vegetation, and red band, which vegetation absorbs. The range is from -1 to 1. The higher value means higher vegetation. Sentinel-2 has the necessary bands for calculating NDVI. Before calculating the NDVI, atmospheric correction has been executed. The formula shows as below:

$$\mathrm{NDVI} = \frac{NIR - RED}{NIR + RED}$$

Where NIR represents the value of the NIR band, and RED represents the value of the red band.

It was worth mentioning that the majority of the neighbourhoods in the database of the first-hand property price of Xi'an in 2018 were still under construction based on the local knowledge. In this research, NDVI aimed to show the current situation of the vegetation in Xi'an and investigate the influence of the vegetation on property price. The influence may change in the future.

After the NDVI calculation, zonal statistics in ArcGIS was executed to extract the sample in a certain radius.

3.4.4. The formulas of OLS and GWR in 2D methods for property valuation

After the data preparation and categorisation, two statistical methods, OLS and GWR, were used to check whether 2D methods could explain the property price variation in the samples.

OLS has been widely applied in the hedonic price model (HPM) to reveal the influence of different indicators on property price. The formula is shown as follows:

$$y_i = \alpha_0 + \sum \alpha_k x_{ik} + \varepsilon_i$$

Where y_i represents the property price, α_0 represents the intercept value, α_k represents the coefficient of the corresponding variable to be estimated, x_{ik} represents the corresponding variable, and ε_i is the error term.

The traditional HPM uses OLS, thus ignores the spatial correlation in property prices and contains bias results. Therefore, GWR is found to be advantageous over OLS. It shows a highly appreciated value in the application of revealing the spatial heterogeneity in property prices. It is a linear model with the same assumptions as OLS. The one big difference is that GWR assumes that the coefficient is a combined function of both the indicator and its spatial coordinates. The formula is shown as follows:

$$\mathrm{y_i} = \alpha_0 + \sum \alpha_k(\mathrm{u_i}, \mathrm{v_i}) x_{ik} + \varepsilon_i$$

Where y_i represents the property price at location i, α_0 represents the intercept value, α_k represents the coefficient of the k^{th} variable at location i, (u_i, v_i) represents the x, y coordinates of property at location i, x_{ik} represents the value of the k^{th} variable at location i, and ε_i is the error term at location i.

The calibration concept of GWR is based on that the variables closer to the sample location have a higher influence on the local parameter estimates for the location. The spatial weighting function can be a Gaussian function:

$$W_{ik} = \exp(\frac{d_{ik}}{h})^2$$

Where W_{ik} represents the weight for the kth variable at location i, d_{ik} represents the distance between the observations i and k, and h represents the bandwidth.

3.5. The 3D method for property valuation

This section introduces the data needed for 3D modeling and the workflow in different stages. It aims to solve part of the research sub-objective 3 and the research sub-objective 4.

3.5.1. Data collection

The secondary data collection method was applied. The data overview is shown in Table 3-2. The questionnaire context regarding the preferences for 3D indicators served as the selection criteria.

Table 3-2 The overview of the secondary data for 3D modeling

Data	Unit	Source	Purpose
Gaofen-2 multispectral satellite image	Tiff	Provided by Dr. Li from Chang'an University, 4-meter resolution, date 12042017	For land cover classification of the study area.
First-hand property prices of the study neighbourhoods.	Yuan/m2	The Price Bureau of Xi'an	For creating the dependent variable for the 3D method.
Floor data of the buildings in Xi'an	Vector	Provided by Dr. Jong Wang from Wuhan University	For extruding the surrounding building.
Footprints of the high-rise apartments in the study neighbourhoods	Vector	Manual work on Google Earth	For the basis of the building construction.

3.5.2. Overall methodology in 3D modeling

In this research, CityEngine was used to build the 3D model of the study neighbourhoods, visualise 3D indicators and analyse their influences on the property price. The whole workflow of the 3D modeling is shown in Figure 3-6.

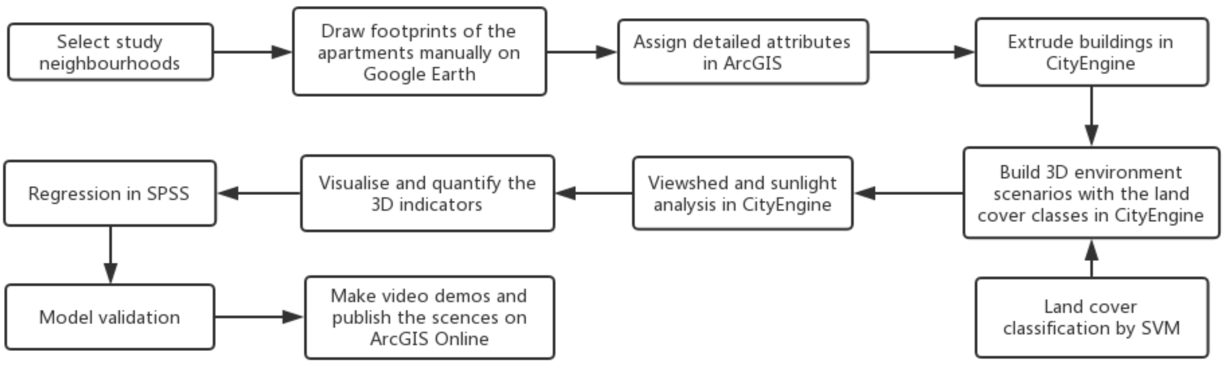


Figure 3-6 The flow diagram of 3D modeling

Because the study neighbourhoods were all under construction, it was impossible to obtain the ground truth data of the building footprints, so the footprints were drawn manually in Google Earth. First, the latest image in Google Earth was selected; second, the footprints of the buildings in two study neighbourhoods were were drawn; Third, the size and orientation of the footprints were adjusted in ArcMap; Lastly, the detailed attributes were assigned to the footprints so that they could be directly linked when extruding the building in CityEngine.

The land cover classification was executed to obtain land cover classes to be imported into CityEngine. A detailed introduction is given in section 3.5.3. 3D scenes were built in CityEngine with the usage of the different land cover classes, the footprints of the high-rise apartments of the study neighbourhoods and the floor data of the buildings in Xi'an.

The different land cover classes were textured by assigning pictures based on the reality to provide a vivid presentation. The footprints of the high-rise apartments of the study neighbourhoods and the floor data of the buildings in Xi'an were extruded by assigning different rule files based on their actual heights to provide the most suitable visualisation in CityEngine. In this research, the storey height of all the buildings was assumed to be 3 m. The rule file for the floor data of the buildings in Xi'an was relatively simple (Appendix 12)[4]. It extruded the buildings in different building heights in LoD1, which created thematic roofs but without the storey representation. The rule file for the high-rise apartments of the study neighbourhoods visualised the storeys and the colours of different buildings to distinguish the property price difference (Appendix 13)[5]. They were constructed in LoD2, as mentioned in section 2.2, which meant it had generalised the thematic roof features, windows, doors and façades. LoD2 was intentionally selected as it was suitable for visualisation at the neighbourhood scale in this research.

Then viewshed analysis and sunlight analysis were carried out to analyse, visualise and quantify the 3D indicators. The parameter setting was adjusted to fit different purposes. Detailed information is given in section 3.5.4. The results were exported to excel and categorised to execute the regression of the 3D method in SPSS, and the 3D scenes were exported to ArcGIS Online for users' visualisation.

The final step was the validation to verify the 3D method and check the accuracy. It was important because no one has ever executed such a validation for the 3D method for property valuation. Leave-one-out cross-validation was applied in this research (section 3.5.5).

3.5.3. Land cover classification and accuracy assessment

It was applied to classify different land cover classes and then prepare for the viewshed analysis in CityEngine. In this research, the support vector machine (SVM) was used to classify the image. It is generally a robust machine learning algorithm and has been proven to show better accuracy than Maximum likelihood (ML) in image classification (Furey et al., 2000). It only needs small amounts of samples and has a solid theoretical basis, which is suitable for this research. It imports features into a high-dimensional feature space with kernel functions to produce an optimal hyperplane, which has the widest margin to identify two different feature classes. ML assumes that the input features are normally distributed and the feature samples are unlimited. However, these preconditions cannot always be achieved in practice, which makes image classification results unreliable (Jin, Li, & Wang, 2005).

The multispectral image used for the classification was taken on 12th April 2017, by Chinese satellite Gaofen-2, with a resolution of 4 m. The cloud coverage was 0.010. Image classification of the study area was executed by SVM supervised classification via ENVI. Five classes were identified, namely, building, green, water, soil

[4] The rule file in pdf format could be accessed via: https://drive.google.com/open?id=1NQgyBxNtjriVqm2uKDnpr7aVn_g1zZYj

[5] The rule file in pdf format could be accessed via: https://drive.google.com/open?id=1tcmqqV79L-ICKZ0Hskf37iTocOhB7oby

and paved. A total of 200 random points were created in ArcGIS, and visual interpretation in Google Earth was applied to validate the classification results. The example scenes are shown in Appendix 11. The results of the classification were exported in vector format according to their land cover classes. The workflow is shown in Figure 3-7.

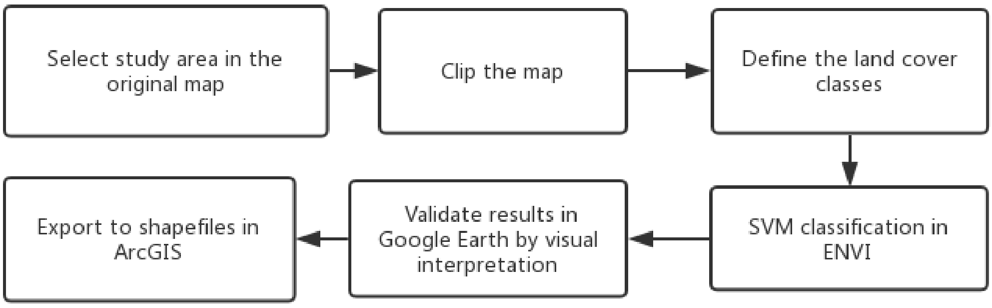


Figure 3-7 The flow diagram of the land cover classification

3.5.4. The analyses of the 3D indicators in CityEngine

This section introduces the workflow of how to build a 3D scene and execute different analyses to visualise and quantify 3D indicators, which included view quality, sky view factor (SVF), sunlight and property orientation. Property orientation was set to a dummy variable, so it was not analysed in CityEngine. If the orientation was south, the value equalled 1; if not, the value equalled zero.

The parameter setting of the building visualisation could be adjusted according to different needs. An example with detailed explanation is shown in Appendix 14. In this research, four scenes under different view distances were set up for comprehensive analysing the changes of 3D indicators, including 50 m, 100 m, 200 m and 500 m. There were 15 buildings in the two study neighbourhoods, and each building had scenes under four different view distances, so there were 60 samples in total.

In Chinese context, building height/floor space =1:1.2. The building heights in this research were 18 m, 54 m, 90 m, and 99 m. According to the simulation, the minimum floor space was approximately 50 m. 100m was the approximate floor space for the buildings with 90 m and 99 m high. 500 m was the distance where people's vision starts blurry ("Usage tip: a suitable viewing distance of SketchUp," 2018). As shown in Figure 3-8, it was obvious that the view types and SVF were different under different view distances. It only included the adjacent buildings and part of the ground with a view distance of 50 m, while the buildings and the ground away from the observer were included under 500 m.

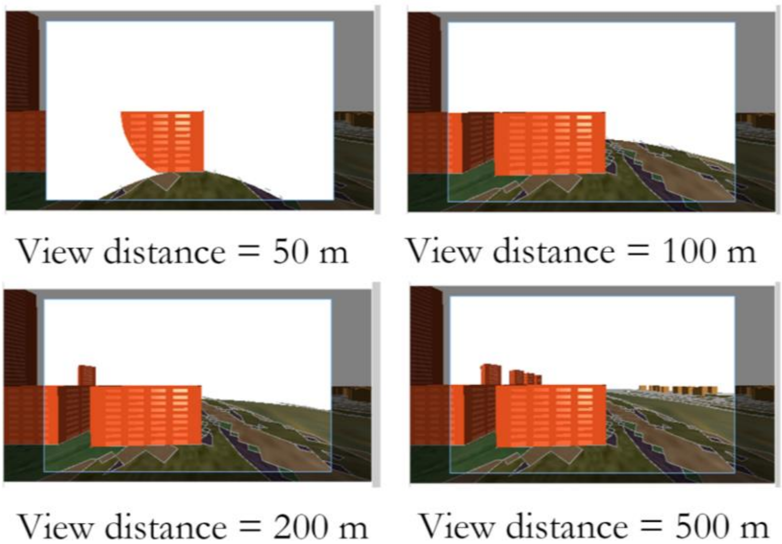


Figure 3-8 The viewshed of Z_1 under different view distances

(1) View quality

Viewshed analysis visualised and quantified the indicators "view quality" and SVF in CityEngine. View quality was defined as the ratio of the visible area of the positive view types to the total visible area. The selection of the positive view types was based on the questionnaire. The formula is given as follows:

$$\text{View quality} = \frac{\text{Visible area}(\mathit{Positive\ view\ types})}{\text{The total visible area}}$$

The parameter setting of viewshed analysis is illustrated in Table 3-3. The observer was assumed to stand in the middle of the building to represent the average value of view quality. The value may change as the storey level changed. This research focused on the neighbourhood scale, so the middle point of the whole building could be taken as the average.

Table 3-3 The parameter setting of the viewshed analysis

Parameter	Value	Reference	Description
Horizontal angle of view	120 degree	The ordinary vision range of people's eyes.	The angle of view measured horizontally when defining a 360-degree panorama from the observer.
The vertical angle of view	90 degree	The ordinary vision range of people's eyes.	The angle of view measured vertically when defining a 360-degree panorama from the observer.
Observer point of X	/	It changes with the observer location.	x coordinate of the observer.
Observer point of Y	The middle storey of the apartment	The observer stays in the middle to represent the average price of each apartment.	y coordinate of the observer.
Observer point of Z	/	It changes with the observer location.	z coordinate of the observer.
Tilt angle	0 degree	The observer looks straight ahead.	Vertical camera view angle.
Heading angle	180/120 degree	Facing south/southeast from the main room.	Horizontal camera view angle.
View distance	50 m, 100 m, 200 m, 500 m	Different view distances contained different view types and areas.	The distance from the observer to the point of interest.

(2) SVF

It was calculated in the same parameter setting with the indicator "view quality". The value of panorama in CityEngine at different view distances represented SVF.

(3) Sunlight

It was carried out by sunlight analysis, which calculated whether a building could receive direct sunlight at the specific orientation during different times of a day. The orientation was determined based on the questionnaire on buyers' preferences. Different time zones, times and months could be set in CityEngine. The mean value at different times in a day represented the indicator "sunlight" in the analysis. In this research, The formula is as follows:

$$\text{Sunlight} = \frac{\text{The apartments not blocked from sunlight by surrounding buildings in one building}}{\text{The total apartments in one building}}$$

Because GWR is not an appropriate method for small datasets (60 samples in this research), OLS was executed in SPSS when the calculation of the 3D indicators finished. The statistical results were exported in Excel to prepare for the model validation.

3.5.5. Model validation

In this research, the validation of the 3D method for property valuation was LOOCV, a special case of leave-*k*-out cross-validation. It leaves one sample for the test set at a time, and the other samples for the training set. The model is trained with the training set and then uses the test set to check the model. Finally, the prediction value and error can be calculated. If there are *k* samples, the train and test sets are both executed *k* times. It is cumbersome but has high sample-efficiency, which is suitable for small sampling size. (Wong, 2015). Error percentage was carried out to measure the degree of the deviation. It was operated by manual work in Excel. The formula of the error percentage is as follows:

$$\text{Error percentage} = \frac{The\ standard\ deviation\ of\ the\ predicted\ prices}{The\ mean\ property\ price\ of\ the\ samples}$$

3.6. Summary

This chapter represents the methods to solve the corresponding research sub-objectives. The qualitative methods of the semi-structured expert interview and focus group aimed to acquire thoughts of people in the related industries. The quantitative analysis of the questionnaire investigated buyers' preferences for the high-rise apartments. In this way, the comprehensive perspectives from different stakeholders could be obtained.

The statistical methods of OLS and GWR were executed to check the influences on the property price from 2D indicators. 3D modeling was applied to analyse and visualise 3D indicators. The model validation was to ensure that the results of the 3D method were effective.

4. RESULTS

This chapter introduces the research results of the quantitative and qualitative analysis in line with the research sub-objectives. First, section 4.1 discusses the pricing policy and the indicators influencing the property prices. Section 4.2 presents the current situation of 3D modeling in China. Section 4.3 demonstrates the statistical results of the questionnaire to identify 2D and 3D indicators buyers valued. The three sections above are in response to the research sub-objective 2.

Section 4.4 and 4.5 together address sub-objective 3 and 4. Section 4.4 presents the statistical results of the 2D methods for property valuation along with the visualisation and analysis of 2D indicators. Section 4.5 describes the 3D method for property valuation, including visualisation, analysis and validation. Finally, it concludes by comparing and assessing the results of 2D and 3D methods.

4.1. The pricing policy

This section introduces the pricing policy of the real estate developers and the indicators influencing the property price. The knowledge was based on the interpretation of the expert interviews with the sales managers, the architectural designer and the landscape designer. It is intended to solve part of the research sub-objective 2.

4.1.1. The general price-making process of the real estate developers

The most common method for property valuation is the cost method. The real estate developers also adopt it. It adds up the total cost at every stage and the interests to calculate the final price. The property price comprises the land transfer fee, development cost, marketing cost and the developer's interests (Wen & Goodman, 2013). The Unified Modeling Language (UML) activity diagram of the general price-making process is shown in Figure 4-1.

When the government announces the residential land parcels for auction and provides their detailed information publicly in advance, the different departments of real estate developer start their jobs. First, the customer analysis, competitor analysis and cost-benefit analysis are executed by the consult and finance department to see whether it can obtain interests. Then the engineering department devises a general architecture design, including the distribution of different apartment sizes and the corresponding floor plans. The work of the marketing department includes product positioning, targeted customer positioning, modeling the sales price based on the local property market and buyers' expectations, and interpreting government policies.

After that, the price is reviewed by the finance department again to calculate the prospective interests. If it can reach a fixed rate (generally 8% in China), the land parcel bidding is approved. After successfully bidding, the neighbourhood construction can officially start. It repeats the cost review at different stages of the construction to control the cost precisely. In the end, the final property price is determined by the company and then submitted to the Price Bureau of Xi'an.

The method adopted by the government is the market comparison method based on the prices of similar neighbourhoods and the current situation of the residential property market. The price is adjusted to which the government considered reasonable. If the price is not approved, the developer should re-declare the price. Only after the government guidance price is established, the sales department can start sales; and they should sell strictly according to the government guidance price.

In conclusion, there are several cost reviews executed at different stages to make sure the cost does not exceed the interests in the cost method. The real estate developers do not adjust the price for some specific indicator. In this way, they maximise the interests by controlling the cost (e.g., less construction for open spaces and landscape and more land dedicated to high-rise apartments.)

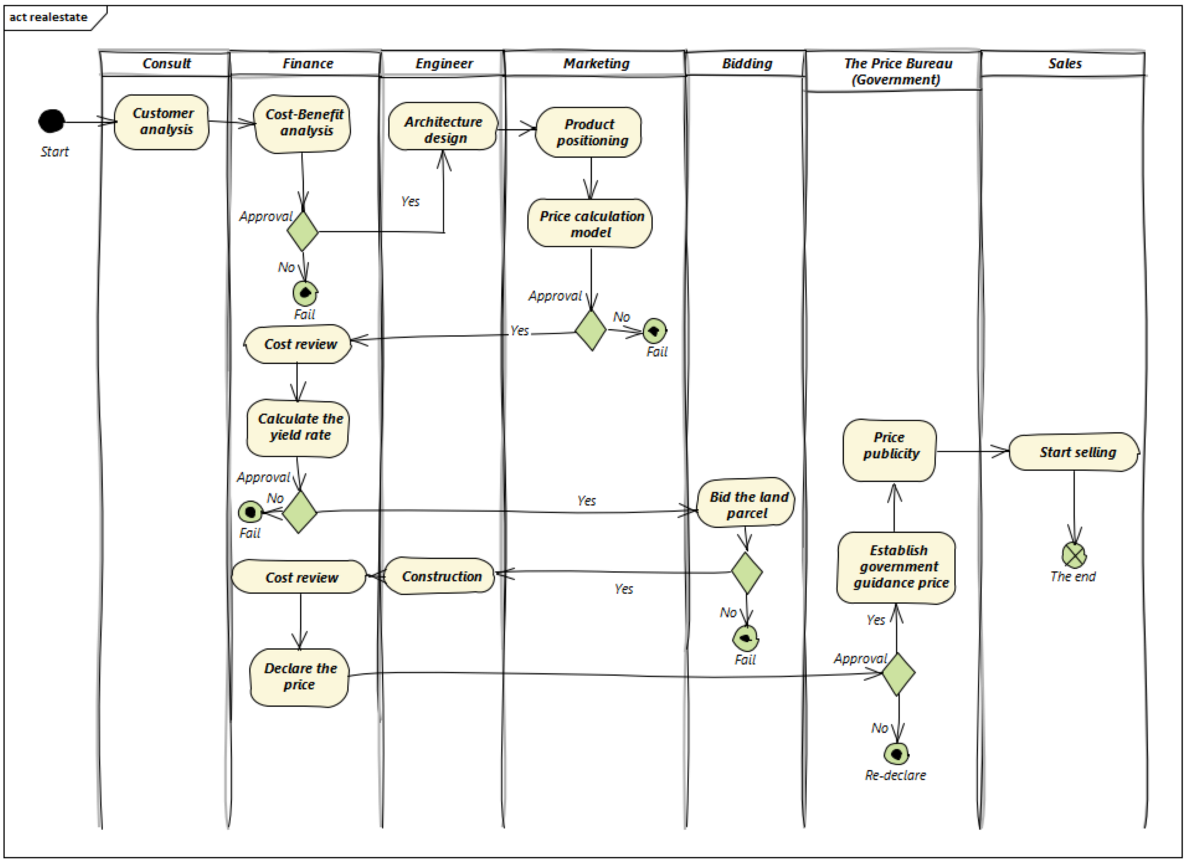


Figure 4-1 UML activity diagram of the general price-making process of real estate developers

4.1.2. The indicators behind the price variation inside the neighbourhood

The pricing policy inside the neighbourhood was as follows. First, according to different geographical locations inside the neighbourhood, the price difference between each building could be set. The indicators included but were not limited to, the proximity to the gate of the neighbourhood, the street, and the garbage station. After that, the price difference between each storey in one building could be set. The property at the middle storey level was the most expensive; then the price went down as the storeys went higher and lower, so the trend was spindle-shaped. Several indicators influencing the price positively or negatively were frequently referred to in the interviews and focus groups. They are separately listed in Table 4-1 and Table 4-2. Some indicators had two sides. For example, although the high storey level had better privacy and broader vision, it was also exposed to more noise from wind.

According to the knowledge gained at the interviews with the sales managers, there were no fixed formulas or models where each indicator represented a certain amount of money. The most important reason for the developer to apply the price difference was the desire to sell the apartments as quickly as possible and maximise the interests. Therefore, the pricing policy was about finding a balance between the price and buyers' expectations. The price difference could be determined based on the influence of the combination of several indicators. Generally, the price difference between each storey fluctuated between 10-40 yuan/m^2.

Table 4-1 The overview of the positive indicators

Name	Reason	Notes
High storey level	Better privacy and broader vision.	
Low storey level (approximately 1-4)	Better living convenience which saves the time waiting for the elevator, especially for the elderly; less noise.	
All-face-south orientation	More daylight hours.	
South-North orientation	More daylight hours; facilitate ventilation.	
Pre-decoration	Save buyers' time for decoration and garnishment. It is especially popular among the youth.	
Green space/ Park / Water	Clear and broad vision; good air quality and less pollution.	
Historical site	Better reputation and better living experience.	
Safety	Better living convenience.	Such as the access control system, 24h security patrol, and the fingerprint/face lock system.
Public cleanness	Better living comfortability.	Such as regular cleaning in the public area.
The brand of the developer	Better reputation and credibility; brand effect.	
Public transport/ shop/ restaurant	Better living convenience.	
Hospital	For the emergency and medical care, especially for the elderly.	
Locations in the centre of the neighbourhood	Convenient for transport; good Fengshui; less noise and pollution from outside.	
Locations near good landscape	Better view; better living experience.	Fengshui is very important.
Regional urban planning/government policy	Better asset appreciation potential.	
School district	No need to pay an additional fee for finding another good school.	Good school districts are rare.

Table 4-2 The overview of the negative indicators

Name	Reason	Notes
High storey level	More noise from wind; longer transport generatrix; more elevator fee and waiting time.	
Low storey level (approximately 1-4)	Possible high humidity; blocks from architecture design and tall trees; narrow vision.	
Specially shaped architecture	Bad Fengshui; deviated from the traditional Chinese principles; inefficient for space utilisation.	Such as the triangle-shaped rooms and the explicit representation of the bearing pillars.
North orientation	No enough daylight hours; bad for ventilation.	
West orientation	West sun exposure makes the apartment hot in the afternoon during summer and autumn.	
Road/street/ gate	More noise and air pollution; bad for living experience.	
Garbage station/ electrical power station/biogas digester /indicatory	Possible stink, air pollution, and the noise of machines at night; bad views.	
Kindergarten, primary and secondary school	More noise during the daytime.	
Historical site	More noise during the daytime; bad public cleanness if not well-maintained.	
Undeveloped area	Potential safety risk; bad view.	Such as urban villages, wasteland, rural-urban fringes.
Locations at the edges of the neighbourhood	Bad Fengshui; longer transport generatrix.	
Close distance between two buildings	Bad living comfortability, narrow vision and short daylight hours.	
Sensitive numbers	Chinese customs and traditions.	The sound to speak "4" in Chinese had the same meaning with "death".

4.2. Current situation of 3D modeling in China

In this section, the current situation of 3D modeling in China is summarised based on the knowledge obtained at the expert interviews and focus groups. First, it briefly introduces the policy background of the property market in Xi'an. Then it describes the current situation of 3D modeling in the perspectives of different stakeholders. It is intended to solve part of the research sub-objective 2 and answer the research question "What is the current situation of 3D modeling in China?".

4.2.1. Policy background

There are two important policies related to the property market established by the Xi'an municipal government at present. They are the purchase-restriction policy and the fixed-price policy.

First, the purpose of the purchase-restriction policy is to control the speculation purchase, as well as to make housing affordable for the residents in Xi'an. When registering intention for a purchase, the buyers are categorised into two classes, "rigid demand" (*gangxu* in Chinese) and "regular" (*putong* in Chinese). If the buyer has no properties under his/her name, then he/she belongs to the "rigid demand" groups; otherwise, he/she belongs to the "regular" group. The "rigid demand" group enjoy the pre-emption rights over the "regular" group.

Second, the purpose of the fixed-price policy is to ensure the stability of the property price. Real estate developers do not have the rights to determine the price; they have to declare the property price to the Price Bureau of Xi'an and ask for the sales permit. In the sales process, they sell the properties strictly according to the government guidance price. For those real estate developers which declare the price significantly higher than that of similar properties, the sales permit will not be issued.

4.2.2. 3D modeling in real estate developers

According to the interviews with the landscape designer and the architectural designer, 3D modeling is frequently applied in architecture and landscape design in the preliminary stage of the neighbourhood construction. However, when it comes to sales, the predominant sales methods are still in 2D in Xi'an.

In the traditional sales office, there are four common sales tools, including 3D sandbox, floorplan, showroom and display area. 3D sandbox refers to a model scaled down according to the size of the actual building (Figure 4-2). Buyers can see the model of the whole neighbourhood and its surrounding environment. Floorplan refers to a scaled-down horizontal top view of the relationship between rooms, spaces and other physical features in architecture. The showroom is temporarily built to show the inner architecture structure and the actual decoration effect. Display area involves both the showroom and landscape (e.g., grass, flowers, and art installations) to offer immersive experiences to the buyers.

Figure 4-2 The 3D sandbox of neighbourhood "Z" (source: author took during the fieldwork)

Regarding the 3D interactive model, the respondents said the most popular one was the virtual reality (VR), which has already been applied for the landscape presentations in larger cities, such as Shanghai and Beijing, but not yet in Xi'an. The reasons lie in the following aspects:

- The high cost. Software maintenance is the dominant factor contributing to the high cost. Besides, a 3D model needs a long production cycle. In the case of a flourishing property market, it adds unnecessary marketing cost.
- Customers' feedback. Buyers tend to believe what they see other than a virtual 3D model. The showroom and display area are enough to simulate the real neighbourhood environment.

4.2.3. 3D modeling for buyers

In this research, most of the respondents only experienced traditional sale tools. They considered the 3D sandbox and showroom were intuitive enough. Many of them have heard about VR. In the perspective of buyers, 3D modeling served as the auxiliary method. It had both advantages and disadvantages.

The advantages of 3D modeling lie in the following aspects:

- It has an intuitive representation. When buyers are confused with the complicated floor plan, 3D visualisation is more intuitive and easy-to-understand, offering more information to them compared to 2D representation.
- It helps the housing decision remotely. 3D modeling helps to filter out the neighbourhoods which the buyers interest in faster, and they do not need to be present in person. "But when I made the final decision, I was more willing to have the real experience, such as the showroom." One respondent said.

The disadvantages of 3D modeling lie in the following aspects:

- The low acceptance. For the elderly, it is hard for them to accept new techniques. For example, VR experience may lead to sickness, a combination symptom of eyestrain, disorientation, and nausea, which are dominant reasons for the refusal.
- The credibility issues. Whether 3D modeling can reflect the reality remains a question to buyers. They are accustomed to the traditional sales tools and feel that showroom and 3D sandbox were more reliable, although showroom may also have the exaggeration problem.

4.2.4. 3D modeling in the planning and survey department of government

The results came from the expert interviews with the Xi'an Survey and Mapping Institute and Huadi Valuation and Consulting Company. 3D modeling helped urban planning in many aspects. In the past, it was all in 2D, and the government could not have intuitive feelings about the surrounding buildings. Now by establishing 3D models for the buildings, it is easy to find out whether the architecture style is consistent, simulate the daylight change, and unify the building volumes. At present, it has not realised the real 3D modeling (mainly 2.5D) yet in Xi'an, but the larger cities in China (e.g., Hangzhou) have already accomplished. Smart 3D and SketchUp are the mainstream software used in the survey and urban planning department in Xi'an at present.

The author was informed that the Emergency Management Office and the Police Bureau of Xi'an have 3D models for the inner structure of the buildings connected with the fire control department for emergency purposes. It is not open to the public. The key issue here is how to make it up-to-date. For an increasingly dense urban area like Xi'an, it is necessary and urgent to construct 3D models of both aboveground and underground spaces for diverse purposes(e.g., property certificate establishment).

The difficulties of 3D modeling in Xi'an lie in the following aspects:

- The low administrative efficiency. There has not been any national policy support towards 3D modeling. The necessary data of building the 3D models are dispersed in different governmental departments, making it hard to integrate them because no department feels obliged to share the data. The data integration consumes time and is often considered unnecessary.
- The vast workload for human resources. The process of automatically constructing the 3D models is quite easy, but manual intervention is required with a high level of detail (LoD). The engineers distinguish each storey of the buildings and add the corresponding attributes manually. The buildings and landscape close to the ground need to be reconstructed.
- National security. The open of 3D modeling is very sensitive in China because it relates to national security.
- The high cost. The current 3D models are mainly for representation, thus lack interaction functions and building details. Updating the data on a timely basis is also an issue. The maintenance and development cost is huge.

4.3. The questionnaire on buyers' preferences

This section provides a statistical analysis of the questionnaires issued by both paper and survey software. The contexts cover the preferences for the storey levels, property orientation, surrounding living facilities, different view types, and their willingness to pay for a good view. This section aims to identify 2D and 3D indicators the buyers valued to address part of the research sub-objective 2. A total of 276 questionnaires were received, and 142 questionnaires from Xi'an were filtered out by Internet Protocol (IP) address via the survey software Wenjuan Xing.

4.3.1. The storey levels

This question had three options, low storey level, middle storey level and high storey level. It took a high-rise building with 33 storeys as an example, which was typical in the high-rise neighbourhoods in Xi'an. The low, middle and high storey level represented 1^{st} -11^{th}, 12^{th} -22^{nd}, and 23^{th} -33^{rd} storeys, respectively.

Out of 126 responses, 22 chose the low storey level, 54 chose the middle storey level, and 50 chose the high storey level (Figure 4-3). Thirty-one respondents gave their reasons. Five respondents chose the low storey level. Four of them explained for "living convenience" and one for "acrophobia". For example, they did not have to wait for elevators for a long time, and they could use the stairs in an emergency. Eleven respondents chose the middle storey level. The reasons could be categorised into "Doctrine of the Mean" and "broad vision". The Doctrine of the Mean (*zhongyong* in Chinese), originated from Confucianism, aims to reach balance and harmony both physically and mentally. Living in the middle, reflected by six respondents, indicated a balance between living convenience, air pollution, noise, and vision. Other five respondents emphasised on the great view and the broad vision out of the window. Fifteen respondents chose the high storey level, and the majority clarified for the following three reasons, "broad vision without blocks", "good view" and "the extended daylight hours".

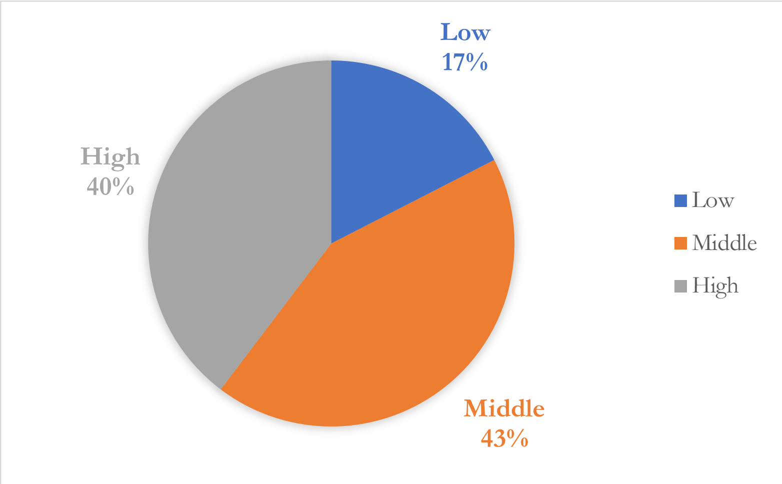


Figure 4-3 The overview of the preference for storey levels

4.3.2. The property orientation

It had 141 responses in this question. As shown in Figure 4-4, only four respondents chose options which were not south-north orientation. Twelve respondents explained specific reasons, and they all chose the "South-North" orientation. Among them, seven mentioned "the good daylight", two referred to "avoiding too much sunlight exposure", and four voted for "ventilation". The results were consistent with the knowledge obtained at the interviews with the architectural designer and sales managers that most of the residents in Xi'an preferred south-north orientation. It could facilitate ventilation, result in cooler temperature in summers and extend the daylight hours. Only two respondents chose "Southwest-Northwest" and "Southeast-Northeast". In Chinese culture, it did not prefer the deflection angle in the housing selection. The due orientations, such as due north and due south were more common in Northern China.

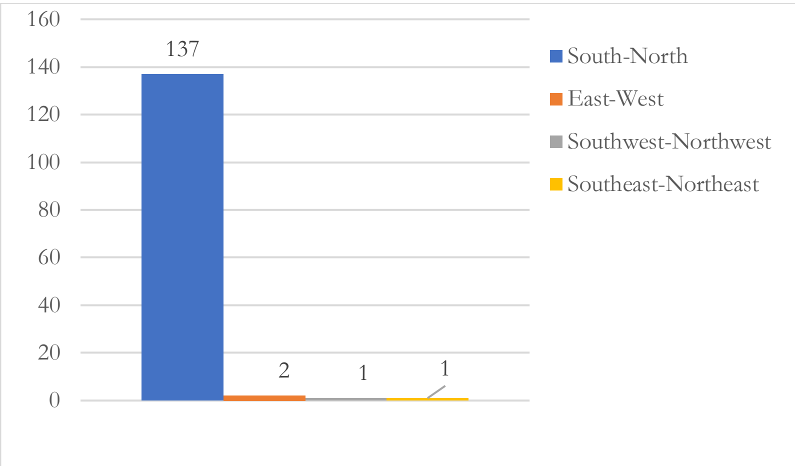


Figure 4-4 The overview of the preference for property orientation

4.3.3. The surrounding environment and the physical property attributes

This question was designed to investigate buyers' preferences for surrounding environment and physical property attributes related to the height by ranking them in a five-point Likert Scale, not much important, not important, undecided/I don't care, important, and very important. The selection criteria of the indicators were based on the knowledge obtained in the literature review and the expert interviews during the fieldwork. The descriptions of some indicators were simplified for a better presentation in diagrams. All the empty/blank options were excluded in statistics.

The results of the preferences of surrounding living facilities were concluded as follows (Figure 4-5). All the respondents chose "very important" and "important" for "public security", indicating they attached great importance to personal safety. "Shopping" and "public transport" were the following two top choices, with the supporting rate of 82.4% and 70.7%. In the group aged 18-25 and 26-35, the rates reached even higher, 83.7% and 75.3%, respectively. It demonstrated the young people had greater demand for shopping and public transport. 69.7% of the respondents considered "leisure" was "important" and "very important". 28.9% went for "undecided/I don't care" while two respondents thought it was "not important". "Educational facility" was the most popular among the group aged 26-35 and 36-45, with the supporting rate of 60.0% and 72.0%, separately. These groups had flourishing demand for education, so the neighbourhood with a high-quality school was highly-valued. 53.3% of the 18-25 group was not concerned about it. The average rate was 55.3%. The similar separated trend also went for "food". 68.9% of the group aged 18-25 thought it was "important" and "very important" to have easy access to food in the surrounding areas. The rate was only 50.0% in the group aged over 55. It was consistent with the current phenomenon that the youth loved to eat outside while the seniors preferred to cook at home.

6.4% of the respondents voted "not important" and "undecided/I don't care" for "sports facility". The group aged 36-45 took the highest value on it, with the supporting rate of 76.0%. It meant that they valued physical health and were willing to invest time and money. "Entertainment facility" and "cultural facility" were the last two indicators with a supporting rate lower than 50.0%. They were also among the three indicators which had respondents selected "not much important".47.5% of the respondents did not care about the "entertainment facility", and 6.5% thought it was "not important". For the "cultural facility", only 41.3% gave positive selections and half of the respondents were not concerned about it.

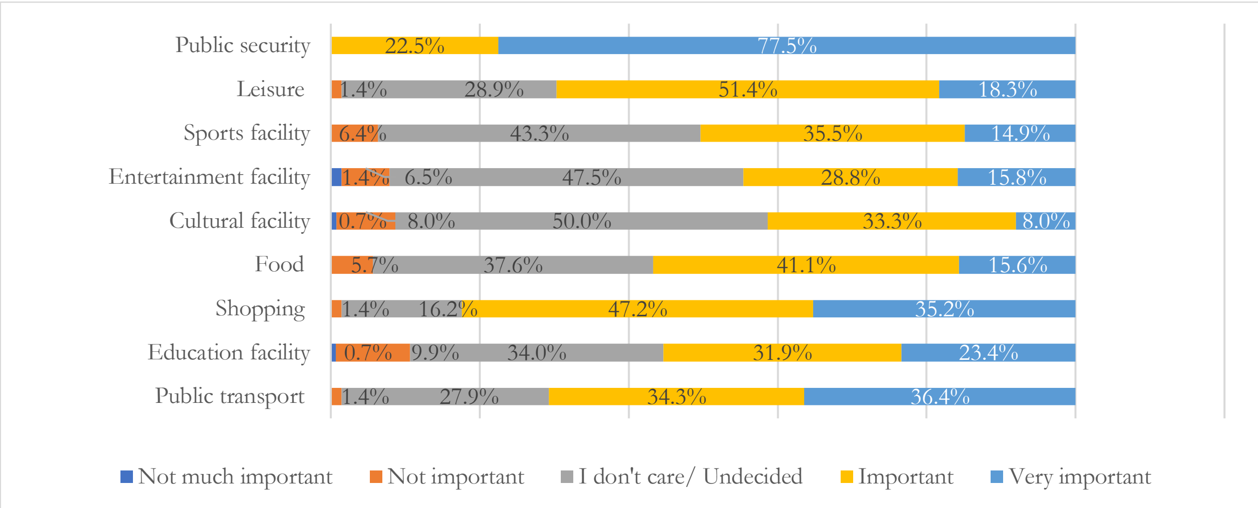


Figure 4-5 The overview of the preference for surrounding environment

The results of the preferences for physical attributes related to the height are shown as follows (Figure 4-6). Generally, all the indicators got relatively high rates, which showed the respondents attached great importance to them. The highest was "property orientation" with a supporting rate of 92.9%. It had a great influence on daily life and was within a controllable range for the buyers, compared to other indicators (e.g., the view and the vision may change over time). The sunlight condition also had a link with the property orientation. For a city facing fast urbanisation and continuous construction, air quality and noise were always two important issues in the housing selection. It was also reflected in the questionnaire. "Less noise" and "less air pollution" were the second and the third important indicators buyers valued. The rates reached 84.5% and 81.6%, respectively. They did not have respondents who thought "not important" or "not much important". The different age groups shared similar results for the indicators "sky view (Vision)" and "view", with the supporting rate of 75.9% and 73.1%, respectively. The indicator "daylight hours" had the highest rate of 26.8% for "undecided/I don't care" and the lowest rate of 25.4% for "very important", which may be because the government established regulations on the real estate developers to ensure the minimum daylight hours. In this way, people did not have to worry much about the sunlight condition.

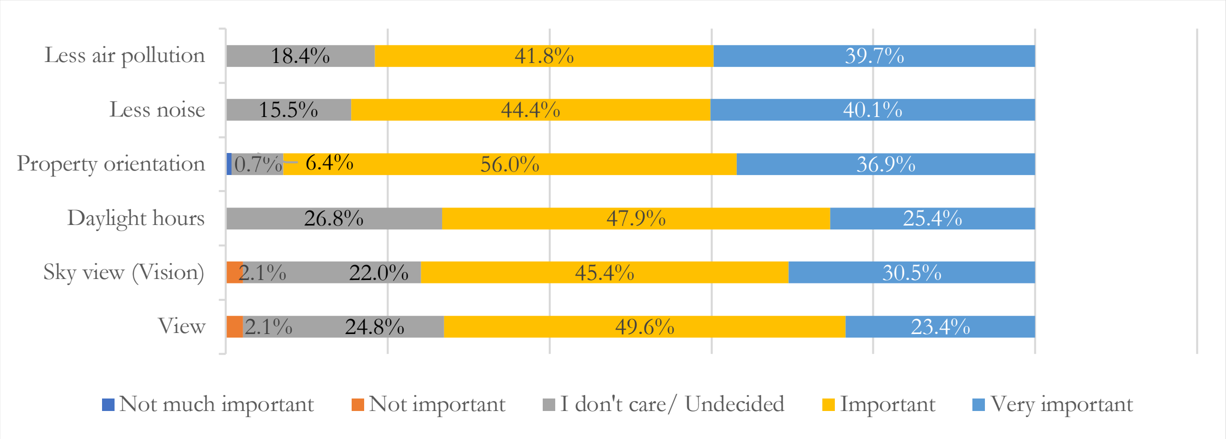


Figure 4-6 The overview of the preference for physical property attributes

After assigning 1-5 to each scale, from "not much important" to "very important", the final marks in descending order of the indicators are illustrated in Table 4-3. The top three indicators were "public security", "property orientation", and "less noise". It scored the lowest at "sports facility", "entertainment facility" and "cultural facility". It served as the selection criteria for indicators in 2D and 3D methods.

Table 4-3 The final marks of the indicators of surrounding environment and physical property attributes

Indicator	Mark	Rank
Public security	4.8	1
Property orientation	4.3	2
Less noise	4.3	3
Less air pollution	4.2	4
Shopping	4.2	5
Public transport	4.1	6
Sky view (Vision)	4.0	7
Daylight hours	4.0	8
View	3.9	9
Leisure	3.9	10
Education facility	3.7	11
Food	3.7	12
Sports facility	3.6	13
Entertainment facility	3.5	14
Cultural facility	3.4	15

4.3.4. Different view types

The indicator selection was based on the observation during the fieldwork in Xi'an. After visiting several residential neighbourhoods, the basic view types were determined. It was a multiple choice question. The detailed information can be seen in Figure 4-7.

Most of the respondents disliked "street/road" and "building" to be the view out of their windows. Only 7 chose these two options. The other four types of view were relatively popular. 76.1% voted for "green land", which ranked first. The second highest was "park/square", with a supporting rate of 54.2%. The green space had a powerful regulating effect on the environment, such as reducing noise and enhancing air quality. The park and square always had several landscape designs with good visual experience. Additionally, being able to see the park meant being close to it and enjoying the convenience. 40.9% and 33.1% of the respondent were favourable for "water" and "open space", respectively. It may be because they had two sides. The river and pool were likely to get stink and attract insects without orderly maintenance, which was reversely bad for the living environment. Besides, "open space" might become high buildings or some area where slum-dwellers lived in the future. Thus, it could reduce the aesthetic value.

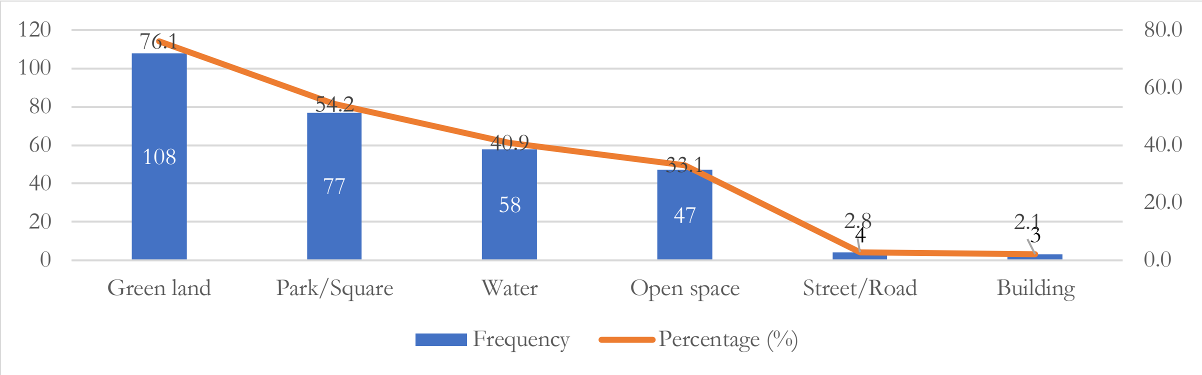


Figure 4-7 The overview of the preference for different view types

4.3.5. Willingness to pay

This question calculated the percentage buyers were willing to pay extra for different view types (multiple choice) and the preferred property orientation (single choice). The percentage was calculated based on the total property price of one apartment.

Table 4-4 shows the responses of the willingness to pay extra for different view types. Ninety-nine respondents chose to pay extra for "green land", following by 63 respondents chose for "park/square". "Water" and "open space" had 19.9% and 14.9% supporting rate, respectively. Only 2.5% and 2.8% of respondents chose to pay extra money for "street/road" and "building", which explained that they were the two most unpopular view types (section 4.3.4).

All the mediums for the other five view types were the same, 5%, except for "building", having only 1.5%. The average value of each type fluctuated, but the change was little. "Building" had the lowest average, 2.75%, and one respondent even gave negative -5% for it. However, only seven respondents voted for the view type "street/road", and they were willing to pay for an average of 5.3%. It could be inferred that the affordable extra price for the buyers was around 5% for each view type.

Each type had some discrete values. One respondent was willing to pay an extra 50% for "park/square" and 40% for "water". However, most of the respondents were willing to pay no more than 10% for each type. The results were consistent with the knowledge obtained at the focus groups that the buyers preferred a lower price, compared to the additional value they got.

Table 4-4 The overview of the willingness to pay for different view types

Name	Frequency	Percentage (%)	Medium (%)	Average (%)	Minimum (%)	Maximum (%)
Green land	99	35.11	5	4.91	0	30
Park/Square	63	22.34	5	6.91	2	50
Water	56	19.86	5	7.03	2	40
Open space	42	14.89	5	4.19	1	10
Street/Road	7	2.48	5	5.29	-5	20
Building	8	2.84	1.5	2.75	0	10

Note: The percentage(%) represents the ratio of the frequency of the specific view type to the total responses; the medium, average, minimum and maximum (%) represents the percentage of the total price which buyers were willing to pay extra.

Out of 133 responses for the preferred property orientation, all chose for the "south-north" orientation. Figure 4-8 shows the results of their willingness to pay extra. The x-axis represents the extra percentage, and the y-axis represents the number of respondents. 87.2% of the respondents were willing to pay for no more than 10%. 67.7% of the respondents were willing to pay no more than 5%. The median was 5%, and the average was 7.5%.

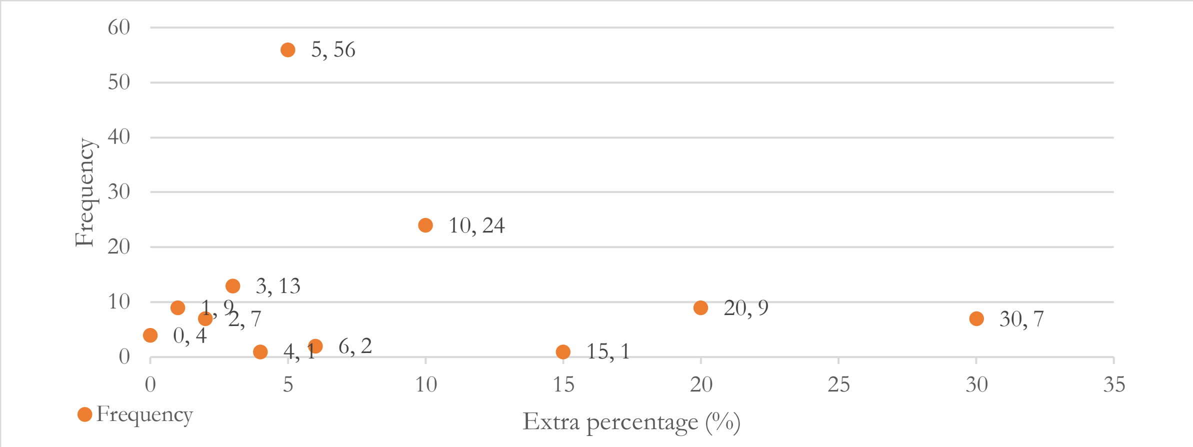


Figure 4-8 The overview of the willingness to pay for the preferred property orientation

4.4. The 2D methods of OLS and GWR for property valuation

This section includes the selection of 2D indicators and the regression results of 2D methods in terms of OLS and GWR. Then the analysis and the visualisation of the significant 2D indicators are illustrated in the following sections. It aims to accomplish the 2D part of the research sub-objective 3. the results serve basis for comparison to achieve the research sub-objective 4 to answer the research question "Can 3D method better describe the property prices in the study area than 2D methods?"

4.4.1. The selection of the 2D indicators

Based on literature review, questionnaire, and local knowledge obtained during the fieldwork, 11 indicators were selected with the usage of POI in Xi'an. They were divided into two categories, neighbourhood and locational characteristics (Table 4-5).

Several indicators were excluded. First, The POI under the categories of "sports facility", "entertainment facility" and "cultural facility" were excluded because they all received less than 50% support rate in the questionnaire. The indicator "historical site" were excluded because there was a great number of historical sites in the urban area of Xi'an, but their protection levels (e.g., under the state, provincial and city protection) varied significantly. It was difficult to quantify whether it had a positive or negative effect on the living experience. In the several test run of the regression models, the p-value all exceeded 0.9, indicating there existed no significance at all. The indicator "water" was excluded because there was no river across the main urban area of Xi'an.

Table 4-5 The overview of 2D indicators and the selection criteria

Indicator	Attribute	Definition	Unit	Criteria	Expected Sign
Property price	Dependent variable	The first-handed residential property price of the high-rise apartment neighbourhood	yuan/m²	N/A	N/A
Density of park	neighbourhood	The density of the parks within 1km	Number	Noise and air pollution; view and vision.	+
NDVI		The mean vegetation around the neighbourhood within 200 m	Number	Green land; air quality.	+
Density of factory		The density of the factories within 1km	Number	Less noise and air pollution.	—
Distance to food		Euclidean distance to the restaurants, fast-food chains, and eateries.	Meter	Food.	—
Distance to college		Euclidean distance to the colleges and universities	Meter	Education facilities.	—
Density of hospital		The density of the big hospitals within 3km	Number	The knowledge based on interviews.	+
Density of supermarket	location	The density of the supermarkets within 1km	Number	Shops, living convenience.	+
Distance to CBD		Euclidean distance to the Central Business District (CBD)	Meter	Shops, living convenience.	—
Distance to subway		Euclidean distance to the subway stations	Meter	Public transport; public security.	—
Density of busstop		The density of the bus stops within 200m	Number	Public transport; public security.	+
Distance to road		Euclidean distance to the primary and secondary roads.	Meter	Dislike of the roads/streets.	—

4.4.2. Property price distribution

There were 298 samples of the average first-hand property price for different high-rise neighbourhoods. The period was from 1st January 2018 to 18th September 2018. The samples located at the central part of the corresponding neighbourhoods. The area covered the seven urban administrative districts and excluded the counties which were not under the purchase-restriction policy. The property sample map is shown in Figure 4-9. The descriptive statistics of the property samples in SPSS is shown in Appendix 7. The minimum was 3326 yuan/m², and the maximum was 32635 yuan/m². The medium (7769) was smaller than the average (8484), indicating that there were more low property prices than those in the high level. It was possible because some areas of Xi'an were still under development; thus the property prices there kept low. They were not in a normal distribution with the skewness of 2.389 and kurtosis of 10.831.

Global Moran's Index is a measure of spatial autocorrelation. ArcGIS was used to generate the report based on the spatial coordinates and property prices (Appendix 8). The Global Moran's Index was 0.048, a positive value, which indicated there existed positive spatial autocorrelation among the property samples. With a z-score of 3.97 and p-value of 0.000071, the conclusion could be drawn that the overall property price distribution showed a spatial clustered pattern and a positive autocorrelation at a 0.000 significance level. Therefore, the traditional HPM using OLS was not suitable for analysis because it had limitations of explaining the spatial heterogeneity. GWR was a good alternative to build models with these property price samples.

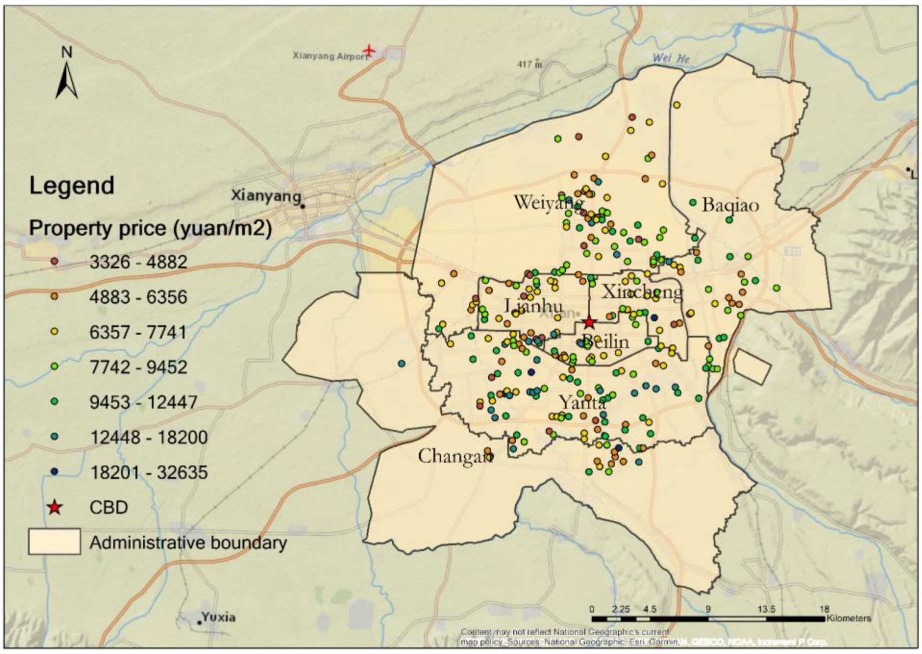


Figure 4-9 The distribution map of the property price samples

4.4.3. OLS model

SPSS was used to execute the OLS model with 2D indicators. The results are shown in Table 4-6. The detailed screenshots of the statistical results in SPSS are shown in Appendix 9.

The R^2 and adjusted R^2 were 0.111 and 0.077, respectively, which indicated this OLS model could explain only approximately 10% dependent variables. Therefore, it could not be generalised. Five variables were significant at a 0.05 significance level, including distance to CBD, distance to subway, distance to food, density of factory and NDVI. Distance to CBD, distance to subway, and density of factory showed a negative effect. As such, the farther from the subway station and CBD, the lower the property price. The standardised coefficients were -0.133 and -0.220. Distance to CBD had the most significant absolute value of the coefficient. The standardised coefficient of density of factory was -0.165. When the density of factory improved, the price reduced.

On the contrary, distance to food showed a positive sign with a standardised coefficient of 0.193. NDVI had a positive standardised coefficient of 0.131. When the distance to food and NDVI increased, the property price increased. Other variables were not statistically significant at a 0.05 significance level. The Durbin-Watson value represented the independence of error. In this case, it was 1.890, close enough to the optimal value 2, which assumed the residuals were uncorrelated. Tolerances were all greater than 0.2, and variance inflation factors (VIF) ranged from 1 to 3, far less than 10, indicating that no collinearity issue existed among these variables, which was suitable for executing GWR.

Table 4-6 The regression results of OLS

Variable name	Standardised coefficient	t-Ratio	p-Value	Tolerance	VIF
NDVI	0.131*	2.121	0.035	0.818	1.223
Density of busstop	0.032	0.128	0.575	0.968	1.033
Density of supermarket	-0.104	-1.345	0.180	0.523	1.910
Density of factory	-0.165*	-2.668	0.008	0.812	1.231
Density of hospital	-0.069	-0.826	0.410	0.443	2.259
Distance to food	0.193*	2.783	0.006	0.643	1.554
Distance to college	-0.015	-0.212	0.832	0.642	1.559
Distance to road	-0.048	-0.795	0.427	0.870	1.150

Density of park	-0.044	-0.707	0.480	0.796	1.256
Distance to subway	-0.133*	-2.109	0.036	0.785	1.274
Distance to CBD	-0.220*	-2.545	0.011	0.417	2.395
Constant	11231.590	10.55	0.000	/	/

R^2= 0.111, Adjusted R^2 =0.077, Durbin-Watson = 1.890

The GWR was executed in ArcGIS. The Fixed Gaussian function was selected as the spatial kernel type, and Akaike information criterion (AICc) was used to define the final bandwidth. The comparison of the two models is shown in Table 4-7. The goodness-of-fit of the two models were both not ideal. However, in general, GWR performed better than OLS, as the adjusted R^2 had improved from 0.077 to 0.128 in explaining the variation of the dependent variable (property price). The residual sum of square (SS_R) in GWR also significantly reduced compared to that in OLS, from 3,392,667,848 to 2,655,158,522. Therefore, GWR was finally chosen to analyse the influence of 2D indicators on property price.

Table 4-7 The comparison of the regression results of OLS and GWR

Name	R^2	Adjusted R^2	SS_R
OLS	0.111	0.077	3392667848
GWR	0.217	0.128	2655158522

4.4.4. GWR model

Table 4-8 shows the descriptive statistics of the coefficients in GWR. The β represents the coefficient of each variable. Distance to CBD was the most significant among the 11 indicators, with a standardised coefficient of -4.880. It had a negative link with the property price. Distance to busstop only had a slightly positive standardised coefficient of 0.231. It may be because of the well-developed bus transportation in Xi'an. Distance to food had the most significant positive standardised coefficient of 2.695, which meant the property price lifted as the distance increased. The R^2 and adjusted R^2 were 0.217 and 0.128, respectively. Since the urban development of different parts in Xi'an was unbalanced, the influence of the indicators on property price had significant spatial heterogeneity.

Besides, since the GWR function in ArcGIS could not provide the significance of each indicator, the significant indicators were assumed to be the same in OLS, and the detailed analyses were given in the following sections. The GWR support output table is in Appendix 10.

Table 4-8 Descriptive statistics of GWR estimation coefficients

Variable name	β mean	β min	β max	β standardised	β standard deviation
NDVI	4136.834	-137.098	6617.045	2.630*	1572.973
Density of busstop	2.037	-26.437	21.607	0.231	8.829
Density of supermarket	-11.377	-29.688	4.423	-1.441	7.896
Density of factory	-870.293	-1585.278	22.264	-2.171*	400.941
Density of hospital	-2880.989	-5843.088	988.861	-2.221	1297.092
Distance to food	5.455	1.488	9.706	2.695*	2.024
Distance to college	0.104	-0.435	0.984	0.341	0.305
Distance to road	-1.001	-2.072	0.225	-1.653	0.605
Density of park	-173.801	-810.403	434.060	-0.680	255.686
Distance to subway	-0.701	-1.433	-0.274	-2.304*	0.304
Distance to CBD	-0.230	-0.381	-0.175	-4.880*	0.047
Local R^2	0.124	0.093	0.207	/	0.022
Intercept	11531.725	8847.235	14826.088	7.338	1571.418
AICc	5670.436				
Adjusted R^2	0.128				

*β: * statistically significant at the 0.05 level in the OLS model. Bandwidth =11834.747*

(1) Local R^2

The range of local R^2 was from 0.093 to 0.207, and the mean was 0.124. As shown in Figure 4-10, the general trend of local R^2 increased from north to south gradually. It indicated the model simulation in the south area was better than in the north area. There were some samples in the north area found to have an abnormally low local R^2. The region with low local R^2 had the potential to be the sub-CBD. Based on local knowledge, the Xi'an municipal government located in the northern region, which may influence regional development.

In reality, the urban development pattern of Xi'an showed great asymmetry. It was more developed in the south area compared to the north area in the past decades. The north and east parts of Xi'an were under-developed areas, whose functions were mainly transport, harbour affairs and industry. The south-eastern region agglomerated a great many higher educational facilities, world-famous historical sites (e.g., Big Goose Pagoda), big shopping malls, which all added up the property price. The south-western region was the National High-tech Development District, which gathered high-tech industries and talents. It was equipped with the good school districts, medical care and neighbourhoods with premium quality. Therefore, it had the highest local R^2.

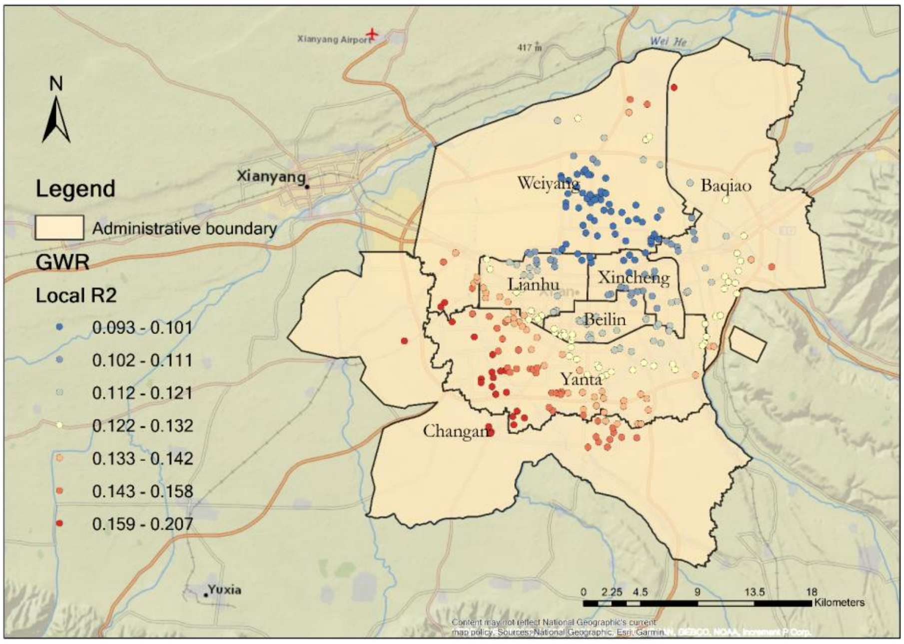


Figure 4-10 The distribution of local R^2 in GWR

(2) Factory

In this research, the factory referred to all the manufactures which had mass productions. It was a broad categorisation. The density radius was set to 1 km. The results showed that only one property in the north part had a positive coefficient of 22.264, which could be taken as an outlier. The left 297 all had negative values, falling between -1585.278 and -22.264 (Figure 4-11); and the mean value was -870.293. The negative trend was the same with the expected sign. As the density improved, the price decreased. 198 out of 298 samples, 66.44% were located at the area where there was less than one factory within 1km². Twenty-seven samples, 9.06% was at where there were more than two factories within 1 km².

The absolute value of the coefficient increased from northeast to southwest. It demonstrated the properties in the southwest area were more likely to be influenced by the density of factory than those in the northeast. The high-tech, business and education industries dominated in the south area, which may be sensitive to environmental changes. There were three blue regions which show great agglomeration trend in the density of factory. They were Weiyang Industrial Zone (north), Chanba Industrial Zone (northeast) and Xianyang High-tech Industrial Zone (northwest). However, it seemed that the highly-dense industry zones did not affect the property prices because the coefficients of the properties close to factories remained normal without turning to very great absolute values.

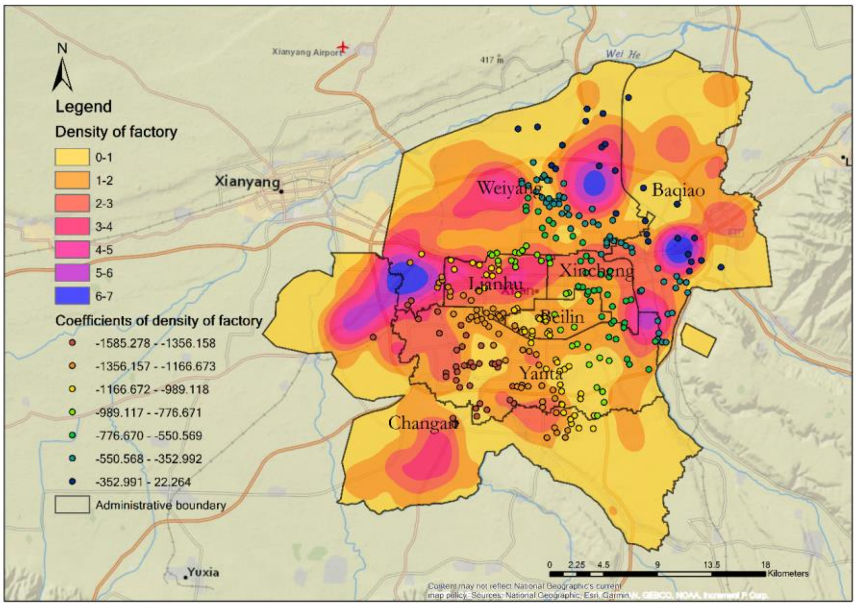


Figure 4-11 The distribution of the coefficients of density of factory

(3) Food

In this research, the food contained all the restaurants, fast-chains and eateries. Not as expected, the coefficients were all positive, ranging from 1.488 to 9.706; and the mean value was 5.455. The positive value meant that the farther from the food, the higher the property price. The map revealed that most of the urban areas in Xi'an were close to the food and the differences between properties were insignificant (Figure 4-12). 252 out of 298, 84.56% had a distance to food less than 200 m, representing easy food accessibility in most areas of Xi'an.

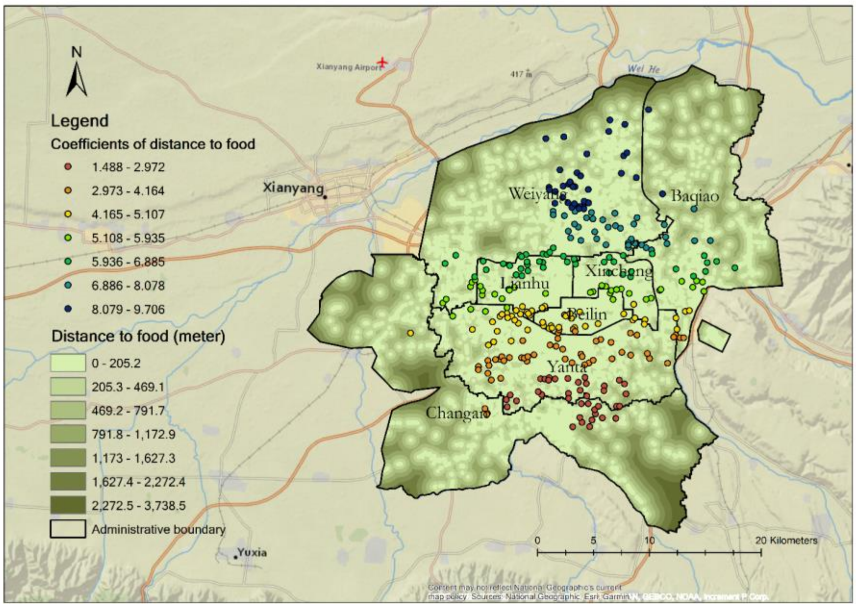


Figure 4-12 The distribution of the coefficients of distance to food

It was also clearly shown that the general trend of the coefficients increased from south to north, indicating that the properties in the north could be influenced more significantly than the properties in the south. The positive influence of this indicator could be explained that the area with too many restaurants or eateries had a negative influence on the living environment concerning noise, public cleanness and air quality. Besides, it could also bring a transient population, having a negative impact on public security. People did not need to choose a property especially because of food accessibility because there were restaurants everywhere in Xi'an.

(4) Subway

Up until September 2018, there were six subway lines in Xi'an, including 139 stations. The coefficient ranged from -1.433 to -0.274. The mean value was -0.701. The negative value indicated that the farther from the subway station, the lower the property price. It was consistent with the expected sign. 63.09% and 26.51% of the property samples were located in the range of 0-1 km and 1-2 km, respectively. The majority were under the reasonable reach of the subway system (Figure 4-13).

From south to north, the coefficients gradually increased. It indicated that the properties in the south were easier to be influenced. It may be because of the macro environment that the north area was less developed than the south. Weiyang and Baqiao District were relatively remote from the city downtown, and the public transport was not well-developed. People did not expect the subway to provide convenient public transport service. While people living in the south, especially in Yanta District, where always had busy traffic, were more sensitive of the distance to subway stations. They had greater demand on the subway to provide a more convenient, fast and affordable alternative compared to bus and taxi.

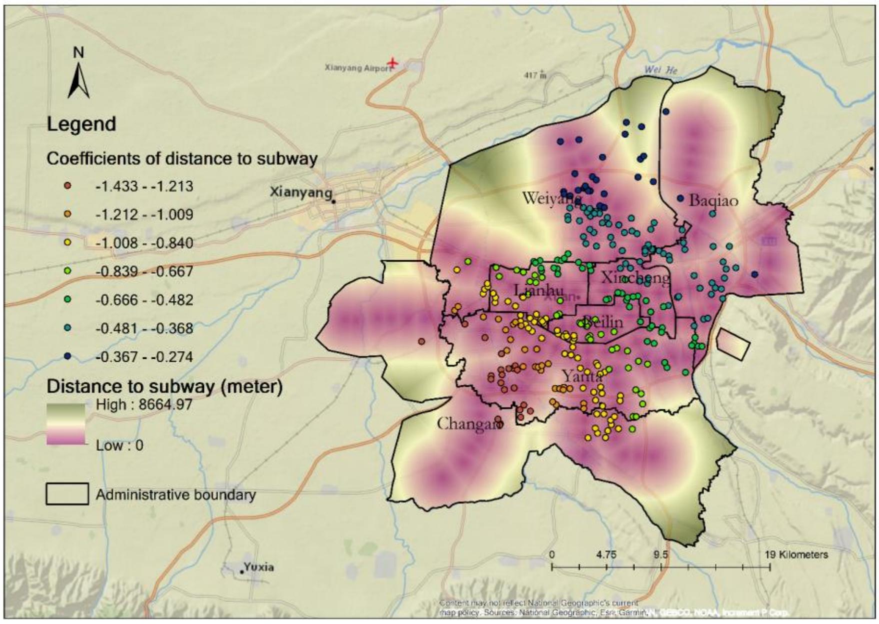


Figure 4-13 The distribution of the coefficients of distance to subway

(5) CBD

Only one CBD was set up in this research. It was Drum Tower, a famous historic site, located at the centre of the city. Up till now, Xi'an has been developing sub-CBDs for political, economic, cultural, business and technological purposes, but Drum Tower remained as the most important one. The coefficients ranged from -0.381 to -0.175, which indicated the negative effect of distance to CBD on the property price. It was in line with the expected sign. The mean value was -0.230. It was the most important among the five significant indicators. 224 out of 298, 75.16% were in the range from -0.25 to -0.15, which was highly centralised.

As shown in Figure 4-14, there were no properties particularly close to the CBD. It was consistent with the reality that no residence was particularly close to the Drum Tower because there were many shopping malls and historical sites around. The all negative value of the coefficients somehow indicated that people in Xi'an all wanted to live near CBD. The likely reason could be the living convenience and symbology of the high social status. In ancient times, only the imperial people could live near Drum Tower. The coefficients increased from southwest to northeast, which meant that properties in the southwest were more vulnerable to the distance to CBD than those in the northeast.

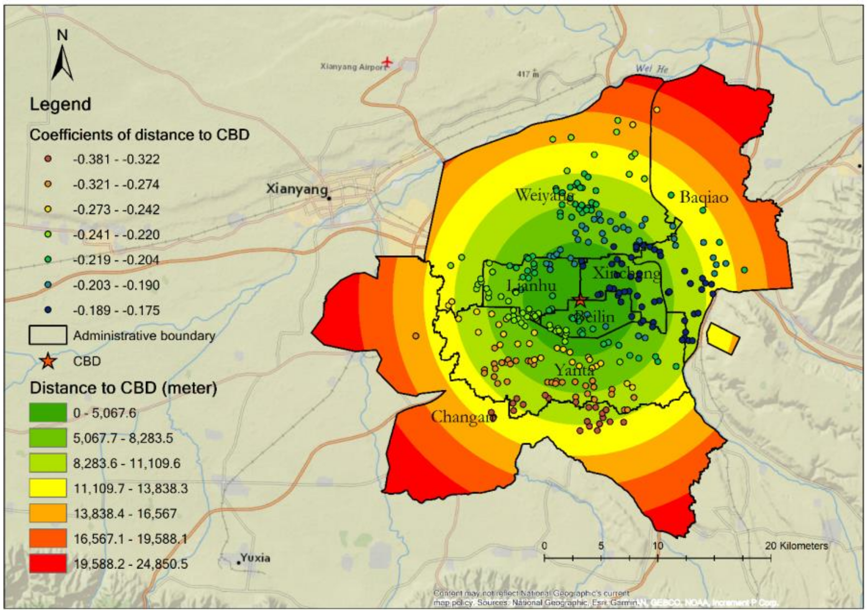


Figure 4-14 The distribution of the coefficients of distance to CBD

(6) NDVI

The radius of NDVI was 50 m, and the mean value was taken in this research. In the trials, as the radius increased to 100 m, 200 m and 500 m, the R^2 decreased, and they were all insignificant. It demonstrated that the property price had a close link with the vegetation status inside the neighbourhoods and had no substantial relationship with the vegetation environment outside the neighbourhoods. Because the neighbourhood size in China differed much, in order to not exceed the neighbourhood boundary, finally the radius was set to 50 m to extract NDVI in the centre of each neighbourhood. As seen from Figure 4-15, the colour yellow dominated in the urban area, indicating that there was not much vegetation. When it came to the fringe of the city, the vegetation coverage increased gradually. The brown area represented the Chan River. In the 298 samples, the maximum and the minimum of NDVI were 0.440 and -0.025, respectively. The mean value was 0.145.

In terms of the coefficients of NDVI, only one sample showed a negative coefficient of -137.098, and the others were all positive. 179 out of 298, 75.21% were in the range between 4000.000 to 6000.000. As expected, it indicated a positive relationship with NDVI and property price. When there was more vegetation inside the neighbourhood, the property price increased. Regarding geographical locations, the coefficients showed an apparent trend, increasing from north to south. People's different preferences for housing and the varying quality of the neighbourhoods may lead to this difference.

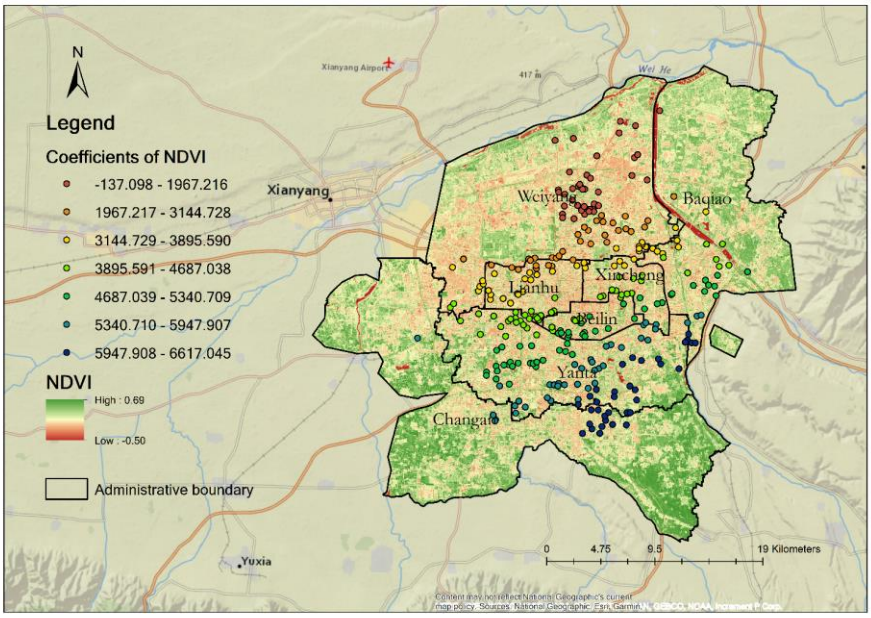


Figure 4-15 The distribution of the coefficients of NDVI

4.5. The 3D method for property valuation

This section illustrates the selection criteria for 3D indicators, the process of how to analyse and visualise them, the regression results of the 3D method and the model validation, which aims to accomplish the research sub-objective 3. The following summary compares the results of 2D (section 4.4.3 and 4.4.4) and 3D methods (section 4.5.3 and 4.5.4) for property valuation and interprets the results to finish the research sub-objective 4.

4.5.1. The selection criteria and description of 3D indicators

Based on quantitative analysis of the questionnaire, literature review and local knowledge obtained during the fieldwork in Xi'an, four 3D indicators were selected (Table 4-9). View quality, SVF and sunlight were quantified and analysed in CityEngine. Property orientation was coded as a dummy variable in this research.

Table 4-9 The overview of 3D indicators and the selection criteria

Indicator	Definition	Unit	Criteria	Expected sign
View quality	How much the positive view types accounted for in the whole view areas.	Percentage	Preferences for a good view.	+/—
SVF	The sky area in the vision scope.	Percentage	Preferences for the vision.	+
Sunlight	The average percentage of the building not blocked from surrounding buildings.	Percentage	(Fleming et al., 2018)	+
Property orientation	If the apartment faces south (1) or not (0).	Dummy variable	Preferences for property orientation.	+/—

4.5.2. The classification accuracy of land cover classification

The reference image for validation was the image taken on April 24th, 2017 by Google Earth. In general, the target was to reach an overall accuracy ⩾ 85% in image classification; and other specific values were rare to be found (Foody, 2008). The accuracy assessment form is shown in Appendix 15. It clarified that the overall accuracy of the support vector machine (SVM) was 87.5%. Therefore, it was validated (Figure 4-16). The scene radius for each neighbourhood was 1 kilometre, which was an appropriate distance to capture the surrounding environment characteristics for visualisation, meet the requirements for the subsequent analyses of 3D indicators and adapt the computing power of the laptop.

During the visualisation preparation, it was found that the class "building" conflicted with the floor data of buildings in Xi'an. It could not extrude building for the two data at the same time. The data were retrieved at different times, and the classification results may exist errors. For a good representation and also keeping in line with the reality, the class "building" was textured the same as "paved" in the 3D scenes. It was put into the class "paved" during viewshed analysis.

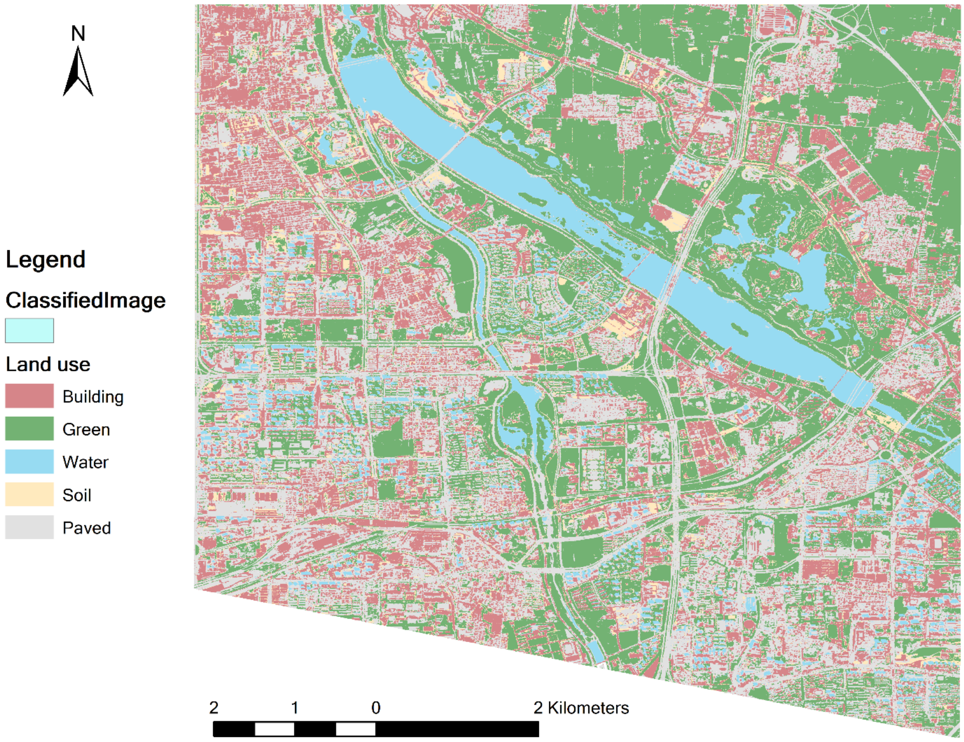


Figure 4-16 The classified image of the study area

4.5.3. The analysis of 3D indicators

This section analyses the 3D indicators and provides detailed reports. The 3D scenes of the two study neighbourhoods were both published in the ArcGIS Online[6].

4.5.3.1. Visualisation for property price variation

Rule files were assigned to the buildings, and the colours were set up to change continuously to represent the property variation. Figure 4-17 takes the neighbourhood Z as an example. It showed apparent price variation between buildings with different heights. The property prices increased when the building height decreased.

[6] Neighbourhood Y could be accessed through the link: http://bit.ly/2IEA3Wy; Neighbourhood Z could be assessed through the link: http://bit.ly/2Iyl4NJ.

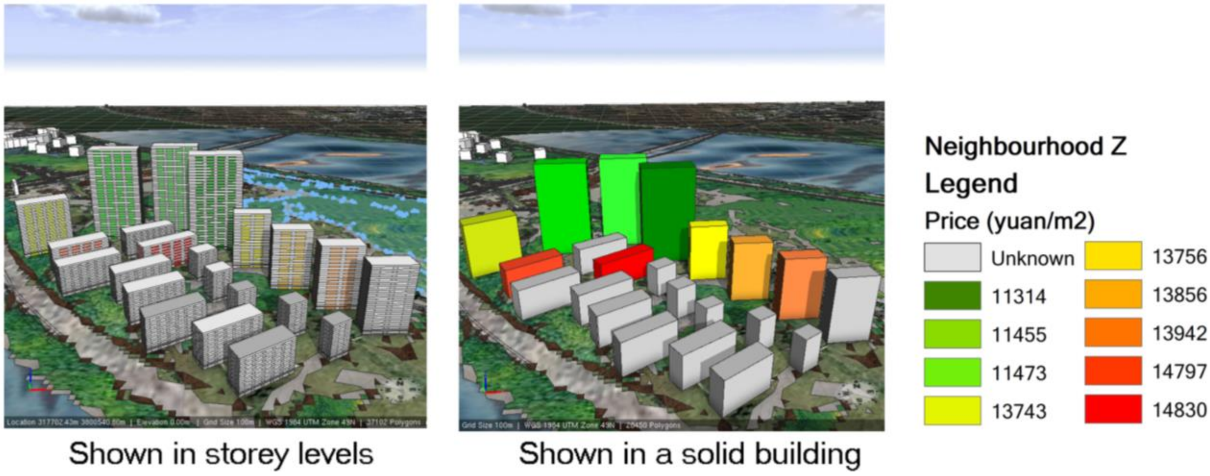


Figure 4-17 Price variation in different presentations (neighbourhood Z)

4.5.3.2. View quality

According to the quantitative analysis of the questionnaire, "green land", "park/square", "water" and "open space" attained the majority of the support (section 4.3.4). In China, "park/square" always contained green land, river and well-paved space, and "open space" contained green land, paved space and soil. Finally, the land cover classes "green" and "water" were defined as the positive view types to be calculated in the formula. The results of the view quality analysis are shown below in Figure 4-18.

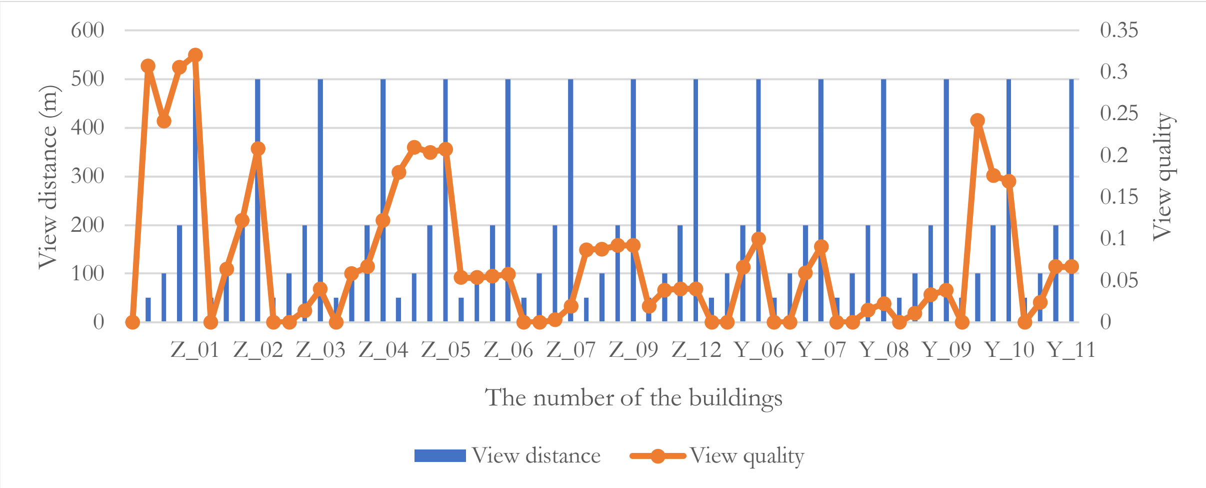


Figure 4-18 The diagram of view quality

The view quality between different buildings fluctuated much. In general, as the view distance increased, the view quality improved as well. The reason may be it could include more view areas and view types when having a longer view distance. When it was 50 m, only the adjacent buildings and the sky were included, so many buildings had zero value. However, including more view areas did not mean improving the view quality. It was notable that unlike other buildings, Z_01 and Y_10 had a decreasing trend after 50m and 100m, respectively. It may be because although the view area for green and water improved, other view areas for road, building and soil increased more. For other buildings, the view quality all improved with the increase of view distance. The average value of neighbourhoods Y and Z was 0.049 and 0.095, respectively. It indicated that neighbourhood Z had a better view quality than the neighbourhood Y generally.

4.5.3.3. SVF

The diagram of the SVF at different view distances is illustrated below (Figure 4-19). It was obvious that as the view distance improved, the SVF decreased for each building because the adjacent buildings blocked most of the sky view. The neighbourhood Y had relatively high SVF for having all buildings more than 30 storeys and 90 m high. The higher the building, the harder they could be blocked. The same situation could also be explained by neighbourhood Z. Z_1, Z_5, Z_6 and Z_7 with the same building height 54 m, had average SVF of 0.463; while Z_2, Z_3 and Z_4, with 99 m high, had the average SVF of 0.632. The least value belonged to Z_09 and Z_12 with the building height of 27 m. The value was 0.250. The average SVF value of Y and Z was 0.486 and 0.472, respectively. It could be concluded that SVF increased with the building height. In general, the neighbourhood Y had better SVF than the neighbourhood Z.

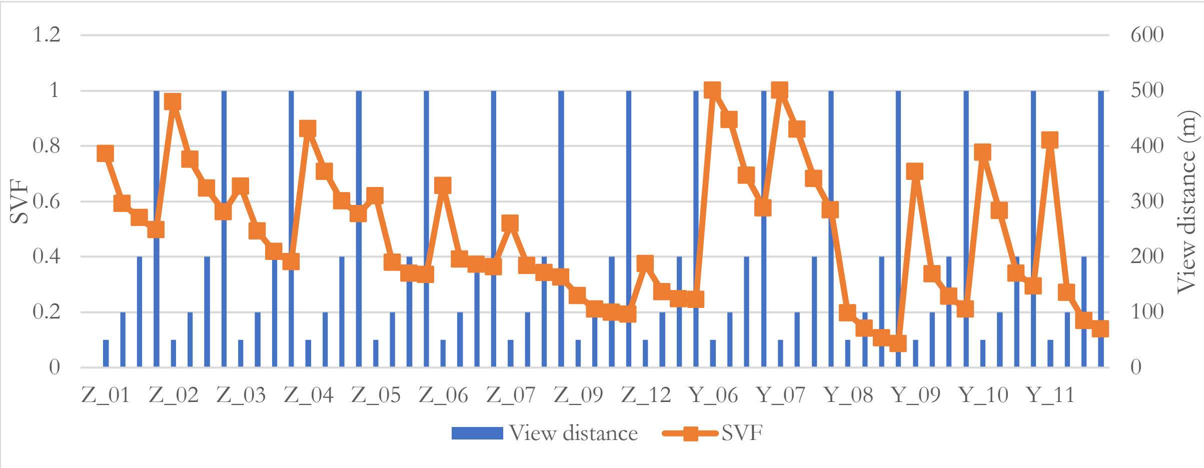


Figure 4-19 The diagram of SVF

As illustrative below in Figure 4-20, the SVF changed both with the locations of the building and the view distances, taking Y_06 and Y_08 as examples[7]. In the south of Y_06 was an open space, and in the south of Y_08 was Y_06. The SVF of Y_06 was relatively good, all above 0.5. Because Y_06 blocked Y_08, the SVF of Y_08 were all below 0.2. As the view distance increased, The SVF became smaller due to the increase in other view types in the viewshed.

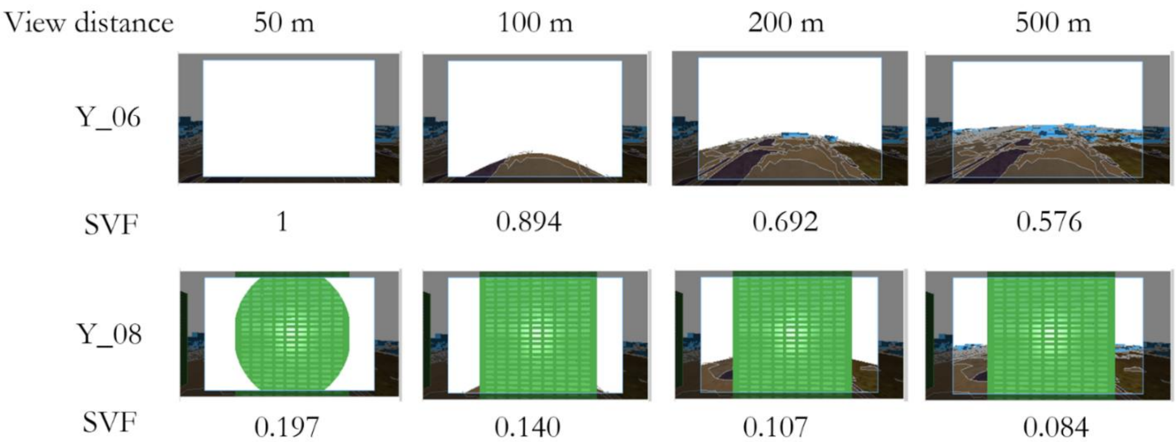


Figure 4-20 SVF change of Y_06 and Y_08 under different view distances

[7] The video was uploaded to YouTube. It simulated view types and SVF at the same time. It can be accessed from the following link: https://youtu.be/FhINQu2J968

4.5.3.4. Sunlight

In the questionnaire, most respondents preferred south orientation (section 4.3.2). It was the orientation for the main bedroom and living room, the most important rooms in one apartment. So it was chosen as the orientation calculated in the analysis. Several times were defined to represent different times of the day. According to the local knowledge, 8 AM represented the time people went to work, 12 PM was the time had the most intense sunlight and 16 PM was the time sun was about to set.

The results of the sunlight analysis are shown in Table 4-10. In both neighbourhoods, there did not exist high buildings in the surrounding environment, so the block came from the buildings in the same neighbourhood. Most of the buildings could not receive direct sunlight at 8 AM in both June and December. Only Z_01 and Z_12 had apartments which could get direct sunlight. All the apartments could receive direct sunlight at 12 June (PM); however, the results at 12 Dec (PM) varied much due to the block from other buildings in the neighbourhood. The low value at 16 Dec (PM) of the three buildings, Y_08, Y_09 and Y_11 were also due to blocking. It was notable that Z_09 and Z_12 had the least two total value, which may be because these two buildings only had nine storeys, 27 m high. The shadow from other buildings easily blocked the sunlight. The average sunlight values of neighbourhood Y and Z were 0.543 and 0.525, respectively. Neighbourhood Z had slightly better sunlight conditions than neighbourhood Y.

Table 4-10 The results of sunlight analysis

Name	Sunlight						Total	Mean
	8 June (AM)	12 June (PM)	16 June (PM)	8 Dec (AM)	12 Dec (PM)	16 Dec (PM)		
Y_06	0.000	1.000	1.000	0.000	1.000	1.000	4.000	0.667
Y_07	0.000	1.000	1.000	0.000	1.000	1.000	4.000	0.667
Y_08	0.000	1.000	1.000	0.000	0.261	0.506	2.767	0.461
Y_09	0.000	1.000	0.977	0.000	0.443	0.773	3.193	0.532
Y_10	0.000	1.000	1.000	0.000	0.902	0.122	3.024	0.504
Y_11	0.000	1.000	1.000	0.000	0.347	0.209	2.556	0.426
Z_01	0.833	1.000	0.000	0.431	1.000	0.000	3.264	0.544
Z_02	0.000	1.000	1.000	0.000	0.970	1.000	3.970	0.662
Z_03	0.000	1.000	0.000	0.000	0.773	0.962	2.735	0.456
Z_04	0.000	1.000	1.000	0.000	0.909	0.848	3.758	0.626
Z_05	0.000	1.000	1.000	0.000	0.656	0.944	3.601	0.600
Z_06	0.000	1.000	1.000	0.000	1.000	0.778	3.778	0.630
Z_07	0.000	1.000	1.000	0.000	0.563	0.806	3.368	0.561
Z_09	0.000	1.000	0.000	0.000	0.556	0.000	1.556	0.259
Z_12	0.625	1.000	0.000	0.000	0.688	0.000	2.313	0.385

According to the knowledge gained in the questionnaire, the west-east orientation was disliked due to the west sun exposure. A scenario was prepared to simulate sunlight in the late afternoon in summer[8]. The comparison of the screenshots is shown in Figure 4-21. The parameter setting in this scenario was time zone 8, August and 17 PM. It was the hottest time of the year in Xi'an. The colour of the buildings indicated the property price. Green meant a low price and red meant a high price. The visibility of the shapes of other land cover classes was set to unavailable during the simulation to provide a better visual experience. It did not affect the final results.

It could be seen in the video that Y_08, Y_10 and Y_11, the three buildings with green colour, had full exposure while some properties in Y_07 and Y_09 with red colours could be in the shadow of the other buildings. It showed that the apartments with less west sun exposure had higher prices. It was remarkable that Y_06 had higher property prices, but it still had west sun exposure. Other indicators such as view quality may influence it because the south of Y_06 was the open space without any blocks from buildings.

[8] The link of the video was uploaded to YouTube. It can be accessed from the following link : https://youtu.be/mqbcp0oIhWs

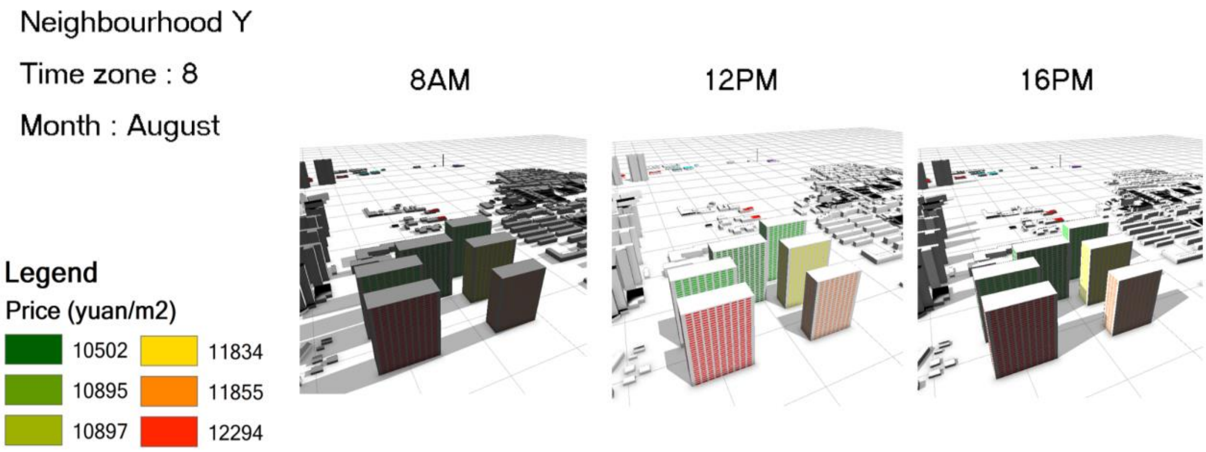


Figure 4-21 The comparison of the sunlight at different times in a day

4.5.4. The OLS of the 3D method

Table 4-11 demonstrates the statistical results of the 3D method. The screenshots in SPSS is shown in Appendix 16. The R^2 and adjusted R^2 was 0.451 and 0.411, respectively, much higher than those in the OLS and GWR of 2D methods.

Regarding the indicators, only view quality was insignificant. SVF and sunlight were both statistically significant at the 0.05 significance level. Property orientation was considered significant at the 0.01 significance level. The residual was 125452566.4. The Durbin-Watson value was 0.432, which indicated positive autocorrelation in the sample. It was true because the samples were repeatedly calculated for four times under different view distances. Tolerances were all greater than 0.2, and VIF ranged from 1 to 3, far less than 10, indicating that no collinearity issue existed among these indicators.

Table 4-11 The regression results of the 3D model

Variable name	Standardised Coefficient	t-Ratio	p-Value	Tolerance	VIF
View quality	-0.123	-1.046	0.300	0.725	1.379
SVF	-0.271	-2.005	0.050*	0.547	1.828
Property orientation	-0.792	-5.747	0.000**	0.526	1.901
Sunlight	0.327	2.000	0.050*	0.812	2.682
Constant	13637.143	19.028	/	/	/

R^2= 0.451, Adjusted R^2 = 0.411, Durbin-Watson = 0.432

**: significant at the 0.05 significance level; **: significant at the 0.01 significance level*

First, It was surprising that the property orientation had a negative standardised coefficient of -0.792, indicating the property price decreased when having the south orientation. It may be because the buildings with nine storeys faced south-east in the neighbourhood Z had relatively higher property prices. It also indicated that the influence of property orientation was the most significant among the four indicators. The indicator "sunlight" had the second most significant standardised coefficient of 0.327, and its significance was 0.050. The statistical results showed that when there was more sunlight, the property price was higher. The significance of the SVF was also 0.050, and its standardised coefficient was -0.271, implying that when the SVF improved, the property price decreased. It was in line with the findings in the questionnaire that people preferred more daylight hours. It may be because the buildings with more storeys had a broader vision scope than those with fewer storeys. However, in reality, the price of the relatively low-rise buildings was much higher than the high-rise ones, partly for better living privacy. For example, in neighbourhood Z, the 9-storey-high building (Z_9, Z_12) contained only 18 apartments while the 33-storey-high building (Z_2, Z_3, and Z_4) had 232 apartments. The prices of Z_9 and Z_12 were significantly higher than those of Z_2, Z_3 and Z_4.

The only insignificant indicator was "view quality", having a significance of 0.300 and the standardised coefficient of -0.123. The negative value implied that when the view quality improved, the price decreased. The reasons may be concluded as follows. First, the view quality of the low-rise buildings was relatively worse for almost only having adjacent buildings in the vision while the high-rise ones compromised more view types and areas. Second, the "view quality" may be a variable under the influences of the other three indicators. For example, the different property orientations could result in different view qualities in one apartment. The overall influence may lead to an insignificant result.

4.5.5. Model validation

The model was validated using leave-one-out cross-validation (LOOCV) via Excel. The error subtracted the real price from the predicted price. The detailed data list is illustrated in Appendix 17. As shown in Figure 4-22, 25 samples had a predicted price lower than the real price while 35 samples had a relatively higher predicted price. 36 out of 60 samples had the absolute value of error less than 1000 RMB. It was notable that one sample had the maximum error of -4864.259749. It was Z_09, the building with nine storeys and 27 m high when the view distance was 50 m. The predicted price was far less than the real price because the SVF and view quality were both poor. The higher price may be because of the larger apartment size and the smaller total number of the apartments in one building.

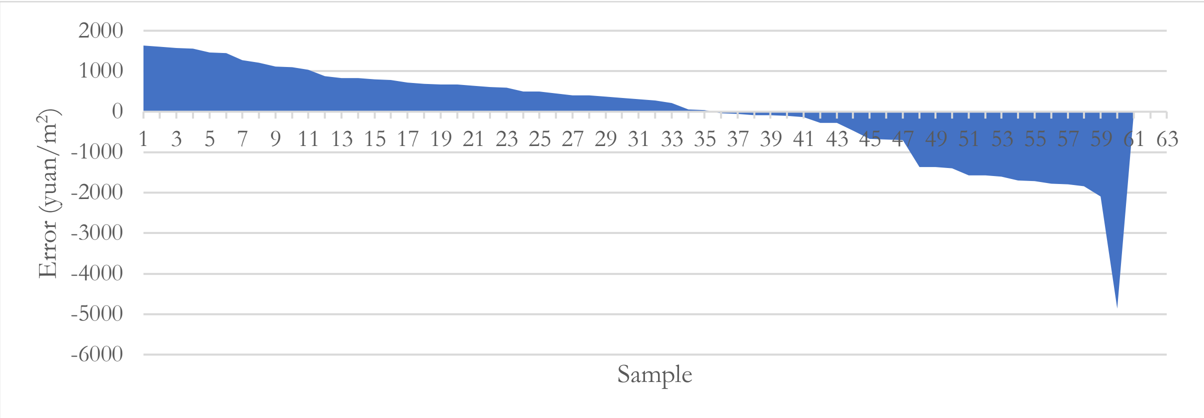


Figure 4-22 The histogram of the error between the predicted price and real price.

In the model, apartments with relatively high building height were predicted to have higher property price, such as Y_08, Y_10, Y_11, and Z_04. The top ten samples with the most positive error were the buildings with 33 storeys and 99 m high for they had better view quality, SVF, and sunlight. Z_05, Z_06, Z_07, all having 18 storeys and 54 m high, had a relatively higher negative error. However, the low-rise buildings contained a less total number of apartments in one building and large apartments size. Thus the price was higher. It was a general pricing policy adopted by real estate companies. However, the 3D model confirmed that it was contrary to reality.

The standard deviation was 1219.294 yuan. The error percentage used to measure the deviation degree was 9.76%. The validation was done from the analysis of the author based on local knowledge since there was no similar model to be used for this purpose.

4.5.6. Summary

As shown in Table 4-12, the R^2 of 3D method was 0.451 (section 4.5.4), higher than that in GWR with 2D indicators (section 4.4.4), which showed that 3D method could explain the property price variation of the high-rise apartments at the neighbourhood scale better than 2D methods. SS_R also showed a significant decrease to 125452566. The model validation of LOOCV indicated that 3D method could predict the price within an approximately 10% error range (section 4.5.5). In conclusion, the 3D model, including indicators of view quality, SVF, sunlight and property orientation, was effective and could reflect the property price difference between different buildings at the neighbourhood scale.

It was worth mentioning that based on the findings in section 4.5.5, there existed a big gap between the buildings with different storey levels as a result of the apartment size and the total number of apartments in one building. Therefore, the 3D method for property valuation should also compromise a tuning parameter to set a price basis for the buildings of different storey levels.

Table 4-12 The comparison between the regression results of 2D and 3D methods

Name	**R^2**	**Adjusted R^2**	**SS_R**
OLS	0.111	0.077	3392667848
GWR	0.217	0.128	2655158522
3D	0.451	0.411	125452566

5. DISCUSSIONS

This chapter summarises the main findings from the results and discusses them in the context of current literature. Section 5.1 concludes the pricing policy and the current situation of the 3D modeling in China from section 4.1 and 4.2. Section 5.2 summarises the results of the questionnaire for buyers' references for high-rise apartments in section 4.3. Section 5.3 represents the regression results of 2D methods for property valuation and the interpretation of 2D indicators in section 4.4 and compares the results with the existing related literature. Section 5.4 summarises the performance of 3D modeling and comparison of 2D and 3D methods in section 4.5. This chapter ends by illustrating the limitations of this research in section 5.5.

5.1. The pricing policy and the current situation of 3D modeling in China

Real estate developers always adopt the cost method in the price-making process to make maximum interests. The cost is reviewed at different stages of the neighbourhood construction to ensure the budget balance. When it comes to the pricing policy inside the neighbourhood, the price difference between different buildings is first determined, then the difference between different storeys in one building is fixed. Generally, the price trend is spindle-shaped, indicating that the price at the middle storey level is the highest and then it decreases on both sides. However, there has been no definitive algorithm or formulas of pricing for real estate developers. The Xi'an municipal government mainly adopt the market comparison method to determine the government guidance price. According to local knowledge, there always exist conflicts between them because of the different purposes of pricing. Real estate developers intend to make it as high as possible to make interests, but the government intends to make it stable.

The current situation of 3D modeling in China was analysed in the perspectives of the government, real estate developers and buyers. 3D modeling has not been very popular among both the government and the real estate developers in Xi'an. Only the real estate developers in a few larger cities (e.g., Shenzhen) have explored 3D modeling in details with interaction functions (Zhang et al., 2014). The Xi'an municipal government mainly adopt 3D modeling in the fields of urban planning, but the use cases are limited due to the low level of detail (LoD), influenced by the huge cost, low technology and public security. However, It can be developed to a higher LoD to serve more purposes in the future (e.g., emergency management). Real estate developers apply 3D modeling in the architecture and landscape design, but they rarely use it in the sales because the traditional 2D sales tools are effective and intuitive. Virtual reality (VR) is the most popular 3D method in China, but it also has disadvantages such as dizzy experience. Buyers do not trust 3D visualisation, either. The open of Hukou policy brings a large population in Xi'an and thus leads to a great demand for housing. Now the property market in Xi'an is a seller's market, making the real estate developers have no impetus to develop new technologies. In conclusion, the fieldwork results showed high regard on 3D modeling in government, but the real estate developers thought it was not very useful. It is suggested that the suitable 3D modeling approach in Xi'an should be determined by the local circumstances, as previously argued by Gimenez et al. (2016).

These findings above have not been explored by other research. The cutting-edge analysis of the pricing policy lists the indicators influencing the property prices in details and provides an overview of the different stakeholders. The interpretation of the current situation of 3D modeling can offer new perspectives on the public awareness of 3D modeling and how to promote it in the future.

5.2. Buyers' preferences for high-rise apartments

Buyers' preferences were collected by questionnaire. It was revealed that nearly half of the respondents chose to live in the middle storey level, which had a link with the Doctrine of the Mean, a Chinese tradition.

The majority chose the "south-north" orientation. With regard to surrounding environment and property physical attributes, "public security", "property orientation", "less noise" were the most favourite three indicators, while the bottom three were "sports facility", "entertainment facility", and "cultural facility". People preferred to see green land and water outside of the window. They disliked the view of building and street; however, they were ubiquitous in the city. The results of the questionnaire can add the new idea of buyers' preferences for high-rise apartments in Xi'an to academia.

5.3. The 2D methods for property valuation

Generally, most research concluded that property price variation could be generalised by different statistical models. However, The R^2 of 2D methods, ordinary least squares (OLS) and geographically weighted regression (GWR) in this research were too low to generalise a model, which meant the models of current 2D indicators could not simulate the property price variation in this research. GWR showed better simulation with a higher R^2, which was consistent with the findings in Dziauddin and Idris (2017) and Dziauddin et al. (2015). It further proved that GWR could explain the spatial heterogeneity existing in the attributes of the variables. The results that both OLS and GWR failed to generalise the model was surprising because in other studies the models always had good performances (Jiao & Liu, 2010; Sander & Polasky, 2009). The reason may be that that first-hand property price data was used in this research; in other studies, the second-hand property price was frequently used (Han et al., 2015; Wen et al., 2017). The first-hand price was generated under the fixed-price and purchase-restriction policy established by the Xi'an municipal government, whose primary purpose was to stabilise the property price. Therefore, the price may not show the impact of the geographical locations and the surrounding environment. Besides, the sample size (298 in this research) was relatively small compared to other studies which always contained thousands of samples.

The results of the significance of 2D indicators also had differences with the previous literature. Distance to CBD, distance to food, distance to subway, density of factory and NDVI were considered to be significant indicators at the 0.05 significance level. However, some indicators significant in other studies were insignificant in this research. For example, Wen et al. (2018) proposed that educational facilities had a positive influence on property price, while in this research it did not. The accessibility of parks did not see a significant influence on property prices, which was different as reported in Jim and Chen (2010). It may be because the first-hand property price was used. In addition, different study areas may show different impact from buyers' preferences and the surrounding environment; and even Fengshui can have potential consequences.

Through the visualisation of the GWR estimation of Local R^2, it was found to have a relatively lower value in the north area than other areas of Xi'an, which was possible to be a sub-Central Business District (CBD). In reality, it was where the Xi'an municipal government located. It also revealed that the development mode of Xi'an was unsymmetrical.

5.4. The 3D method for property valuation

As shown in section 4.5.3, property orientation, sky view factor (SVF), and sunlight were three significant indicators in the 3D model, except for view quality, although buyers highly valued the view types according to the questionnaire. The indicator "view quality" contained positive view types of "green" and "water", was not found to have a significant influence on the property price. It conflicted with the findings in Wen et al. (2017), and Panduro and Veie (2013). Both river and urban green spaces were reported to have positive impacts on the price. It may be because of different calculation techniques of the variable. Jim and Chen (2010) adopted a dummy variable to calculate view types, while the view area was directly used in this research. It was also probably because of the different sampling strategy and sampling size. There were 60 samples included in 3D modeling, which was a quite small sampling size due to data accessibility.

For the property orientation, it showed that the south orientation had negative effect on property price, inconsistent with the findings in Jim and Chen (2006). In their research, it was also defined as the dummy variable, and the coefficient was positive. The difference may result from the samples. Only two orientation types were included in the study neighbourhoods. For the SVF, most studies have adopted it to calculate the UHI effect, and few interfered with property valuation. In this research, it was found to have a negative influence on the property price. It contradicted the common sense that the apartment with higher SVF had a higher price.

Lastly, the sunlight showed a positive impact on the property price. Only 17% of respondents chose the properties at a low storey level in the questionnaire (section 4.3.1), which was in line with the findings that the property price was lower with less sunlight. It has been widely known that the apartments at a low storey level have fewer opportunities to be exposed to sunlight. Fleming et al. (2018) also found that there was a positive relationship between sunlight exposure and property price. It is also worth pointing out that the sunlight is a variable partly influenced by property orientation.

The error percentage measuring the deviation degree of the predicted price and the real price in the model validation for 3D method was 9.76% (section 4.5.5). It is not a very big number, though, as there has been no experience validating a 3D method, a specific threshold value can be not issued. The author agrees with the point that validation remains an issue (El-Mekawy et al., 2012). However, the validation method here opens up possibilities for furthe research.

The findings disclosed that 3D method could explain the property price variation better compared to 2D methods, for it had higher R^2 (0.414) in the regression. The 3D visualisation in CityEngine also showed great performance regarding quantifying and analysing 3D indicators.

5.5. The limitations of the research

First, it could not cover all stakeholders in interviews due to the time limit during the 3-week fieldwork. For example, the author was not able to get in touch with government staff to directly get government opinions. During the focus groups, some of the respondents showed their lack of interests on the topic.

Second, regarding the data consistency, the Gaofen-2 multispectral image and the floor data of the buildings in Xi'an were both taken in 2017. However, the database of the first-hand property prices was established in 2018. The surrounding environment could be different from the past.

Third, for 2D methods, it was better to contain more first-hand property price samples to improve the simulation accuracy; however, due to the limited time and data access it only contained 298 samples. For 3D method, more study neighbourhoods could be included if time permitted. Drawing footprints of the buildings of the study neighbourhoods manually in Google Earth may contain errors in 3D modeling and thus influenced the output.

Fourth, it should have used the roads and water bodies from OpenStreetMap to clean up the classified map from land cover classification.

Lastly, there was no time to do the feedback questionnaire of 3D method evaluation in the perspective of buyers, which was set up in the research proposal.

6. CONCLUSION AND RECOMMENDATIONS

The previous chapter summarises the main findings and limitations of this research. This chapter presents the conclusions in line with four research sub-objectives and the corresponding research questions. Recommendations are illustrated for further research in the perspectives of different stakeholders.

6.1. Conclusion

The mixed qualitative-quantitative methodology was applied to accomplish the general research objective, to assess 2D and 3D methods for property valuation using remote sensing data at the neighbourhood scale in Xi'an, China. It was divided into four sub-objectives. The pre-fieldwork stage contained the literature review to identify the basic concepts of this research, and the questionnaire design, which was a preparation for the fieldwork in Xi'an. The fieldwork helped to obtain the basic knowledge of the property market of Xi'an, the pricing policy of real estate developers, and 2D and 3D indicators influencing the property price via semi-structured expert interviews, focus groups and questionnaire. The work in this stage also prepared for the detailed visualisation and analysis in the post-fieldwork stage. In the post-fieldwork, data were categorised and interpreted according to the overall methodology. The descriptions of how to achieve the research sub-objectives are illustrated in the following sections.

This research contributes to the limited research investigating the role of 3D indicators playing in the property price and assessing 2D and 3D methods for property valuation through comparison. The spatial changes on the vertical dimension, no matter small or large, all make a significant and long-term effect on the surrounding environment. It is critical to figure out the influence of 3D indicators to estimate the property price more accurately. The findings disclose that the integration of Geographical Information System (GIS), remote sensing data and 3D modeling for property valuation are feasible, and the 3D method can work as an effective complementary method for conventional 2D methods.

6.1.1. Research sub-objective one

The first sub-objective was to identify the existing property valuation methods relevant to the study area. Literature review and expert interview were adopted to answer the research questions. There has been abundant research focusing on different aspects of property valuation using a hedonic price model (HPM). The indicators were mainly 2D-based and could be categorised into locational, neighbourhood, physical attributes. However, no indicators regarding the geographical information in the vertical dimension were taken consideration in property valuation, and no literature have explored the quantification and visualisation of these indicators in property valuation. Government adopts market-comparison method and real estate developers adopts the cost method. Up till now, no 3D data has been included in the property valuation process in the perspective of government in Xi'an.

6.1.2. Research sub-objective two

The second sub-objective was to identify and calculate the 2D and 3D indicators which influence the property price in the study area. Expert interview was applied to answer the research question "What is the current situation of 3D modeling for property valuation in China?" Expert interview, focus group and questionnaire was adopted to answer the research question "What are the relevant 2D and 3D indicators that influence property prices in the study area?"

The interview guides of the expert interviews and focus groups contained questions related to 3D modeling to obtain opinions from different stakeholders. The interpretation results revealed that 3D modeling have not been well developed in Xi'an and people's awareness of the effectiveness in 3D visualisation was quite low. It has great potential for development in the level of detail (LoD) and use scenarios. The questionnaire issued via both paper and online investigated different aspects of buyers' preferences. The importance ranking of the indicators was measured in a five-point Likert scale, based on which 2D and 3D indicators were selected.

6.1.3. Research sub-objective three

The third sub-objective was to analyse, visualise and validate 2D and 3D methods for property valuation. The analysis of 2D indicators in ordinary least squares (OLS) was carried out by SPSS, and those in geographically weighted regression (GWR) was carried out by ArcGIS. The findings disclosed that GWR performed better than OLS. However, they both could not generalise the model for producing a low R^2. Therefore, the regression results of GWR were visualised in ArcGIS by producing different maps. It figured out the different patterns of the significant indicators influencing property price and produced interpretations with local knowledge. It is assumed that the reasons for not generalising the model came from the fixed-price policy and purchase-restriction policy. They have put great influence on the first-hand property price.

The visualisation and quantified analysis of 3D indicators was achieved in CityEngine. The results of the land cover classification by support vector machine (SVM) provided a credible data source for 3D modeling. The 3D indicators, view quality, sky view factor (SVF), and sunlight were automatically quantified in CityEngine. The results indicated that the 3D model could simulate the property price variation in 41.4% of the total samples. It was also shown via both graphs and videos that 3D modeling had an intuitive and clear representation of 3D indicators.

The model validation method was leave-one-out cross-validation (LOOCV). The error between the predicted price and the real price was 9.76%. As no similar model validation for property valuation purpose could be referred to, the validation was completed according to the local knowledge obtained by the author.

6.1.4. Research sub-objective four

The fourth research sub-objective was to assess the added value and effect of 3D indicators for property valuation. By comparing the results of 2D and 3D methods, the findings revealed that the 3D method could explain the property price variation between different buildings at the neighbourhood scale better than 2D methods. 3D indicators had significant influences on the property price. They showed geographical information on the vertical dimension via 3D visualisation, which the 2D-based property valuation failed to represent. With the help of remote sensing data and Geographical Information System (GIS), including the 3D indicators into property valuation could make it more comprehensive and accurate. The applications of 3D method can serve as the basis for further property taxation in China and the complementary method which real estate developers can refer to for pricing. However, it still has to overcome difficulties during the implementation, such as the low public awareness of 3D modeling and the current situation of low LoD in the 3D models.

6.2. Ethical considerations

All the data collected at the interviews, questionnaires and focus groups remained secured and were used only for research purposes. The personal information of the respondents kept confidential. It obtained the prior consent of the respondents when audio recording the interviews and focus groups.

6.3. Recommendations

The recommendations are structured regarding different stakeholders.

(1) Government

Since the results proved that the 3D method could explain the property price variation better than 2D methods, the government may take 3D indicators into their traditional market comparison method. It also helps to formulate a more systematic and graphically-specific housing policy (Wang et al., 2017). The results that the 2D method could not explain the first-hand price variation may lead to a reconsideration of the fixed-price policy. The level of government intervention in the property market should be re-evaluated.

(2) Real estate developer

The findings of buyers' preferences can be taken as a reference to adjust the architectural and landscape design, and the pricing policy in the future. Investigation of their preferences for apartment size and living facility support, which did not cover in this research, is encouraged.

(3) Buyer

The analyses of 3D indicators showed property price variation between two similar and adjacent buildings. If they have open-source geographical data access (e.g., Google Earth and OpenStreetMap) and 3D dynamic simulation tools, instead of having the static 3D sandbox only, they can analyse the 3D environment of the properties they want precisely. It can intuitively represent which property is the best for the bargain. It is technically feasible to develop a software which the public can easily use for 3D analysis.

(4) Researcher

First, visualisation and quantification of 3D indicators in this research should be developed further. With a higher LoD, accuracy can be improved. Besides, different calculation techniques may influence the research outputs, so it is necessary to figure out a concise and effective method to quantify 3D indicators.

Second, when considering the impact from view on property price, it is desirable to take the visual quality into account, not only the view types. For example, a large and well-organised public park is better than a small and narrow green-belt, although they can be both regarded as green land. Besides, the visual quality depends on the colour, structure and the context of the specific view. The identification of how to quantify the visual quality can be a focus of further research. It is also important to cover the specific context of different view types (e.g., tree, farmland, grass can all be categorised into green). In conclusion, the view is not a homogeneous entity, which should be treated separately.

Third, a tuning parameter should be added into the method to neutralise the effect from apartment size and the total number of apartments in one building. With the knowledge gained during the fieldwork, the apartments in lower storey levels tended to have bigger apartment size and fewer the total number of apartments in one building, and they had higher property price. The apartment size can be positive, and the total number of apartments in one building can be negative. The details can be explored in further research.

Lastly, this research contained a huge amount of manual work. Deep learning and machine learning can be combined with 3D modeling to predict the property price automatically in the future.

7. REFERENCES

Biljecki, F., Ledoux, H., & Stoter, J. (2016). An improved LOD specification for 3D building models. *Computers, Environment and Urban Systems*, *59*, 25–37. https://doi.org/10.1016/j.compenvurbsys.2016.04.005

Biljecki, F., Ledoux, H., & Stoter, J. (2017a). Does a finer level of detail of a 3D City Model bring an improvement for estimating shadows? In A. Abdul-Rahman (Ed.), *Advances in 3D geoinformation* (pp. 31–47). Springer, Cham. https://doi.org/10.1007/978-3-319-25691-7_2

Biljecki, F., Ledoux, H., & Stoter, J. (2017b). Generating 3D city models without elevation data. *Computers, Environment and Urban Systems*, *64*, 1–18. https://doi.org/10.1016/j.compenvurbsys.2017.01.001

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

Buyukdemircioglu, M., Kocaman, S., & Isikdag, U. (2018). Semi-automatic 3D City Model generation from large-format aerial images. *ISPRS International Journal of Geo-Information*, *7*(9), 339. https://doi.org/10.3390/ijgi7090339

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

Clifford, N., Cope, M., French, S., & Valentine, G. (2010). *Key Methods in Geography*. (N. Clifford, M. Cope, T. Gillespie, & S. French, Eds.), *Geographical Research* (Third edit). London: Sage. https://doi.org/10.1017/CBO9781107415324.004

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

De Nadai, M., & Lepri, B. (2018). The economic value of neighborhoods: Predicting real estate prices from the urban environment. In *IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 323–330). Italy: IEEE. https://doi.org/10.1016/S0014-3057(01)00225-7

Dziauddin, M. F., & Idris, Z. (2017). Use of geographically weighted regression (GWR) method to estimate the effects of location attributes on the residential property values. *Indonesian Journal of Geography*, *49*(1), 97–110. https://doi.org/10.22146/ijg.27036

Dziauddin, M. F., Powe, N., & Alvanides, S. (2015). Estimating the effects of Light Rail Transit (LRT) system on residential property values using geographically weighted regression (GWR). *Applied Spatial Analysis and Policy*, *8*(1), 1–25. https://doi.org/10.1007/s12061-014-9117-z

El-Mekawy, M., Östman, A., & Hijazi, I. (2012). A unified building model for 3D Urban GIS. *ISPRS International Journal of Geo-Information*, *1*(3), 120–145. https://doi.org/10.3390/ijgi1020120

Escobedo, F. J., Adams, D. C., & Timilsina, N. (2015). Urban forest structure effects on property value. *Ecosystem Services*, *12*, 209–217. https://doi.org/10.1016/j.ecoser.2014.05.002

Feng, Q., & Wu, G. L. (2015). Bubble or riddle? An asset-pricing approach evaluation on China's housing market. *Economic Modelling*, *46*, 376–383. https://doi.org/10.1016/j.econmod.2015.02.004

Fernandez, L., Mukherjee, M., & Scott, T. (2018). The effect of conservation policy and varied open space on residential property values: A dynamic hedonic analysis. *Land Use Policy*, *73*, 480–487. https://doi.org/10.1016/j.landusepol.2017.12.058

Fleming, D., Grimes, A., Lebreton, L., Maré, D., & Nunns, P. (2018). Valuing sunshine. *Regional Science and Urban Economics*, *68*, 268–276. https://doi.org/10.1016/j.regsciurbeco.2017.11.008

Foody, G. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, *29*(11), 3137–3158. https://doi.org/10.1080/01431160701442120

Furey, T. S., Cristianini, N., Duffy, N., Bednarski, D. W., Schummer, M., & Haussler, D. (2000). Support vector machine classification and validation of cancer tissue samples using microarray expression data. *Bioinformatics*, *16*(10), 906–914. https://doi.org/10.1093/bioinformatics/16.10.906

Gimenez, L., Hippolyte, J. L., Robert, S., Suard, F., & Zreik, K. (2015). Review: Reconstruction of 3D building information models from 2D scanned plans. *Journal of Building Engineering*, *2*, 24–35. https://doi.org/10.1016/j.jobe.2015.04.002

Gimenez, L., Robert, S., Suard, F., & Zreik, K. (2016). Automatic reconstruction of 3D building models from scanned 2D floor plans. *Automation in Construction*, *63*, 48–56. https://doi.org/10.1016/j.autcon.2015.12.008

Ha, J., Lee, S., & Park, C. (2016). Temporal effects of environmental characteristics on urban air temperature: The influence of the Sky View Factor. *Sustainability*, *8*(9), 895. https://doi.org/10.3390/su8090895

Hamilton, S. E., & Morgan, A. (2010). Integrating lidar, GIS and hedonic price modeling to measure amenity values in urban beach residential property markets. *Computers, Environment and Urban Systems*, *34*(2), 133–141. https://doi.org/10.1016/j.compenvurbsys.2009.10.007

Han, N., Zhang, W., & Liang, K. (2015). The design and implementation of Shenzhen house price indexes system based on 3D-GIS. In *2015 23rd International Conference on Geoinformatics* (pp. 1–4). Wuhan: IEEE. https://doi.org/10.1109/GEOINFORMATICS.2015.7378676

Herbert, G., & Chen, X. (2015). A comparison of usefulness of 2D and 3D representations of urban planning. *Cartography and Geographic Information Science*, *42*(1), 22–32. https://doi.org/10.1080/15230406.2014.987694

Huang, Z., Chen, R., Xu, D., & Zhou, W. (2017). Spatial and hedonic analysis of housing prices in Shanghai. *Habitat International*, *67*, 69–78. https://doi.org/10.1016/j.habitatint.2017.07.002

Hui, E. C. M., Chau, C. K., Pun, L., & Law, M. Y. (2007). Measuring the neighboring and environmental effects on residential property value: Using spatial weighting matrix. *Building and Environment*, *42*(6), 2333–2343. https://doi.org/10.1016/j.buildenv.2006.05.004

Hui, E. C. M., Zhong, J. W., & Yu, K. H. (2012). The impact of landscape views and storey levels on property prices. *Landscape and Urban Planning*, *105*(1–2), 86–93. https://doi.org/10.1016/j.landurbplan.2011.12.002

"Hurun Global House Price Index 2017." (2018). Hurun Global House Price Index 2017. Retrieved August 21, 2018, from http://www.hurun.net/CN/Article/Details?num=61C2A98F9932

Isikdag, U., Horhammer, M., Zlatanova, S., Kathmann, R., & van Oosterom, P. (2015). Utilizing 3D building and 3D cadastre geometries for better valuation of existing real estate. In *FIG Working Week 2015: From the Wisdom of the Ages to the Challenges of the Modern World*. Sofia, Bulgaria: International Federation of Surveyors (FIG). Retrieved from https://repository.tudelft.nl/islandora/object/uuid:4253db43-a734-4641-ab6b-cd13742ec279

Jazayeri, I., Rajabifard, A., & Kalantari, M. (2014). A geometric and semantic evaluation of 3D data sourcing methods for land and property information. *Land Use Policy*, *36*, 219–230. https://doi.org/10.1016/j.landusepol.2013.08.004

Jiao, L., & Liu, Y. (2010). Geographic Field Model based hedonic valuation of urban open spaces in Wuhan, China. *Landscape and Urban Planning*, *98*(1), 47–55. https://doi.org/10.1016/j.landurbplan.2010.07.009

Jim, C. Y., & Chen, W. Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning*, *78*(4), 422–434. https://doi.org/10.1016/j.landurbplan.2005.12.003

Jim, C. Y., & Chen, W. Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning*, *91*(4), 226–234. https://doi.org/10.1016/j.landurbplan.2009.01.009

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

Jin, S., Li, D., & Wang, J. (2005). A comparison of support vector machine with maximum likelihood classification algorithms on texture features. In *International Geoscience and Remote Sensing Symposium (IGARSS)* (Vol. 5, pp. 3717–3720). Seoul, South Korea: IEEE. https://doi.org/10.1109/IGARSS.2005.1526659

Kocaman, S., Zhang, L., Gruen, A., & Poli, D. (2006). 3D city modeling from high-resolution satellite images. In *Proceedings of ISPRS Workshop on Topographic Mapping from Space* (pp. 14–16). Ankara, Turkey. Retrieved from https://www.semanticscholar.org/paper/3-D-City-Modeling-from-High-resolution-Satellite-Kocaman-Zhang/15af229565f5044fe3242a6d72460fd78a079472

Lake, I. R., Lovett, A. A., Bateman, I. J., & Langford, I. H. (1998). Modelling environmental influences on property prices in an urban environment. *Computers, Environment and Urban Systems*, *22*(2), 121–136. https://doi.org/10.1016/S0198-9715(98)00012-X

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132–157. https://doi.org/10.1086/259131

Liasis, G., & Stavrou, S. (2016). Satellite images analysis for shadow detection and building height estimation. *ISPRS Journal of Photogrammetry and Remote Sensing*, *119*, 437–450. https://doi.org/10.1016/j.isprsjprs.2016.07.006

Lin, L., Homma, R., & Iki, K. (2018). Preferences for a lake landscape: Effects of building height and lake width. *Environmental Impact Assessment Review*, *70*, 22–33. https://doi.org/10.1016/j.eiar.2018.03.001

Liu, J., Yang, Y., Xu, S., Zhao, Y., Wang, Y., & Zhang, F. (2016). A geographically temporal weighted regression approach with travel distance for house price estimation. *Entropy*, *18*(8), 303. https://doi.org/10.3390/e18080303

Liu, L., & Jakus, P. M. (2015). Hedonic valuation in an urban high-rise housing market. *Canadian Journal of Agricultural Economics*, *63*(2), 259–273. https://doi.org/10.1111/cjag.12052

Liu, Y., Gevers, T., & Li, X. (2015). Estimation of sunlight direction using 3D object models. *IEEE Transactions on Image Processing*, *24*(3), 932–942. https://doi.org/10.1109/TIP.2014.2378032

Lu, B., Charlton, M., & Fotheringham, A. S. (2011). Geographically Weighted Regression using a non-Euclidean distance metric with a study on London house price data. *Procedia Environmental Sciences*, *7*, 92–97. https://doi.org/10.1016/j.proenv.2011.07.017

McMillen, D. P. (2004). Geographically weighted regression: the analysis of spatially varying relationships. *American Journal of Agricultural Economics*, *86*(2), 554–556. https://doi.org/10.1111/j.0002-9092.2004.600_2.x

Ohori, K., Ledoux, H., Biljecki, F., & Stoter, J. (2015). Modeling a 3D City Model and its levels of detail as a true 4D model. *ISPRS International Journal of Geo-Information*, *4*(3), 1055–1075. https://doi.org/10.3390/ijgi4031055

Onyimbi, J. R., Koeva, M., & Flacke, J. (2017). Public participation using 3D city models. *GIM International*, *31*(7), 29–31. Retrieved from https://www.gim-international.com/content/article/public-participation-using-3d-city-models

Panduro, T. E., & Veie, K. L. (2013). Classification and valuation of urban green spaces-A hedonic house price valuation. *Landscape and Urban Planning*, *120*, 119–128. https://doi.org/10.1016/j.landurbplan.2013.08.009

Rabiee, F. (2004). Focus-group interview and data analysis. *Proceedings of the Nutrition Society*, *63*(4), 655–660. https://doi.org/10.1079/PNS2004399

Remondino, F., & El ‐ Hakim, S. (2006). Image-based 3D modelling: A review. *The Photogrammetric Record*, *21*(115), 269–291. https://doi.org/10.1111/j.1477-9730.2006.00383.x

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55. https://doi.org/10.1086/260169

Sander, H. A., & Polasky, S. (2009). The value of views and open space: Estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. *Land Use Policy*, *26*(3), 837–845. https://doi.org/10.1016/j.landusepol.2008.10.009

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

Song, M., Wang, S., Wu, J., & Yang, L. (2011). A new space-time correlation coefficient and its comparison with Moran's Index on evaluation. *Management Decision*, *49*(9), 1426–1443. https://doi.org/10.1108/00251741111173925

Tavernor, R. (2007). Visual and cultural sustainability: The impact of tall buildings on London. *Landscape and Urban Planning*, *83*(1), 2–12. https://doi.org/10.1016/j.landurbplan.2007.05.010

the Royal Institution of Chartered Surveyors (RICS). (2012). RICS Professional Information, Global Comparable evidence in property valuation. Retrieved from www.ricsbooks.com

Tomić, H., Roić, M., & Ivić, S. M. (2012). Use of 3D cadastral data for real estate mass valuation in the urban areas. In P. van Oosterom (Ed.), *Proceedings of the 3rd International Workshop on 3D Cadastres: Developments and Practices* (pp. 73–86). Copenhagen, Denmark: International Federation of Surveyors, FIG. https://doi.org/10.1109/TDEI.2009.5211872

Unger, J. (2009). Connection between urban heat island and sky view factor approximated by a software tool on a 3D urban database. *International Journal of Environment and Pollution*, *36*(1), 59. https://doi.org/10.1504/IJEP.2009.021817

Usage tip: a suitable viewing distance of SketchUp. (2018). Retrieved January 24, 2019, from http://wemedia.ifeng.com/76443610/wemedia.shtml van Lammeren, R., Houtkamp, J., Colijn, S., Hilferink, M., & Bouwman, A. (2010). Affective appraisal of 3D land use visualization. *Computers, Environment and Urban Systems*, *34*(6), 465–475. https://doi.org/10.1016/j.compenvurbsys.2010.07.001

Wang, Y., Wang, S., Li, G., Zhang, H., Jin, L., Su, Y., & Wu, K. (2017). Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique. *Applied Geography*, *79*, 26–36. https://doi.org/10.1016/J.APGEOG.2016.12.003

Wen, H., & Goodman, A. C. (2013). Relationship between urban land price and housing price: Evidence from 21 provincial capitals in China. *Habitat International*, *40*, 9–17. https://doi.org/10.1016/j.habitatint.2013.01.004

Wen, H., Xiao, Y., Hui, E. C. M., & Zhang, L. (2018). Education quality, accessibility, and housing price: Does spatial heterogeneity exist in education capitalization? *Habitat International*, *78*, 68–82. https://doi.org/10.1016/j.habitatint.2018.05.012

Wen, H., Xiao, Y., & Zhang, L. (2017). Spatial effect of river landscape on housing price: An empirical study on the Grand Canal in Hangzhou, China. *Habitat International*, *63*, 34–44. https://doi.org/10.1016/j.habitatint.2017.03.007

Wen, H., Zhang, Y., & Zhang, L. (2014). Do educational facilities affect housing price? An empirical study in Hangzhou, China. *Habitat International*, *42*, 155–163. https://doi.org/10.1016/j.habitatint.2013.12.004

Wong, T. T. (2015). Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation. *Pattern Recognition*, *48*(9), 2839–2846. https://doi.org/10.1016/j.patcog.2015.03.009

Wu, J., Gyourko, J., & Deng, Y. (2012). Evaluating conditions in major Chinese housing markets. *Regional Science and Urban Economics*, *42*(3), 531–543. https://doi.org/10.1016/j.regsciurbeco.2011.03.003

Wu, J., Song, Y., Liang, J., Wang, Q., & Lin, J. (2018). Impact of mixed land use on housing values in high-density areas : Evidence from Beijing. *Journal of Urban Planning and Development*, *144*(1), 1–12. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000422.

Wyatt, P. J. (1997). The development of a GIS-based property information system for real estate valuation. *International Journal of Geographical Information Science*, *11*(5), 435–450. https://doi.org/10.1080/136588197242248

Xie, J., Zhang, L., Li, J., Wang, H., & Yang, L. (2012). Automatic simplification and visualization of 3D urban building models. *International Journal of Applied Earth Observation and Geoinformation*, *18*(1), 222–231. https://doi.org/10.1016/j.jag.2012.01.014

Xu, Z., & Coors, V. (2012). Combining system dynamics model, GIS and 3D visualization in sustainability assessment of urban residential development. *Building and Environment*, *47*(1), 272–287. https://doi.org/10.1016/j.buildenv.2011.07.012

Yamagata, Y., Murakami, D., Yoshida, T., Seya, H., & Kuroda, S. (2016). Value of urban views in a bay city: Hedonic analysis with the spatial multilevel additive regression (SMAR) model. *Landscape and Urban Planning*, *151*, 89–102. https://doi.org/10.1016/j.landurbplan.2016.02.008

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

Yu, X., & Su, Y. (2015). Daylight availability assessment and its potential energy saving estimation-A literature review. *Renewable and Sustainable Energy Reviews*, *52*, 494–503. https://doi.org/10.1016/j.rser.2015.07.142

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. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* (Vol. 40, pp. 363–367). Suzhou, China. https://doi.org/10.5194/isprsarchives-XL-4-363-2014

APPENDICES

Appendix 1 The interview guides for the semi-structured expert interviews

1# Interview guide for the architectural designer

1. What is your general architecture design principles for high-rise apartments?
2. Does the architecture plan affect the property price in certain scenarios?
3. What is the price difference between the price developers report for approval and the final price approved by the Price Bureau of Xi'an?
4. Which type of residence is most popular based on your experience? What are the common attributes of them?
5. Which administrative districts are popular for residence selection?
6. Do you think the preferences of buyers for residence has changed in time?
7. Do you think buyers will pay more for a better view?
8. Do you have 3D models for buyers at the sales office? What software do you use to create them? What is the cost of finance and time?
9. Do you think interactive 3D models can improve the performance or better communicate with buyers? Is it necessary?
10. What do you think is the main factor causing the huge property price growth in the past two years in Xi'an?
11. What is your general price-making policy?
12. Is the price influenced by view/environment/skyline, etc.?
13. The price of different storeys in one building is different. What is the price difference and how you determine it? Do you adjust the price of some specific storey?
14. What are the main considerations when designing the landscape inside the neighbourhood? What are the indicators that buyers value?
15. How do you optimise the distribution of the apartments limited by floor area ratio to reach the best vision or daylight?

2# Interview guide for the landscape designer

1. What kind of view do the buyers like? Do they value the view?
2. Does the housing preference of buyers change over time?
3. What role does the landscape play? How do the real estate developers balance the relationship between cost and price?
4. What are the main steps of the landscape design for a neighbourhood?
5. Do you use 3D models for landscape design?
6. What are the main contexts do you value in landscape design?
7. How does the landscape balance functionality and aesthetics?

3# Interview guide for the sales managers of the real estate developers

1. Which type of residence is the most popular based on your experience? What are the common attributes of them?
2. Do you think that the preferences of buyers for residence has changed in time?

3. In your experience, which indicators do buyers consider when buying an apartment?
4. What is your general price-making policy? What are the main steps/procedures and what method/technique is used?
5. What influence does fixed-price policy have on your pricing policy?
6. How do you determine the price difference between different storeys? Which indicators are important?
7. What are the living experiences for apartments on different storey levels?
8. Do you have some certain algorithm to calculate the price difference of the apartments on different storey levels?
9. How do you handle the supporting facilities around the neighbourhood? Is it possible to have a situation where the facilities cannot keep the pace with the neighbourhood construction?
10. Have you ever used a 3D model at the sales office to the customers? What is the customers' feedback?
11. Does the 3D model help you better sell the properties? Is it necessary? Why?
12. What is the price difference among each administrative district in Xi'an? What is the main reason causing this kind of difference?
13. What do you think is the main indicator causing the huge property price growth in the past two years in Xi'an?

4# Interview guide for the university professor in Chang'an University

1. Would you please briefly introduce us about the knowledge of the land valuation?
2. What do you think of the role of 3D modeling in property valuation?
3. Which indicators do you think promote the land parcel price and the property price in Xi'an?
4. Is the scope of property registration still determined according to the 2D floor plan? Does it contain 3D information?
5. Have you ever used 3D data in land valuation? Why?
6. Do you think it is necessary to include 3D data into the land valuation?
7. Is there any difficulty in data acquisition or administration when using 3D data or building a 3D system?
8. In your opinion, what can be improved or added to the current land/property valuation framework?

5# Interview guide for the valuation & consult company

Section 1: Land Price & Residential Property Price

1. What do you think is the main indicator causing the huge property price growth in the past two years in Xi'an?
2. What is the main reason causing the land parcel price growth in Xi'an?
3. How does the Price Bureau of Xi'an approve the property price under the fixed-price policy?
4. The population growth in Xi'an has caused a huge pressure on the housing. What are the current countermeasures taken by the government? How effective is it? How long will this situation be expected to last?
5. The unbalanced supply-demand relationship in the first-hand property market has also contributed to the active second-hand market. How does the government view the phenomenon of the reverse price of second-hand property prices? Is there already a prepared policy for this phenomenon?
6. When selling the land parcels to the real estate developers, there will be a series of limited indicators (such as floor area ratio). How does the Xi'an government set these indicators? How to supervise in the construction process?

Section 2: Urban Planning

1. What is the city orientation of Xi'an at past and in future in perspective of urban planning?
2. What indicators are specifically considered for construction land planning? What is the reference to the quantity of new construction land?
3. Why does the Xi'an municipal government open the Hukou policy?
4. In your opinion, in addition to population growth, what other indicators have contributed to the property price growth in Xi'an?
5. How do property price and urban planning affect each other?
6. How does urban planning intend to keep up infrastructure construction with huge population growth?
7. What is the future development orientation of the different administrative districts in Xi'an? How does the government allocate the resources?
8. Have you ever considered the development of the city in terms of height in the planning?
9. What is the application status of 3D technology in the urban planning of Xi'an? In your opinion, what can be the possible future application scenarios?

6# Interview guide for the Xi'an Survey and Mapping Institute

1. What is the fixed-price policy in Xi'an residential property market?
2. How does the Xi'an municipal government determine land use and sell residential land parcel?
3. Which indicators will you take into consideration when making the residential land use planning? Which factors among them do you think will influence the property price?
4. What kind of planning will influence property price? How does the government handle conflicts or problems?
5. Do you use remote sensing data (e.g., satellite image, UAV, LiDAR) in the planning? Have you ever considered the 3D modelling part?
6. What techniques do you use to build the 3D model?
7. Do you take residential property price as an important indicator in the urban planning process?
8. Which governmental department is responsible for determining the residential property price?
9. In your opinion, what can be improved according to current property valuation procedure?
10. Which indicators do you think caused the continuous rise in residential property prices in Xi'an in 2018?
11. Do you think it will be helpful to consider the status and future development of the city in the vertical dimension during the planning process?
12. Will Xi'an have such a large-scale 3D application for urban planning in the future? What problems will you face?
13. What is the level of details (LoD) the current 3D model application has? What is the cost?

Appendix 2 The overview of semi-structured expert interviews

Number	Respondents	Institution/Position	Contexts	Limitation
1	Two males	Xi'an Survey and Mapping Institute/ Engineer	RS data collection techniques and the current status of the 3D modeling in Xi'an; land use distribution; The fixed-price policy in Xi'an; their forecast of the future price.	Their professional did not include urban planning.
2	One male and one female	Radiance Group Northwest Headquarter/ Architecture designer and landscape designer	How to define the property price; the roles of 3D indicators play in the architecture; buyers' preferences and dislikes.	The interview was short because the respondents were in a hurry before their next meeting.
3	Two males	Ziwei Real Estate/ sales manager	The general price-making policy; buyers' preferences and dislikes; the roles of 3D indicators play in the property price; the current situation of 3D modeling in Xi'an.	N/A
4	One female	Radiance World City/ sales manager	The general price-making policy; buyers' preferences and dislikes; the roles of 3D indicators play in the property price; urban planning in Xi'an; the current situation of 3D modeling in Xi'an.	N/A
5	One male	Greentown Real Estate/ landscape engineer	The balance between landscape and budget; how to design the landscape; people's preferences on different views.	N/A
6	One female	Shanghai Industrial Urban Development Group Limited/ sales manager	The general price-making policy; buyers' preferences and dislikes; the roles of 3D indicators play in the property price; the urban planning in Xi'an; the current situation of 3D modeling in Xi'an.	N/A
7	One male	Chang'an University/ associate professor	The future trend for property valuation; 3D modeling in land valuation and its promotion difficulty; related knowledge of property tax; the reasons behind increasing property price in Xi'an; the forecast of the future price.	His research interest was in land valuation, not property valuation so he could only offer general perspectives.
8	Two males	Huadi Valuation and Consulting Company/ manager	The Xi'an planning and city orientation; the reasons behind the increasing property and land price; 3D modeling in urban planning.	N/A

Appendix 3 The interview guide for the focus group

1. What do you think of the residential property price growth in Xi'an?
2. What attributes do you value in a high-rise apartment? Why?
3. What kind of apartment do you dislike? Why?
4. Does your preference for housing change over time?
5. In your opinion, what are the reasons behind the price difference of apartments on different storeys? What are the factors related to the height you value when buying an apartment?
6. What kind of view do you most want to see/not want to see? Why?
7. How much are you willing to pay for these apartments on different storeys? (Show pictures of the south-facing balconies of the apartments on different storeys)
8. How much are you willing to pay for these different kinds of view? (Show pictures of different views, including green land, street, square)
9. Have you experienced 3D technology during your purchase, such as VR? Do you think the existing sand table, model room, and display area are enough for you to understand the whole scenario? Is it necessary for a 3D model?
10. In your opinion, what are the factors promoting the residential property price in Xi'an? What are your expectations for the future trend of Xi'an residential property prices?
11. Have you ever had a problem with the real estate developers' description after you bought an apartment? What impact does it have? (Examples, supporting facilities are not perfect/slow, the unreasonable design of the apartment)
12. Will the planning of Xi'an affect your housing choices? If so, what kind of planning will affect?
13. In the future, if you do housing choice, which administrative district will you choose? Why?

Appendix 4 The overview of focus groups

Number	Respondent	Purchase experience	Background	Place	Limitation
1	Four young females	One had bought an apartment, two rented apartments, and one lived with parents.	All had a bachelor degree, doing art related works in one company.	Wuwei Art and Living Space	Some respondents showed no interests in the questions.
2	Three males, two senior and one young	They all had house purchase experience.	One elderly worked in Jihua 3513 Industry Corporation, another elderly was retired, and the young man was a salaryman.	Bo'ao Badminton hall	Some respondents showed a lack of interest in our topic; it was more like a group interview.

Appendix 5 A example of the questionnaire in Chinese

对于高层住宅购买偏好的用户调查问卷

性别: ☐ 男 ☑ 女　　年龄: ☐< 18 ☐ 18-25 ☑ 26-35 ☐ 36-45 ☐46-55 ☐ >55

1. 在一幢高层住宅中，哪个高度是您最喜欢的？

   ☐低楼层 ☑ 中楼层 ☐高楼层

   为什么？ 供水、电梯方便

2. 在住宅选择中，以下哪些因子会对您造成影响呢？请按照您对以下因子的偏好程度在对应的方框打钩。

影响因子	重要度排序				
	非常不重要	不重要	一般/无所谓	重要	非常重要
景色				√	
视野				√	
日照时间				√	
房间朝向				√	
少噪音、安静					√
少空气污染					√
公共交通（公交车站、地铁站等）				√	
学校（小学/中学/大学、幼儿园等）			√		
购物（超市、商业中心、书店）				√	
餐饮				√	
文化设施（图书馆、博物馆、美术馆等）				√	
娱乐设施（茶馆、酒吧、电影院等）			√		
体育设施（健身房、体育馆、游泳馆等）				√	
休闲（公园、人民广场、河滨公园等）				√	
人身安全、治安					√

3. 您喜欢的主要房间朝向是？ (比如：客厅，主卧室)

   ☑南北朝向 ☐东西朝向 ☐东南-西北 ☐西南-东北

   为什么？ 采光好，空气流通.

4. 您愿意为一个好的房间朝向多付出总房价的百分之多少？ (比如，+5%，+6%或-10%)

   ____

5. 在您的住宅中，您喜欢哪种景色？ （可多选）

   ☐街道 ☑开放空间（广场、公园） ☐绿地 ☐建筑物、高楼 ☐ 水

6. 您愿意为您喜欢的景色多付出总房价的百分之多少？(比如，+5%，+6% 或-10%) （转反面）

   ☐街道________ ☐开放空间________ ☑绿地 ______ ☐建筑物 ______ ☐水__________

7. 您预想的西安合理房价(元/平方米)是:

   ☐10000 以下 ☐10000-15000 ☐15001-20000 ☐20001-25000 ☐25001-30000 ☐30000 以上

在我完成了课题之后，想邀请您参加评估我的 3D 模型研究成果。如果您愿意，请在下面留下您的电子邮件地址、微信或者 QQ，我会发给您我的评估问卷。这份问卷依旧会保护您的个人信息，用途只将会是用于我的硕士论文课题研究。

电子邮件/微信/QQ: [redacted]

Appendix 6 The questionnaire template in English

Gender: ☐ Male ☐Female Age: ☐< 18 ☐ 18-25 ☐ 26-35 ☐ 36-45 ☐46-55 ☐ >55

1. Which storey level do you prefer in a high-rise apartment?

☐Low ☐ Middle ☐High

Why? ____

2. What indicators do you think are important in your housing decision? Please mark them in the following table.

	Very disagree	disagree	Undecided/I don't care	Agree	Very agree
View	○	○	○	○	○
Sky view (vision)	○	○	○	○	○
Daylight	○	○	○	○	○
Property orientation	○	○	○	○	○
Less noise	○	○	○	○	○
Less air pollution	○	○	○	○	○
Public transport (bus stop, subway station)	○	○	○	○	○
Education facility (kindergarten, primary/middle school, university)	○	○	○	○	○
Shopping (convenient shop, shopping mall)	○	○	○	○	○
Food (restaurant, fast-food chain)	○	○	○	○	○
Culture facility (library, museum, art gallery)	○	○	○	○	○
Entertainment facilities (tea house, theatre, bar)	○	○	○	○	○
Sports (gym, stadium, swimming pool)	○	○	○	○	○
Leisure (park, square, riverside)	○	○	○	○	○
Public safety	○	○	○	○	○

3. What is your preferred choice for the orientation of the major room (e.g., the main bedroom, living room)? (multiple choice)

☐South ☐ North ☐ East ☐ West ☐Southwest ☐Southeast ☐Northwest ☐Northeast

Why? ____

4. What percentage of the total price are you willing to pay for your preferred orientation? (e.g., +5%, -10%)

____

5. Which type of view do you prefer? (multiple choice)

☐Street ☐Open space ☐Green ☐Building ☐ Water ☐ Park

6. What percentage of the total price are you willing to pay in additional for a property having following view? (e.g., +5%, -10%) (multiple choice)

☐Street______________ ☐Open space__________ ☐Park_________

☐Green __________☐Building _________☐ Lake _______☐ Tourist site_________

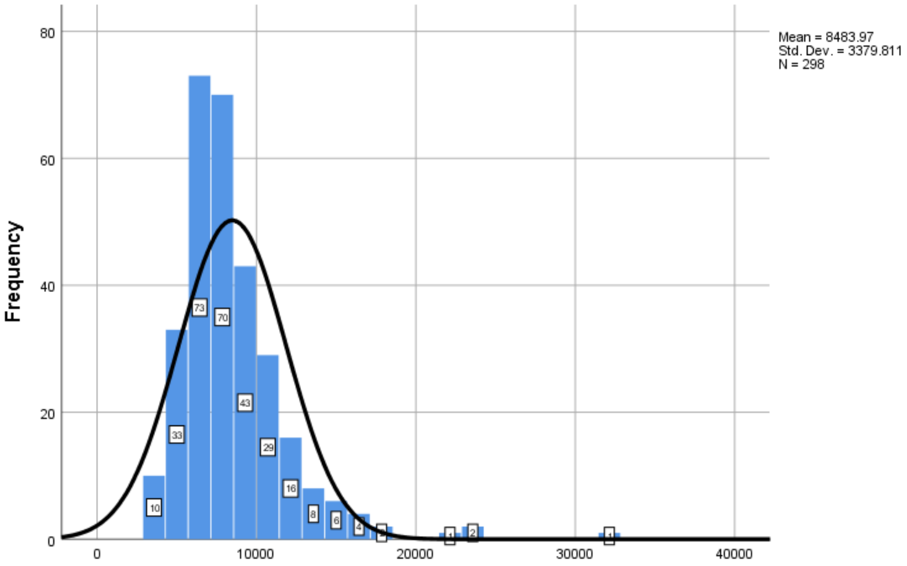
7. What do you think is the reasonable residential property price (yuan/m²) of Xi'an?

☐Under 10000 ☐10001-15000 ☐15001-20000 ☐20001-25000 ☐ 25001-30000 ☐ Over 30000

After I finish the research, may I invite you for a short feedback questionnaire to evaluate my 3D model? If you are willing to do, please leave your WeChat or email so that I can send you a questionnaire. It is voluntary and the information will be kept confidential and only for research purposes.

Email/WeChat/QQ:

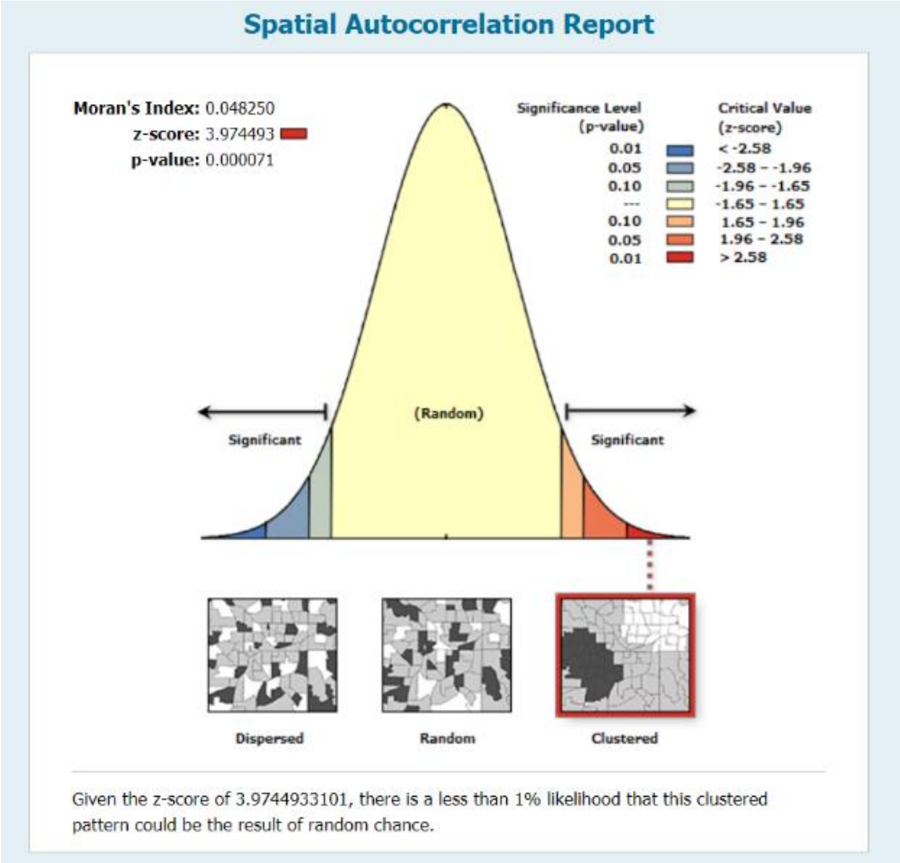
Appendix 7 The descriptive statistics of the property price samples



Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Observed	298	29309	3326	32635	8483.97	3379.811	2.389	.141	10.831	.281
Valid N (listwise)	298									

Appendix 8 The Global Moran's Index report



Appendix 9 The statistical results of OLS

Coefficients[a]

	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
(Constant)	11231.590	1064.399		10.55	.000	9136.541	13326.639					
NDVI_50	5297.212	2497.061	.131	2.121	.035	382.264	10212.160	.104	.124	.118	.818	1.223
kd_busstop_200	8.296	14.768	.032	.562	.575	-20.771	37.364	.020	.033	.031	.968	1.033
kd_supermarket_1km	-13.017	9.681	-.104	-1.345	.180	-32.072	6.038	-.082	-.079	-.075	.523	1.910
kd_factory_1km	-602.100	225.714	-.165	-2.668	.008	-1046.371	-157.829	-.196	-.156	-.149	.812	1.231
kd_sanjia_3km	-2352.669	2849.416	-.069	-.826	.410	-7961.155	3255.818	-.005	-.049	-.046	.443	2.259
ed_food	5.016	1.802	.193	2.783	.006	1.469	8.563	.138	.162	.155	.643	1.554
ed_college	-.078	.368	-.015	-.212	.832	-.803	.646	.002	-.013	-.012	.642	1.559
ed_road_pri_sec	-.801	1.008	-.048	-.795	.427	-2.785	1.182	-.066	-.047	-.044	.870	1.150
kd_park_1km	-190.988	270.141	-.044	-.707	.480	-722.705	340.728	.039	-.042	-.039	.796	1.256
ed_subway	-.572	.271	-.133	-2.109	.036	-1.106	-.038	-.121	-.124	-.118	.785	1.274
ed_CBD	-.242	.095	-.220	-2.545	.011	-.429	-.055	-.055	-.149	-.142	.417	2.395

a. Dependent Variable: Property price

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	.334[a]	.111	.077	3246.569	.111	3.262	11	286	.000	1.890

a. Predictors: (Constant), ed_CBD, kd_busstop_200, ed_road_pri_sec, kd_factory_1km, kd_park_1km, NDVI_50, ed_subway, ed_food, ed_college, kd_supermarket_1km, kd_sanjia_3km

b. Dependent Variable: Property price

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	332410221.4	10	33241022.14	3.153	.001[b]
	Residual	3067575941	291	10541498.08		
	Total	3399986162	301			

a. Dependent Variable: Sheet0__16

b. Predictors: (Constant), kd_supermarket_500m_1, kd_park_ori_1km, kd_busstop_200, ed_road_pri_sec, kd_factory_1km_1, ed_food_1, ed_sub_simple, ed_college_1, kd_sanjia_3km, ed_CBD

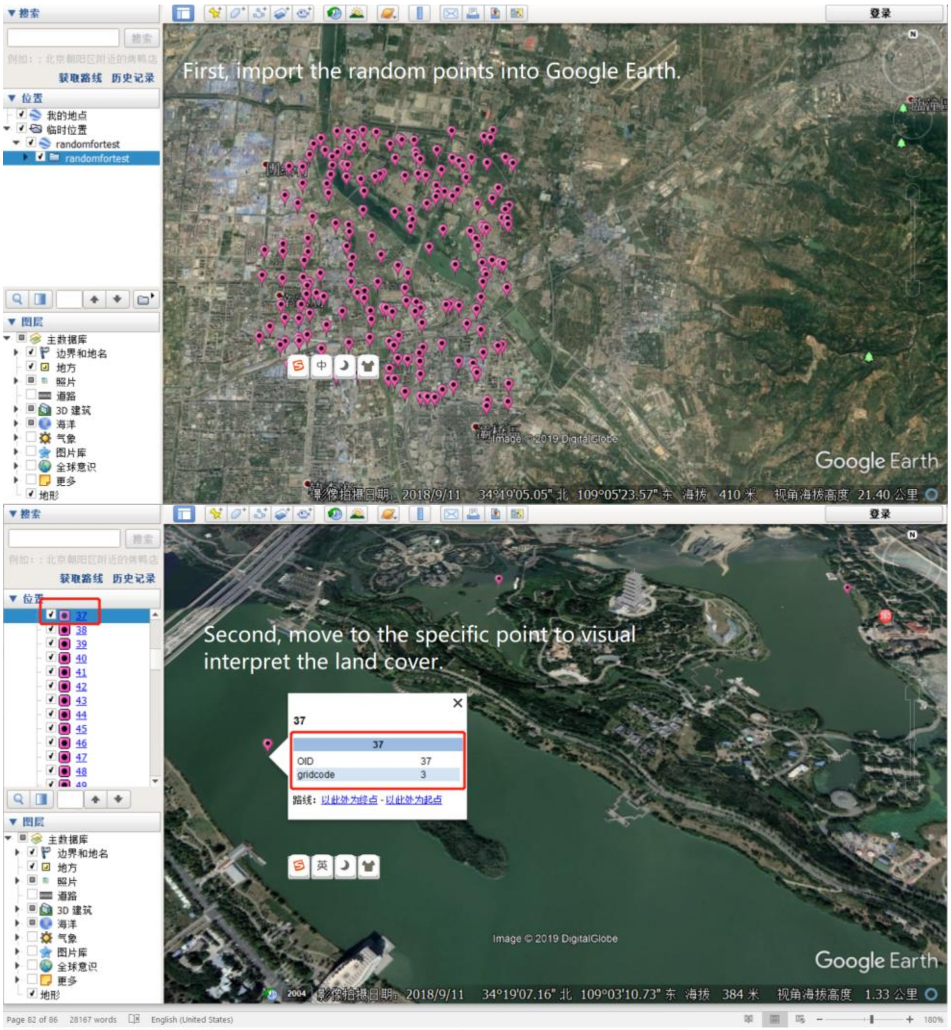
Appendix 10 The GWR support output table

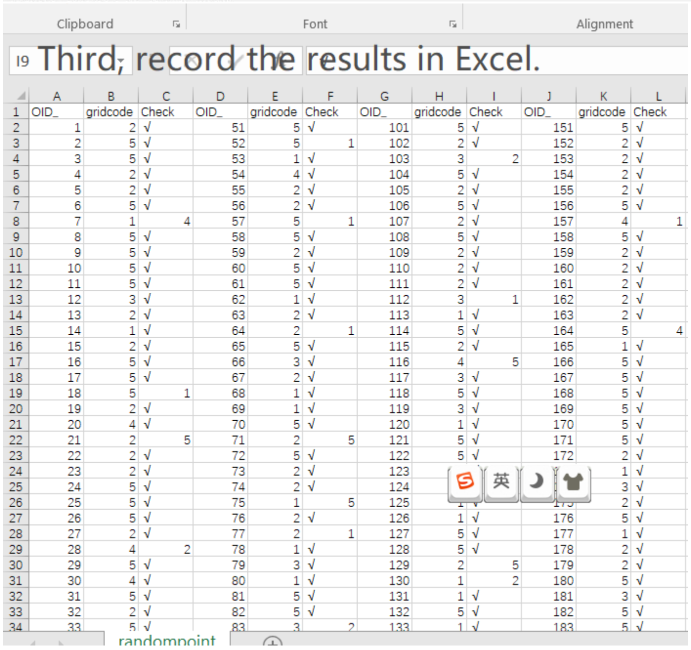
Table

GWR_50_supp

OBJECTID *	VARNAME	VARIABLE	DEFINITION
1	Bandwidth	11834.747381	
2	ResidualSquares	2655158522.638239	
3	EffectiveNumber	31.511103	
4	Sigma	3156.499087	
5	AICc	5670.435676	
6	R2	0.217383	
7	R2Adjusted	0.127779	
8	Dependent Field	0	Property_clip.Sheet0__16
9	Explanatory Field	1	Property_clip.kd_busstop_200
10	Explanatory Field	2	Property_clip.kd_supermarket_1km_1
11	Explanatory Field	3	Property_clip.kd_factory_1km_1
12	Explanatory Field	4	Property_clip.kd_sanjia_3km
13	Explanatory Field	5	Property_clip.ed_food_1
14	Explanatory Field	6	Property_clip.ed_college_1
15	Explanatory Field	7	Property_clip.ed_road_pri_sec
16	Explanatory Field	8	Property_clip.kd_park_ori_1km
17	Explanatory Field	9	Property_clip.ed_sub_simple
18	Explanatory Field	10	Property_clip.ed_CBD
19	Explanatory Field	11	zonal_buffer50.MEAN

Appendix 11 The process of the accuracy assessment for land cover classification in Google Earth





	A	B	C	D	E	F	G	H	I	J	K	L
1	OID_	gridcode	Check	OID_	gridcode	Check	OID_	gridcode	Check	OID_	gridcode	Check
2	1	2	√	51	5	√	101	5	√	151	5	√
3	2	5	√	52	5	1	102	2	√	152	2	√
4	3	5	√	53	1	√	103	3	2	153	2	√
5	4	2	√	54	4	√	104	5	√	154	2	√
6	5	2	√	55	2	√	105	2	√	155	2	√
7	6	5	√	56	2	√	106	5	√	156	5	√
8	7	1	4	57	5	1	107	2	√	157	4	1
9	8	5	√	58	5	√	108	5	√	158	5	√
10	9	5	√	59	2	√	109	2	√	159	2	√
11	10	5	√	60	5	√	110	2	√	160	2	√
12	11	5	√	61	5	√	111	2	√	161	2	√
13	12	3	√	62	1	√	112	3	1	162	2	√
14	13	2	√	63	2	√	113	1	√	163	2	√
15	14	1	√	64	2	1	114	5	√	164	5	4
16	15	2	√	65	5	√	115	2	√	165	1	√
17	16	5	√	66	3	√	116	4	5	166	5	√
18	17	5	√	67	2	√	117	3	√	167	5	√
19	18	5	1	68	1	√	118	5	√	168	5	√
20	19	2	√	69	1	√	119	3	√	169	5	√
21	20	4	√	70	5	√	120	1	√	170	5	√
22	21	2	5	71	2	5	121	5	√	171	5	√
23	22	2	√	72	5	√	122	5	√	172	2	√
24	23	2	√	73	2	√	123	[illegible]	[illegible]	[illegible]	1	√
25	24	5	√	74	2	√	124	[illegible]	[illegible]	[illegible]	3	√
26	25	5	√	75	1	5	125	1	√	[illegible]	2	√
27	26	5	√	76	2	√	126	1	√	176	5	√
28	27	2	√	77	2	1	127	5	√	177	1	√
29	28	4	2	78	1	√	128	5	√	178	2	√
30	29	5	√	79	3	√	129	2	5	179	2	√
31	30	4	√	80	1	√	130	1	2	180	5	√
32	31	5	√	81	5	√	131	1	√	181	3	√
33	32	2	√	82	5	√	132	5	√	182	5	√
34	33	5	√	83	3	2	133	1	√	183	5	√

Appendix 12 The rule file of the floor data of the buildings

```
###################################
# Attributes
# ----------------------------
# driven by object attributes

@Group("Building Parameters",1) @Order(1) @Range(0,20) @Descrip-
tion("Distance from ground to bottom of roof")
attr eaveHeight = 20

@Group("Building Parameters") @Order(2) @Range(0,20) @Descrip-
tion("Distance from ground to top of roof")
attr totalHeight = 30

@Group("Building Parameters") @Order(3) @Range(
      "flat","shed","pyramid","gable","hip",                    #
basic roof types
      "half-hip","gablet",                                      #
gable/hip combinations
      "gambrel","mansard",                                      #
gable/hip double-pitched
      "gambrel-flat","mansard-flat",                            #
gable/hip with flat top
      "vault","dome",
      # gable/hip rounded
      "saltbox","butterfly")
      # gable & shed combinations
attr roofForm = "hip"

@Group("Building Parameters") @Order(
attr OBJECTID = 2

@Hidden
attr Roof_Ht = (totalHeight - eaveHeight) * unitScale

# ----------------------------
```

```
@Group("Facade Texturing",2) @Order(1) @Description("If true, random
textures are shown for facades")
attr Show_Textures = true

@Group("Facade Texturing") @Order(2) @Range(2.9,5.2) @Descrip-
tion("in Meters")
attr Floor_Ht = 4

@Group("Facade Texturing") @Order(3)
attr Facade_Image = fileRandom("Voorbeeld/buildings/fa-
cades/fac_*_floors"+texFloors+"_*.jpg")    # potential texture which
is high enough (see below)

# ----------------------------
# roof texturing (using aerial map)

@Group("Roof Texturing",3) @Order(1) @Description("Use same values
as in corresponding map layer.")
attr Aerial_Image = "data/Voorbeeld/aerial/aerial.jpg"

@Group("Roof Texturing") @Order(2) @Description("Use same values as
in corresponding map layer.")
attr Aerial_Size_X = 1519.035

@Group("Roof Texturing") @Order(3) @Description("Use same values as
in corresponding map layer.")
attr Aerial_Size_Z = 1411.032

@Group("Roof Texturing") @Order(4) @Description("Use same values as
in corresponding map layer.")
attr Aerial_Offset_X = 819719.205//819715.793

@Group("Roof Texturing") @Order(5) @Description("Use same values as
in corresponding map layer.")
```

(1)

```
attr Aerial_Offset_Z = -73251.564//-73249.384

# ----------------------------
# controlled by user

@Group("Options",4) @Order(1)
attr Material_Transparent = false

@Group("Options") @Order(2) @Description("Unit of Object Attrib-
utes") @Range("Meters","Feet")
attr Unit = "Meters"

@Group("Options") @Order(3) @Description("CityEngine interprets the
inner polygons of donut geometries as hole i.e. the attribute is
needed to drive the rules")
attr isHole = false

## Panels

@Group("Panels",6) @Order(1) @Range("None","On Sides", "Roofs",
"All") @Description("Turn on to split the whole model into rectangu-
lar panels (usable e.g. for analysis)")
attr Panels_Generate = "None"

@Group("Panels") @Order(2) @Range(1,20) @Description("Note that
panel size is adjusted/rounded to the geometry's dimensions on the
side")
attr Panel_Size = 5

@Group("Panels") @Order(3) @Range(0,3                "Distance of the
sampling point in front of the panel's center.")
attr Panel_Sampling_Point_Distance = 0.1

###################################
# Consts
#
```

```
# user-driven constants
const opacity    = case Material_Transparent: 0.45 else: 1
const unitScale = case Unit=="Feet": 1/0.3048006096012192 else: 1

# for curved roofs such as dome or vault
const curvedAngleResolution = 10

# needed to determine which facade texture file to select according
to its number of floors
# it should be 'high enough to use as texture' e.g. a 6-storey
building should not use a 3-story texture (otherwise the groundfloor
gets repeated)
const texFloors =
      case nFloors <= 3 && p(0.7) : 3
      case nFloors <= 4 && p(0.7) : 4
      case nFloors <= 5 && p(0.6) : 5
      case nFloors <= 6 && p(0.7) : 6
      case nFloors <= 7 && p(0.4) : 7
      else                        : 60
# after a texture with a compatible floor number has been randomly
selected, the
# filename is parsed to get information how many tiles are in this
image:
const texTiles = float(getRange(Facade_Image,"tiles",".jpg"))
                  # truncate the file name to get actual number of
tiles

###################################
# Functions
#

# for curved roofs such as dome or vault
calcSegmentHt(n) = Roof_Ht * (cos(n*curvedAngleResolution) -
```

(2)

```
cos((n+1)*curvedAngleResolution))

# for facade texturing (operating on the *current* geometry)
nFloors = rint(scope.sy/Floor_Ht)
nTiles  = ceil(scope.sx/Floor_Ht*0.75)
# needed to setup the texture projection to the current facade so
that the texture fits
getFacadeTexProjectionHeight     = scope.sy/nFloors*texFloors
getFacadeTexProjectionWidth      = scope.sx/nTiles*texTiles

# for roof texturing
getRoofTextureSizeScale = case scope.sx > 30 && scope.sy > 20: 3
else: 1

# for panels
getWorldDir =
      case geometry.isOriented(world.north) : "north"
      case geometry.isOriented(world.south) : "south"
      case geometry.isOriented(world.west)  : "west"
      case geometry.isOriented(world.east)  : "east"
      case geometry.isOriented(world.up)        : "up"
      else                                        : "down"
getLocalDir =
      case geometry.isOriented(object.front)     : "front"
      case geometry.isOriented(object.back) : "rear"
      case geometry.isOriented(object.left) : "left"
      case geometry.isOriented(object.right)     : "right"
      case geometry.isOriented(object.
      else                                        : "bottom"


###################################
###################################
#
# RULES
```

```
#
###################################
###################################

@StartRule
Lot -->
      case isHole: NIL else:
      alignScopeToAxes(y) s('1,0,'1)        # make it horizontal i.e.
scale it flat
      report("Footprint Area (m2)",geometry.area) report("Nbr of
Floors",rint(eaveHeight*unitScale/Floor_Ht)) report("Gross Floor
Area (m2)",geometry.area*rint(eaveHeight*unitScale/Floor_Ht))
      extrude(eaveHeight*unitScale)
      set(material.opacity,opacity)
      comp(f){side : Facade | top : Roof }

###################################
# Roof Generation
#

Roof -->
      case roofForm == "shed"              : ShedRoof
      case roofForm == "pyramid"      : PyramidRoof
      case roofForm == "gable"        : GableRoof
      case roofForm == "hip"               : HipRoof
      case roofForm == "half-hip"          : HalfHipRoof
      case roofForm == "gablet"       : GabletRoof
      case roofForm == "gambrel"      : GambrelRoof
      case roofForm == "mansard"      : MansardRoof
      case roofForm == "gambrel-flat": GambrelFlatRoof
      case roofForm == "mansard-flat": MansardFlatRoof
      case roofForm == "vault"        : VaultRoof
      case roofForm == "dome"              : DomeRoof
      case roofForm == "saltbox"      : SaltboxRoof
```

(3)

```
      case roofForm == "butterfly"    : ButterflyRoof
      else                              : FlatRoof

# basic roof types

ShedRoof -->
      roofShed(15) RoofMassScale

GableRoof -->
      roofGable(45,0,0,false,0) RoofMassScale

HipRoof -->
      roofHip(45) RoofMassScale

PyramidRoof -->
      roofPyramid(45) RoofMassScale

# gable & hip combinations

HalfHipRoof -->
      roofGable(45,0,0,false,0) s('1,Roof_Ht,'1)        # creates a
gable roof and sets its height to the given roof height
      split(y){ '0.5: RoofMass(true)                    # cuts the
lower part ...
                  comp(f){ bottom: NIL | horizontal:
set(Roof_Ht,Roof_Ht*0.5) HipRoof } } # ... and invokes a hip roof on
the top

GabletRoof -->
      roofHip(45) s('1,Roof_Ht,'1)
      split(y){ '0.5: RoofMass(true)
                  comp(f){ bottom: NIL | horizontal:
set(Roof_Ht,Roof_Ht*0.5) GableRoof } }

# gable/hip double-pitched

DomeRoof -->
      DomeRoof(90/curvedAngleResolution-1)

DomeRoof(n) -->
      case n > 0:
            roofHip(n*curvedAngleResolution)
            split(y){ (calcSegmentHt(n)): RoofMass(n!=1)
                                          comp(f){ bottom:
NIL | horizontal: DomeRoof(n-1) } }
      else: NIL

# gable & shed combinations

SaltboxRoof -->
      roofShed(45) s('1,1.5*Roof_Ht,'1)
      split(y){ '0.333: RoofMass(true)
                  comp(f){ bottom: NIL | horizontal:
set(Roof_Ht,Roof_Ht*0.5) roofGable(45,0,0,false,geometry.nVertices-
1) RoofMassScale } }

ButterflyRoof -->
      split(y){ '0.5: roofShed(45,geometry.nVertices/2) Roof-
MassScale | '0.5: ShedRoof }

# flat roof

FlatRoof -->
      case Roof_Ht > 0.1:
            RoofPlane offset(-0.4,border) extrude(Roof_Ht) Roof-
Mass(false)
      else:
            RoofPlane

# roof volume

             set(material.dirtmap,fileRandom("assets/Voor-
beeld/buildings/roofs/*.bw.jpg")) # some visual candy: adding some
structure to the aerial image
      else:
            Panels("Roof")

//RoofPlane -->
//    setupProjection(0,world.xz,Aerial_Size_X,-Aerial_Size_Z,Aer-
ial_Offset_X,Aerial_Offset_Z) projectUV(0)
//    texture(Aerial_Image)
//    alignScopeToGeometry(zUp,0,longest)
//    setupProjection(2,scope.xy,~20*getRoofTextureSize-
Scale,~13*getRoofTextureSizeScale) projectUV(2)
//    set(material.dirtmap,fileRandom("buildings/roofs/*.bw.jpg")) #
some visual candy: adding some structure to the aerial image


####################################
# Facade Generation
#

Facade -->
      set(seedian,OBJECTID*180000)
      Facade(getFacadeTexProjectionWidth,getFacadeTexProjection-
Height,0,0)

RoofFacade -->
      case nFloors > 0:
            Facade(getFacadeTexProjectionWidth,getFacadeTexProjec-
tionHeight,0,scope.sy)          # through the shift it is assured
that the textures 'starts on top'
      else:
            Facade(getFacadeTexProjectionWidth,tex-
Tiles*Floor_Ht*1.5,0,scope.sy)

# set facade texture and project the texture coordinates accordingly
```

```
GambrelRoof -->
      roofGable(70,0,0,false,0)
      split(y){ Roof_Ht*0.7: RoofMass(true)
                                    comp(f){ bottom: NIL | horizon-
tal: set(Roof_Ht,Roof_Ht*0.3) GableRoof } }

MansardRoof -->
      roofHip(70)
      split(y){ Roof_Ht*0.7: RoofMass(true)
                                    comp(f){ bottom: NIL | horizon-
tal: set(Roof_Ht,Roof_Ht*0.3) HipRoof } }

# gable/hip with flat top

GambrelFlatRoof -->
      roofGable(45,0,0,false,0)
      split(y){ Roof_Ht: RoofMass(false) }

MansardFlatRoof -->
      roofHip(45)
      split(y){ Roof_Ht: RoofMass(false) }

# round roofs

VaultRoof -->
      VaultRoof(90/curvedAngleResolution-1)

VaultRoof(n) -->
      case n > 0:
            roofGable(n*curvedAngleResolution,0,0,false,0)
            split(y){ (calcSegmentHt(n)): RoofMass(n!=1)
                                          comp(f){ bottom:
NIL | horizontal: VaultRoof(n-1) } }
      else: NIL
```

(4)

```
RoofMassScale -->
      s('1,Roof_Ht,'1)
      RoofMass(false)

RoofMass(removeBottomAndTop) -->
      case removeBottomAndTop:
            comp(f){ horizontal: NIL | vertical: RoofFacade | all:
RoofPlane }
      else: # remove only the bottom face
            comp(f){ bottom: NIL | vertical: RoofFacade | all:
RoofPlane }

# roof surfaces

@Group("Roof Texturing") @Order(1)
attr Use_Generic_Textures = false
@Group("Roof Texturing") @Order(2)
attr myRoofTexture = fileRandom("assets/Voorbeeld/build-
ings/roofs/metalRoofTextures/*.jpg")

RoofPlane -->
      case Panels_Generate == "None" || Panels_Generate == "On
Sides":
            case Use_Generic_Textures:
             alignScopeToGeometry(zUp, 0, world.lowest)
             setupProjection(0,scope.xy,'1,'1) projectUV(0)
             texture(myRoofTexture)
            else:
             setupProjection(0,world.xz,Aerial_Size_X,-Aer-
ial_Size_Z,Aerial_Offset_X,Aerial_Offset_Z) projectUV(0)
             texture(Aerial_Image)
             alignScopeToGeometry(zUp,0,longest)
             setupProjection(2,scope.xy,~20*getRoofTextureSize-
Scale,~13*getRoofTextureSizeScale) projectUV(2)
```

(5)

```
Facade(w,h,offsetW,offsetH) -->
      case Panels_Generate == "None" || Panels_Generate == "Roofs":
            case Show_Textures:
                  setupProjection(0,scope.xy,w,h,offsetW,offsetH) pro-
jectUV(0)
                  texture(Facade_Image)
            else:
                  Facade.
      else:
            Panels("Wall")

## Panels ###############################

Panels(type) -->
      split(x,noAdjust){ ~Panel_Size: split(y){ ~Panel_Size:
Panel(type) }* }*              # THE split

Panel(type) -->
      case geometry.area() < 0.02:
            NIL

      else:
            alignScopeToGeometry(zUp,0,world.lowest)
            texture("")
            report("ID",uid)
                                                            # switch-
ing off texture
            report("Type",type) report("Area",geometry.area)
            report("Local Orientation",getLocalDir) report("World
Orientation",getWorldDir)
            Panel.
            [ s(0,0,0) center(xyz) t(0,0, rand(Panel_Sam-
pling_Point_Distance, Panel_Sampling_Point_Distance+1))
            comp(v){ 0: report("Z",scope.elevation) Sampling-
Point. } ]
```

(6)

Appendix 13 The rule file of the high-rise apartments in the study neighbourhoods

```
@Hidden(Usage,BuildingHeight,UpperfloorHeight)
import Facade_Textures:"/ESRI.lib/rules/Facades/Facade_Tex-
tures.cga" (BuildingHeight=Eave_Ht,Upperfloor-
Height=Floor_Ht*unitScale,Usage=Usage)
@Hidden(Usage,UpperfloorHeight)
import Facade_Schematic:"/ESRI.lib/rules/Facades/Facade_Sche-
matic.cga" (UpperfloorHeight=Floor_Ht*unitScale,Usage=Usage)
import Roof_Textures:"/ESRI.lib/rules/Roofs/Roof_Textures.cga"


####################################
# Attributes
#

@Group("Building Settings",1)

@Order(1) @Range(1,400) @Description("Distance from ground to
bottom of roof")
attr Eave_Ht         = _getInitialEaveHeight
@Order(2) @Range(1,400) @Description("Distance from ground to
top of roof")
attr Ridge_Ht        = _getInitialRidgeHeight
@Order(3) @Range("Random","Agricultural","Assembly","Educa-
tional","Industry","Mercantile","Office","Other","Public","Resi-
dential","Service","Transport","Unknown","Utility")
attr Usage                = _getInitialUsage
@Order(4) @Range("extrusion","setba[illegible]ck fa-
cade","setback base","setback every[illegible]
attr Building_Form  = _getInitialBuildingForm
@Order(5) @Range("flat","shed","pyramid","gable","hip","half-
hip","gablet","gambrel","mansard","gambrel-flat","mansard-
flat","vault","dome","saltbox","butterfly")
                    # gable & shed combinations

# for curved roofs such as dome or vault
const curvedAngleResolution = 10

####################################
# Functions
#

# for curved roofs such as dome or vault
calcSegmentHt(n) = Roof_Ht * (cos(n*curvedAngleResolution) -
cos((n+1)*curvedAngleResolution))

_getInitialBuildingForm =
     case Eave_Ht*unitScale < 50 : "extrusion"
     case Eave_Ht*unitScale > 100: "setback everywhere"
     else                        : 5%:"extrusion" 15%:"setback
top" 15%:"setback facade" 15%:"setback base" else:"setback eve-
rywhere"

_getInitialUsage =
     case Eave_Ht>30: "Random" else: 80%:"Residential"
else:"Random"

_getInitialEaveHeight =
     case geometry.area < 100 : geometry.area/rand(5,10)
     case geometry.area < 1000: geometry.area/rand(15,25)
     case geometry.area < 7000: geometry.area/rand(10,25)
     else                     : geo[illegible]d(70,200)

_getInitialRidgeHeight =
     case Eave_Ht<30: Eave_Ht+rand(3,6) else: Eave_Ht

_getInitialRoofForm =
     case Ridge_Ht < Eave_Ht+1: "flat"
     else: 40%: "hip" 50%: "gable" else: "gambrel"

      else:
           Extrusion(Eave_Ht,true,1)

 SetbackTop -->
      split(x){ 'rand(0.1,0.3): Extrusion(Eave_Ht-
 rint(rand(3))*Floor_Ht,false,4)
                | ~1            : Extrusion(Eave_Ht,true,6)
                | 'rand(0.1,0.3): Extrusion(Eave_Ht-
 rint(rand(3))*Floor_Ht,false,4) }

 SetbackFacade -->
      split(z){ 'rand(0.03,0.2): Extru-
 sion(Eave_Ht*rand(0.2,0.8),false,2)
                | ~1                : Extrusion(Eave_Ht,true,6)
                | 'rand(0.03,0.2): Extru-
 sion(Eave_Ht*rand(0.2,0.8),false,2) }

 SetbackBase -->
      [ extrude(3*Floor_Ht) Mass(false) ]
      t(0,3*Floor_Ht,0)
      split(x){ 'rand(0.6,0.8): Extrusion(Eave_Ht-
 3*Floor_Ht,true,6) }

 SetbackAll -->
      [ extrude(3*Floor_Ht) Mass(false) ]
      t(0,3*Floor_Ht,0)
      set(Eave_Ht,Eave_Ht-3*Floor_Ht[illegible]
      split(x){ 'rand(0.6,0.8):
           split(z){ '0.2: Extru-
 sion(Eave_Ht*rand(0.2,0.8),false,2)
                     | ~1  : SetbackTop
                     | '0.2: Extru-
 sion(Eave_Ht*rand(0.2,0.8),false,2) }
```

```
attr Roof_Form       = _getInitialRoofForm
@Order(6) @Range(2.9,5.2) @Description("in Meters")
attr Floor_Ht        = 3.7
@Hidden
attr Roof_Ht         = (Ridge_Ht - Eave_Ht) * unitScale

@Group("Visualization Options",2)

@Order(1) @Range("realistic with facade textures","schematic fa-
cades","solid color")
attr Representation = "realistic with facade textures"
@Order(2) @Range(0,1)
attr Transparency    = 0
@Order(3) @Color
attr OverwriteColor = "#ffffff"
@Order(4) @Color
attr RoofColor = OverwriteColor

@Group("Rule Options")

@Order(2) @Range("Meters","Feet") @Description("Units of height
attributes")
attr Unit = "Meters"

@Order(3) @Range("None","All") @Description("Report infor-
mation")
attr Reporting = "None"

####################################
# Consts
# user-driven constants
const unitScale = case Unit=="Feet": 1/0.3048006096012192 else:
1
```

(1)

```
####################################
####################################
#
# RULES
#
####################################
####################################

@StartRule
Generate -->
     cleanupGeometry(all,1)
     alignScopeToAxes(y) s('1,0,'1)      # make it horizontal
i.e. scale it flat
     alignScopeToGeometry(yUp, 0, longest)
     set(Eave_Ht,Eave_Ht*unitScale)
     set(Floor_Ht,Floor_Ht*unitScale)
     Reports_Lot
     set(material.opacity,1-Transparency)
     color(OverwriteColor)
     Footprint
####################################
# Building Mass
#
Footprint -->
     case scope.sz < 10 || scope.sx < 10:
          Extrusion(Eave_Ht,true,1)
     case Building_Form == "setback top":
          SetbackTop
     case Building_Form == "setback facade":
          SetbackFacade
     case Building_Form == "setback base":
          SetbackBase
     case Building_Form == "setback everywhere":
          SetbackAll
```

(2)

```
     }

Extrusion(height,constructRoof,maxLength) -->
     convexify(maxLength)
     comp(f){ all: alignScopeToGeometry(yUp, 0, longest) Extru-
sionConvexified(height,constructRoof,maxLength) }

ExtrusionConvexified(height,constructRoof,maxLength) -->
     case scope.sx < maxLength+1 || scope.sz < maxLength+1: NIL
     else:
          Reports GFA(height)
          extrude(height) Mass(constructRoof)

Mass(constructRoof) -->
     case constructRoof:
          comp(f){side : Facade | top : Roof }
     else:
          comp(f){side : Facade | top : RoofPlane }

####################################
# Roof Generation
Roof -->
     case Roof_Ht == 0              : RoofPlane
     case Roof_Form == "shed"       : ShedRoof
     case Roof_Form == "pyramid"    : PyramidRoof
     case Roof_Form == "gable"      : GableRoof
     case Roof_Form == "hip"        : HipRoof
     case Roof_Form == "half-hip"   : HalfHipRoof
     case Roof_Form == "gablet"     : GabletRoof
     case Roof_Form == "gambrel"    : GambrelRoof
     case Roof_Form == "mansard"    : MansardRoof
     case Roof_Form == "gambrel-flat": GambrelFlatRoof
     case Roof_Form == "mansard-flat": MansardFlatRoof
     case Roof_Form == "vault"      : VaultRoof
```

(3)

```
      case Roof_Form == "dome"       : DomeRoof
      case Roof_Form == "saltbox"         : SaltboxRoof
      case Roof_Form == "butterfly"  : ButterflyRoof
      else                                : FlatRoof

 # basic roof types

 ShedRoof -->
      roofShed(15) RoofMassScale

 GableRoof -->
      roofGable(45,0,0,false,0) RoofMassScale

 HipRoof -->
      roofHip(45) RoofMassScale

 PyramidRoof -->
      roofPyramid(45) RoofMassScale

 # gable & hip combinations

 HalfHipRoof -->
      roofGable(45,0,0,false,0) s('1,Roof_Ht,'1)    # creates a
 gable roof and sets its height to the given roof height
      split(y){ '0.5: RoofMass(true)                # ...
                        comp(f){ bottom: NIL | horizontal:
 set(Roof_Ht,Roof_Ht*0.5) HipRoof } } #      and invokes a hip
 roof on the top

 GabletRoof -->
      roofHip(45) s('1,Roof_Ht,'1)
      split(y){ '0.5: RoofMass(true)
                        comp(f){ bottom: NIL | horizontal:
 set(Roof_Ht,Roof_Ht*0.5) GableRoof } }

 # gable/hip double-pitched

 GambrelRoof -->
      roofGable(70,0,0,false,0)
      split(y){ Roof_Ht*0.7: RoofMass(true)
                                  comp(f){ bottom: NIL | horizon-
 tal: set(Roof_Ht,Roof_Ht*0.3) GableRoof } }

 MansardRoof -->
      roofHip(70)
      split(y){ Roof_Ht*0.7: RoofMass(true)
                                  comp(f){ bottom: NIL | horizon-
 tal: set(Roof_Ht,Roof_Ht*0.3) HipRoof } }

 # gable/hip with flat top

 GambrelFlatRoof -->
      roofGable(45,0,0,false,0)
      split(y){ Roof_Ht: RoofMass(false) }

 MansardFlatRoof -->
      roofHip(45)
      split(y){ Roof_Ht: RoofMass(false) }

 # round roofs

 VaultRoof -->
      VaultRoof(90/curvedAngleResolution-1)

 VaultRoof(n) -->
      case n > 0: roofGable(n*curvedAngleResolution,0,0,false,0)
                  split(y){ (calcSegmentHt(n)): RoofMass(n!=1)
```

(4)

```
comp(f){ bottom: NIL | horizontal: VaultRoof(n-1) } }
     else: NIL

DomeRoof -->
     DomeRoof(90/curvedAngleResolution-1)

DomeRoof(n) -->
     case n > 0: roofHip(n*curvedAngleResolution)
                 split(y){ (calcSegmentHt(n)): RoofMass(n!=1)

comp(f){ bottom: NIL | horizontal: DomeRoof(n-1) } }
     else: NIL

# gable & shed combinations

SaltboxRoof -->
     roofShed(45) s('1,1.5*Roof_Ht,'1)
     split(y){ '0.333: RoofMass(true)
                         comp(f){ bottom: NIL | horizontal:
set(Roof_Ht,Roof_Ht*0.5) roofGable(45,0,0,false,geometry.nVerti-
ces-1) RoofMassScale } }

ButterflyRoof -->
     split(y){ '0.5: roofShed(45,geometry.nVertices/2) Roof-
MassScale | '0.5: ShedRoof }

# flat roof

FlatRoof -->
     case Roof_Ht > 0.1:
          RoofPlane offset(-0.4,border) extrude(Roof_Ht) Roof-
Mass(false)
     else:
          RoofPlane

 # roof volume

 RoofMassScale -->
      s('1,Roof_Ht,'1)
      RoofMass(false)

 RoofMass(removeBottomAndTop) -->
      case removeBottomAndTop:
           comp(f){ horizontal: NIL | vertical: Facade | all:
 RoofPlane }
      else: # remove only the bottom face
           comp(f){ bottom: NIL | vertical: Facade | all:
 RoofPlane }
 ##################################
 # Surface Texturing & Coloring
 RoofPlane -->
      case Representation == "realistic with facade textures":
           Roof_Textures.Generate
      else:
           color(RoofColor)

 Facade -->
      case Representation == "realistic with facade textures":
           Facade_Textures.Generate
      case Representation == "schematic facades":
           case OverwriteColor == "#ffffff":
                Facade_Schematic.Generate
           else:
                set(Facade_Schematic.SecondaryColor,Overwrit-
 eColor)
                Facade_Schematic.Generate
      else:
           color(OverwriteColor)
```

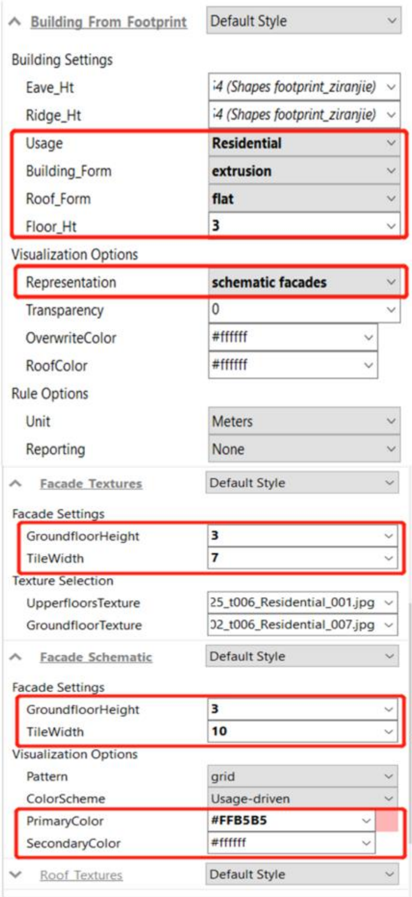
(5)

```
###################################
# Reports
#
Reports_Lot -->
      case Reporting=="All":
            report("Footprint Area (m2)",geometry.area)
            report("Nbr of Floors",rint(Eave_Ht/Floor_Ht))
            NIL
      else:
            NIL

# height  height of extruded part
Reports_GFA(height) -->
      case Reporting=="All":
            report("Gross Floor Area (m2)",geome-
try.area*rint(height/Floor_Ht))
            NIL
      else:
            NIL
```

(6)

Appendix 14 The parameter setting in the rule files of the high-rise apartments in the study neighbourhoods



Choose different land uses to determine the basic building appearance.
Choose different construction styles of the building.
Define the roof types.
The floor height was assumed to be 3 m.

Choose different representation styles of the building.

When the representation was "texture facades", these columns could be activated.

The floor height was assumed to be 3 m.
Change the value to simulate different property densities on one storey

Change the window color or wall color to represent different property prices.

Appendix 15 The accuracy assessment form of SVM

OID_	gridcode	Check	OID_	gridcode	Check	OID_	gridcode	Check	OID_	gridcode	Check
1	2	√	51	5	√	101	5	√	151	5	√
2	5	√	52	5	1	102	2	√	152	2	√
3	5	√	53	1	√	103	3	2	153	2	√
4	2	√	54	4	√	104	5	√	154	2	√
5	2	√	55	2	√	105	2	√	155	2	√
6	5	√	56	2	√	106	5	√	156	5	√
7	1	4	57	5	1	107	2	√	157	4	1
8	5	√	58	5	√	108	5	√	158	5	√
9	5	√	59	2	√	109	2	√	159	2	√
10	5	√	60	5	√	110	2	√	160	2	√
11	5	√	61	5	√	111	2	√	161	2	√
12	3	√	62	1	√	112	3	1	162	2	√
13	2	√	63	2	√	113	1	√	163	2	√
14	1	√	64	2	1	114	5	√	164	5	4
15	2	√	65	5	√	115	2	√	165	1	√
16	5	√	66	3	√	116	4	5	166	5	√
17	5	√	67	2	√	117	3	√	167	5	√
18	5	1	68	1	√	118	5	√	168	5	√
19	2	√	69	1	√	119	3	√	169	5	√
20	4	√	70	5	√	120	1	√	170	5	√
21	2	5	71	2	5	121	5	√	171	5	√
22	2	√	72	5	√	122	5	√	172	2	√
23	2	√	73	2	√	123	2	√	173	1	√
24	5	√	74	2	√	124	5	√	174	3	√
25	5	√	75	1	5	125	1	√	175	2	√
26	5	√	76	2	√	126	1	√	176	5	√
27	2	√	77	2	1	127	5	√	177	1	√
28	4	2	78	1	√	128	5	√	178	2	√
29	5	√	79	3	√	129	2	5	179	2	√
30	4	√	80	1	√	130	1	2	180	5	√
31	5	√	81	5	√	131	1	√	181	3	√
32	2	√	82	5	√	132	5	√	182	5	√
33	5	√	83	3	2	133	1	√	183	5	√
34	2	√	84	3	√	134	1	5	184	1	√
35	2	√	85	1	4	135	4	√	185	5	√
36	5	√	86	5	√	136	2	√	186	5	√
37	3	√	87	5	√	137	5	√	187	5	√
38	2	√	88	5	√	138	2	√	188	1	5
39	2	√	89	1	√	139	2	√	189	1	√
40	4	1	90	5	√	140	2	√	190	2	√
41	2	√	91	1	√	141	5	√	191	5	√
42	3	1	92	2	√	142	2	√	192	2	√
43	1	√	93	5	√	143	5	√	193	2	√
44	3	√	94	1	√	144	4	√	194	2	√
45	2	√	95	2	√	145	5	√	195	2	√
46	2	√	96	3	3	146	2	√	196	2	√
47	4	√	97	5	√	147	2	√	197	2	√
48	5	√	98	2	√	148	5	√	198	5	√
49	5	1	99	5	√	149	2	√	199	5	√
50	2	√	100	3	√	150	5	√	200	5	√
Building-1	Green-2	Water-3	Soil-4	Road-5		OA=87.5%					

Appendix 16 The statistical results of the 3D method

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	.671[a]	.451	.411	1119.384	.451	11.280	4	55	.000	.432

a. Predictors: (Constant), Sunlight, Good view, SVF, Orientation

b. Dependent Variable: Price

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	13637.143	716.704		19.028	.000	12201	15073.4					
	Good view	-2045.388	1955.090	-.123	-1.046	.300	-5963.5	1872.70	.204	-.14	-.10	.725	1.379
	SVF	-1621.786	808.683	-.271	-2.005	.050	-3242.4	-1.149	-.218	-.26	-.20	.547	1.828
	Orientation	-2959.468	514.999	-.792	-5.747	.000	-3991.5	-1927.39	-.633	-.61	-.57	.526	1.901
	Sunlight	4142.031	2070.950	.327	2.000	.050	-8.245	8292.31	-.260	.260	.200	.373	2.682

a. Dependent Variable: Price

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56536448.57	4	14134112.14	11.280	.000[b]
	Residual	68916117.83	55	1253020.324		
	Total	125452566.4	59			

a. Dependent Variable: Price

b. Predictors: (Constant), Sunlight, Good view, SVF, Orientation

Appendix 17 The checklist of LOOCV results

Name	View distance	Good view	SVF	Orientation	Sunlight	Price	Intercept	b1	b2	b3	b4	estimated	Error
Y_08	500	0.0222469	0.084	1	0.461174242	10897	13698.74452	-2226.605241	-1854.36825	-2931.281977	4269.076224	12530.94845	1633.948452
Y_08	200	0.0147225	0.107	1	0.461174242	10897	13702.2386	-2249.386008	-1834.07224	-2933.443846	4249.88334	12499.36909	1602.36909
Y_08	100	0	0.14	1	0.461174242	10897	13707.64769	-2301.070799	-1809.364154	-2938.773617	4232.129417	12467.31217	1570.312167
Y_10	500	0.169059	0.294	1	0.503954802	10502	13671.5978	-1515.36572	-1665.799327	-2843.666689	3911.471332	12053.20464	1551.204642
Y_10	200	0.1758621	0.34	1	0.503954802	10502	13677.50202	-1496.601242	-1625.334107	-2840.195457	3853.191619	11963.332	1461.331995
Y_08	50	0	0.197	1	0.461174242	10897	13712.33915	-2258.31776	-1752.086745	-2932.820887	4152.901324	12349.5683	1452.568295
Y_11	500	0.0667491	0.139	1	0.425925926	10895	13731.79818	-1936.415488	-1710.738531	-2885.046211	3953.841636	12163.74904	1268.749035
Y_11	200	0.0665813	0.169	1	0.425925926	10895	13731.96048	-1931.541888	-1687.848027	-2885.155067	3930.67197	12107.12961	1212.129612
Y_11	100	0.0238764	0.271	1	0.425925926	10895	13739.14024	-2053.535404	-1636.775	-2900.315791	3909.104815	12011.21641	1116.216407
Y_10	50	0	0.776	1	0.503954802	10502	13729.60431	-2085.98554	-1428.446733	-2905.536437	3752.243613	11606.5544	1104.554399
Y_10	100	0.2421652	0.565	1	0.503954802	10502	13692.04243	-1385.42873	-1484.128611	-2826.552557	3648.558371	11530.16304	1028.16304
Z_04	200	0.0664894	0.6	1	0.626262626	11314	13596.072	-2081.651212	-1626.10046	-2961.805162	4259.272934	12187.62236	873.6223552
Z_01	500	0.3200935	0.496	0	0.543981481	13743	13622.2062	-1712.811998	-1626.47658	-3024.087695	4251.959637	14580.2012	837.2011996
Z_04	500	0.1222494	0.555	1	0.626262626	11314	13592.3895	-1948.651207	-1632.267036	-2945.953926	4227.099324	12149.58028	835.5802782
Z_01	100	0.2413793	0.591	0	0.543981481	13743	13633.28751	-1897.591239	-1604.485348	-3040.46618	4261.982752	14545.4371	802.4370962
Z_01	200	0.3053435	0.54	0	0.543981481	13743	13627.63414	-1762.028173	-1611.563091	-3021.037881	4228.860248	14519.78786	776.7878619
Z_04	100	0.057971	0.707	1	0.626262626	11314	13612.80957	-2071.925148	-1587.033368	-2956.944405	4178.9558	12030.84481	716.8448054
Z_02	200	0.1223881	0.646	1	0.661616162	11455	13585.89092	-1978.35878	-1618.979294	-2955.096448	4241.244965	12148.88257	693.8825708
Z_02	500	0.2080201	0.562	1	0.661616162	11455	13578.84835	-1818.299444	-1632.264182	-2936.414619	4214.306651	12135.11191	680.1119105
Y_09	500	0.03861	0.209	1	0.53219697	11834	13630.20775	-2123.456871	-1711.742776	-2960.276908	4269.25056	12502.27206	668.2720619
Z_02	100	0.0635593	0.75	1	0.661616162	11455	13598.35528	-2079.722653	-1594.977208	-2964.925746	4224.379095	12099.92835	644.9283462
Z_04	50	0	0.862	1	0.626262626	11314	13628.65079	-2147.631752	-1553.791051	-2963.243549	4136.287961	11916.44192	602.4419205
Y_09	200	0.0326975	0.257	1	0.53219697	11834	13634.49431	-2117.13244	-1687.643439	-2959.048201	4234.36591	12426.01341	592.0134122
Y_07	500	0.0902778	0.569	1	0.666666667	11855	13593.74961	-2060.251152	-1646.590561	-2967.690759	4276.264679	12353.99705	498.9970495
Y_09	100	0.010687	0.337	1	0.53219697	11834	13639.94071	-2127.932093	-1659.560788	-2960.011518	4199.012223	12332.61753	498.6175322
Z_02	50	0	0.958	1	0.661616162	11455	13621.85231	-2130.400579	-1562.049398	-2966.591639	4154.449134	11907.46804	452.4680354
Z_03	500	0.0398671	0.382	1	0.455808081	11473	13668.96818	-2031.260928	-1612.442194	-2937.328247	4050.583195	11880.99506	407.995061
Z_03	200	0.0138648	0.417	1	0.455808081	11473	13670.664	-2059.455973	-1608.108462	-2940.531122	4052.380775	11878.10557	405.1055668
Y_07	200	0.0593472	0.681	1	0.666666667	11855	13609.87549	-2079.91857	-1621.81001	-2966.597449	4220.940355	12229.34836	374.348357
Z_01	50	0.3072626	0.771	0	0.543981481	13743	13642.381	-1898.444896	-1576.57856	-2978.840	4110.757	14079.69361	336.6936089
Z_03	100	0	0.492	1	0.455808081	11473	13665.74039	-2062.677627	-1600.366193	-2944.606924	4058.442065	11783.62399	310.6239908
Y_11	50	0	0.819	1	0.425925926	10895	13679.67456	-2024.932249	-1550.196221	-2934.4592	3964.899353	11164.35809	269.3580871
Y_07	100	0	0.859	1	0.666666667	11855	13626.78018	-2091.344098	-1606.108538	-2965.107171	4169.157826	12061.46433	206.4643265
Y_06	500	0.099768	0.576	1	0.666666667	12240	13631.6523	-2045.314751	-1624.544089	-2960.227415	4157.976836	12303.61512	63.61511996
Z_03	50	0	0.654	1	0.455808081	11473	13641.05461	-2045.722172	-1616.404942	-2957.275847	4127.626609	11508.05549	35.05548987
Y_07	50	0	1	1	0.666666667	11855	13638.54669	-2037.674416	-1628.109046	-2958.853064	4141.693904	11812.71385	-42.28615367
Y_06	200	0.0662651	0.692	1	0.666666667	12240	13641.54009	-2041.215146	-1622.255586	-2958.534619	4130.232382	12178.63162	-61.36838146
Z_12	500	0.03989	0.245	0	0.385416667	14830	13628.6602	-2017.209637	-1615.054141	-2947.878242	4127.372813	14743.2638	-86.73620305
Z_12	200	0.0399449	0.246	0	0.385416667	14830	13628.45635	-2016.607791	-1614.948456	-2947.624251	4127.122792	14741.28774	-88.71226353
Y_09	50	0	0.706	1	0.53219697	11834	13631.98483	-2035.845977	-1633.455135	-2962.335072	4162.023849	11731.44691	-102.5530851
Z_12	100	0.0384068	0.272	0	0.385416667	14830	13623.6794	-2002.538293	-1613.268982	-2941.915493	4122.415222	14696.80663	-133.1933742
Y_06	100	0	0.894	1	0.666666667	12240	13649.6952	-1987.336571	-1647.506681	-2952.875941	4114.521819	11966.96283	-273.0371658
Z_12	50	0.0194805	0.373	0	0.385416667	14830	13605.53822	-1947.855545	-1617.162788	-2923.198389	4118.88245	14551.87721	-278.1227895
Y_06	50	0	1	1	0.666666667	12240	13652.86137	-1959.01625	-1692.580995	-2952.585934	4138.257635	11766.53286	-473.4671397
Z_09	500	0.0922882	0.192	0	0.259259259	14797	13501.01207	-2033.441192	-1635.31869	-2924.406234	4333.409552	14122.84472	-674.1552783
Z_09	200	0.0918367	0.199	0	0.259259259	14797	13497.95343	-2033.6472	-1637.983998	-2924.077269	4340.693423	14110.59606	-686.4039395
Z_09	100	0.0878553	0.21	0	0.259259259	14797	13494.58877	-2027.154023	-1641.477782	-2923.024479	4347.238437	14098.84404	-698.1559633
Z_06	500	0.0577849	0.363	1	0.62962963	13856	13744.19057	-1854.311617	-1438.684777	-2919.220838	3644.346987	12490.16476	-1365.835236
Z_06	200	0.0550162	0.371	1	0.62962963	13856	13743.25178	-1845.029893	-1442.543074	-2918.480799	3646.923083	12484.29183	-1371.708171
Z_06	100	0.0536013	0.391	1	0.62962963	13856	13741.75423	-1843.3547	-1453.333188	-2919.462741	3659.922461	12459.62755	-1396.372448
Z_07	200	0.0029851	0.341	1	0.561342593	13942	13667.94568	-1689.811512	-1461.877331	-2929.684798	3794.292983	12364.61476	-1577.385244
Z_07	500	0.0190337	0.325	1	0.561342593	13942	13671.53903	-1759.50501	-1455.716587	-2937.780194	3804.387311	12362.72573	-1579.27427
Z_07	100	0	0.368	1	0.561342593	13942	13663.25777	-1680.028005	-1479.830869	-2931.021071	3818.831533	12331.33174	-1610.668263
Z_05	200	0.2036364	0.34	1	0.600115741	13756	13736.02172	-2619.133613	-1487.609182	-3033.804513	3978.795639	12050.81713	-1705.182872
Z_05	500	0.2075812	0.335	1	0.600115741	13756	13737.56537	-2639.476193	-1484.555328	-3036.087907	3979.376303	12044.33208	-1711.667921
Z_05	100	0.2097087	0.379	1	0.600115741	13756	13732.52708	-2699.210145	-1520.698096	-3048.095015	4045.995291	11970.105	-1785.895001
Z_06	50	0.0534125	0.656	1	0.62962963	13856	13714.52188	-1919.742277	-1653.505671	-2950.990821	3937.597072	12055.52097	-1800.479034
Z_07	50	0	0.519	1	0.561342593	13942	13633.49474	-1707.309864	-1604.636039	-2952.156946	4016.072504	12102.92424	-1839.075756
Z_05	50	0.1795666	0.619	1	0.600115741	13756	13687.20372	-2763.447126	-1747.722566	-3083.128507	4388.35652	11659.53406	-2096.465936
Z_09	50	0.0868966	0.259	1	0.259259259	14797	12488.882	-3972.068385	-2322.933019	-3754.847656	8275.517762	9932.740251	-4864.259749
						average	error percentage						average deviation
						12492.6	0.097601317						1219.294208