Cities 151 (2024) 105115

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Automated land valuation models: A comparative study of four machine learning and deep learning methods based on a comprehensive range of influential factors

Peyman Jafary [a,b,*], Davood Shojaei [b], Abbas Rajabifard [b], Tuan Ngo [a,c]

[a] Building 4.0 CRC, Caulfield East, Victoria, Australia
[b] Centre for Spatial Data Infrastructures and Land Administration, Department of Infrastructure Engineering, The University of Melbourne, Melbourne, VIC, Australia
[c] Department of Infrastructure Engineering, The University of Melbourne, Melbourne, VIC, Australia

A R T I C L E I N F O

Keywords:
Automated valuation models
Land price
Machine learning
Deep learning
Spatial data analysis

A B S T R A C T

Accurate land valuation is necessary for tax purposes, land resources allocation, real estate management and urban development and planning. Since various factors from different domains affect land prices through non-linear relationships, automating the land valuation process on a large scale is a complex task. Advanced technologies in big data analysis and artificial intelligence have demonstrated superior capabilities in knowledge extraction in such cases. Accordingly, this paper develops and compares the performance of four Automated Valuation Models (AVMs) based on machine learning and deep learning techniques utilizing physical, geographical, socio-economic, environmental, legal and planning factors in Melbourne Metropolitan, Australia. According to the results, the eXtreme Gradient Boosting (XGBoost) method outperforms other algorithms of Support Vector Regression (SVR), random forest and Deep Neural Network (DNN). This method has achieved the coefficient of determination (R^2) of 0.862, Mean Absolute Percentage Error (MAPE) of 0.139, and normalized Root Mean Square Error (nRMSE) of 0.281. The achieved high accuracy is due to incorporating a wide range of driving factors and applying innovative feature selection and hyperparameter tuning procedures evaluating various possible feature sets and hyperparameters. Accordingly, this paper can contribute to research, governmental and industry-based activities in terms of developing AVMs for mass land valuation.

1. Introduction and background

Urbanization, as the process of the growth and expansion of cities and urban areas both in horizontal and vertical dimensions, is often associated with significant social, economic and cultural changes. Land availability and land price are among the main components affecting the urban development process. In big cities where urban planning and optimal land use management are too complex procedures, land price remarkably impacts the dynamics of supply and demand in relation to land resources (Deng & Huang, 2004; Hu et al., 2013; Silveira & Dentinho, 2018; Zhang et al., 2021). In addition, an accurate valuation of land properties is a crucial foundation for the establishment of policies related to real estate taxation that are necessary for sustainable urban and territorial development (Codosero Rodas et al., 2018). In a real estate market, the price of land also serves as an indication of the level of development within the land market, so it should be considered by planning authorities when making policies regarding the housing sector (Hu et al., 2016; Ma et al., 2020). Hence, developing a reliable and accurate database on land prices at large scales is necessary for the optimal allocation of land resources, creating a sustainable taxation system, fair and transparent management of the market and making planning decisions that are economically sound (Derdouri & Murayama, 2020; Inoue et al., 2007; Wang, 2022).

Amidst the ongoing global housing crisis, particularly prevalent in advanced countries like Australia, Canada, France, Germany, Iceland, Ireland, New Zealand, Sweden, the United Kingdom and the United States, where housing prices have experienced a dramatic surge, the importance of reliable land valuation models has become even more pronounced. This escalation can be attributed to various factors, including the lingering effects of the COVID-19 pandemic and increased

* Corresponding author at: Centre for Spatial Data Infrastructures and Land Administration, Department of Infrastructure Engineering, The University of Melbourne, Melbourne, VIC, Australia.

E-mail address: pjafary@student.unimelb.edu.au (P. Jafary).

https://doi.org/10.1016/j.cities.2024.105115
Received 19 January 2024; Received in revised form 2 May 2024; Accepted 11 May 2024
Available online 15 May 2024

migration (Hardin, 2023; Lakševics et al., 2023; Pawson et al., 2022). Fig. 1 illustrates the upward trend in the Organization for Economic Co-operation and Development (OECD) nominal house price index from 2016 to 2022 in some of the advanced countries with high rates of immigrant acceptance, demonstrating a notable acceleration in this trend since 2020 across many countries (OECD, 2023). Australia serves as a prime example, grappling with housing affordability challenges influenced by distinctive demographics and a scarcity of residential lands in urbanized areas proximate to employment hubs and essential services. The interplay of factors, including the COVID-19 pandemic, migration patterns and fluctuations in interest rates and inflation, further compounds the complexity of the issue (ANZ-CoreLogic, 2023; PEXA, 2023). Addressing this global crisis necessitates effective management of the supply and demand dynamics, prudent land use policies, reforms in mortgage and lending systems and enhanced decision-making in construction practices (Lima, 2024; Saiz, 2023). However, a critical component in all these mitigation strategies lies in developing accurate land valuation models.

For the mass appraisal of real estate assets through Automated Valuation Models (AVMs), the value of the property is determined as the dependent variable through a mathematical model based on a set of independent factors affecting the value (Hong et al., 2020; Yilmazer & Kocaman, 2020). Various factors from different domains affect land prices, while non-linear relationships could exist between these factors and land value (Mete & Yomralioglu, 2021; Sampathkumar et al., 2015). In addition, almost all the factors affecting land value either have an absolute spatial nature or their spatial distribution is different (Tsutsumi et al., 2011). Thus, issues like spatial distribution, spatial dependency and spatial heterogeneity can cause more complex non-linear connections between the factors and real estate assets, including lands and properties (Crosby et al., 2018; Jiao & Liu, 2012; L. Krause & Bitter, 2012). The most popularly adopted method for mass appraisal of real estate assets is the Multiple Regression Analysis (MRA), which is also known as the Hedonic Price Model (HPM). Considering the mentioned complexities with regard to non-linearity, however, many scholars have demonstrated the superior performance of more advanced Artificial Intelligence (AI)-based methods, including Artificial Neural Network (ANN) and Machine Learning (ML) for valuation purposes compared to hedonic methods. This arises from the greater capacity of these techniques to address the non-linear relationships between the different variables and land price (Goundar et al., 2021; Ho et al., 2021; Hong et al., 2020; Jafary et al., 2024; Yilmazer & Kocaman, 2020).

In highly urbanized areas, the process of land valuation using AVMs is more complex than the automatic valuation of constructed properties. Indeed, unlike built properties, it is arduous to collect data on the transactions of vacant lands without any associated enhancement or development (Kim et al., 2021; Mangioni, 2014). Moreover, the relationships that exist between the potential determinant factors and land value are more intricate than the relationships between the features affecting constructed properties and their value (Zhang et al., 2021). As a result, the level of uncertainty of the mass valuation of land parcels can be increased. For instance, factors like construction year, number of bedrooms, bathrooms and car spaces, floor, lift and balcony have relatively more specific and linear relationships with the property value compared to the factors that are usually considered for land valuation purposes (Hu et al., 2016; Jafary et al., 2022; Kok et al., 2014). Accordingly, determining the value of land with an acceptable accuracy using AVMs requires more sophisticated analysis and consideration of a larger number of variables than determining the value of a constructed property.

In the literature, the scholarly focus on land valuation remains comparatively modest compared to studies concentrating on constructed properties (Kim et al., 2021). Initial attempts at automating land valuation primarily employed conventional techniques like Ordinary Least Squares regression (OLS) (Kim & Kim, 2016), HPM (Demetriou, 2016, 2018; Yalpir & Unel, 2017), Multi-criteria analysis (MCA) (Tezcan et al., 2020), Geographically Weighted Regression (GWR) (Demetriou, 2016; Hu et al., 2016), Kriging methods (Inoue et al., 2007) and Free Cash Flow (FCF) (Codosero Rodas et al., 2018). However, due to the imperative of developing more sophisticated land valuation models capable of handling non-linearity and spatial complexities, researchers started comparing the capabilities of ML methods and ANN for land valuation with traditional models. Sampathkumar et al. (2015) conducted a comparative study of ANN and MLR models in land valuation across 13 different areas within the Chennai Metropolitan Area in Tamil Nadu, India, considering primarily macro socio-economic parameters. According to their results, the ANN model demonstrated superior performance in most instances. Similarly, Derdouri and Murayama (2020) employed a set of 17 variables for mass land valuation across Fukushima prefecture, Japan, predominantly geographical

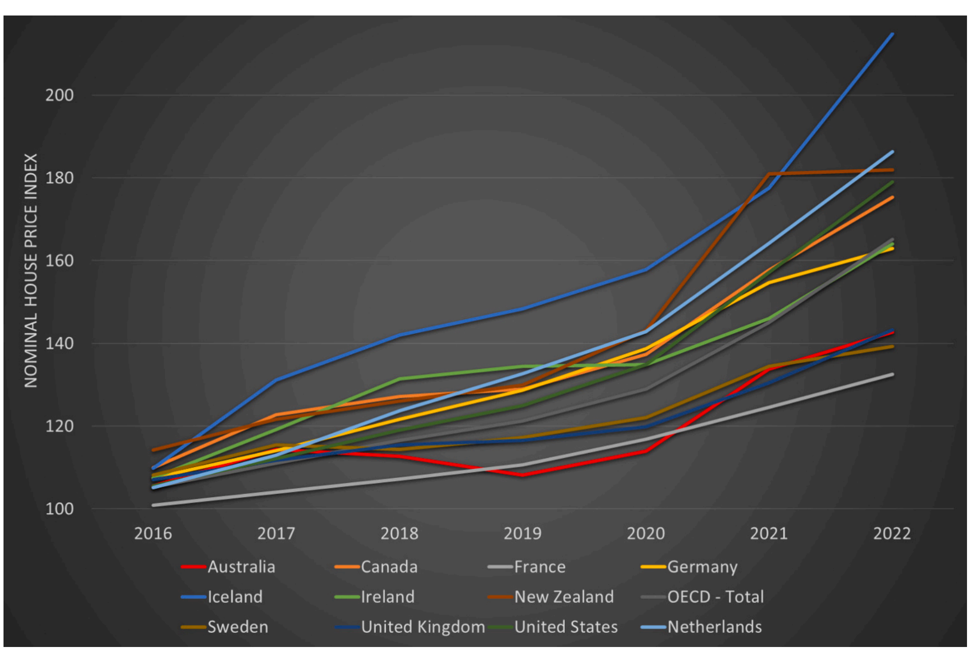

Fig. 1. Trends in OECD Nominal House Price Index (2016–2022) in some advanced countries.

and location-based. Their study encompassed ten models, including regression kriging, Generalized Linear Model (GLM), Generalized Additive Model using Splines (GAMS), Support Vector Machine (SVM), Multivariate Adaptive Regression Spline (MARS), K-Nearest Neighbors (KNN), Cubist, Gradient Boosting (GB) and Random Forest (RF), with RF exhibiting higher accuracy compared to other models, especially linear ones. Louati et al. (2022) also developed three models based on linear regression, decision tree and RF techniques for land price estimation in the northern area of Riyadh, Saudi Arabia, utilizing data from 5946 lands. Their findings favored RF, marking one of the initial studies on mass land valuation employing ML techniques with hyperparameter tuning, albeit constrained by a narrow feature set and lacking a feature selection procedure.

By demonstrating the superior performance of advanced ML models over traditional methods, researchers started to focus entirely on developing more complex and customized ML-based AVMs to estimate land prices. Zhang et al. (2021) utilized various ML methods to estimate land prices in Wuhan, China, focusing predominantly on geographical features. The authors employed Support Vector Regression (SVR), RF and Extra-Trees Regression (ETR) on 552 residential land transaction samples. The results showed higher accuracy for SVR with a Radial Basis Function (RBF) kernel and ETR in two different periods. Despite considering the grid search method for hyperparameter tuning and applying the feature selection process, the study's limitations included a narrow focus on geographic variables, a small sample size and tuning a small number of hyperparameters. Kim et al. (2021) also assessed the capabilities of two cutting-edge ensemble learning techniques of RF and eXtreme Gradient Boosting (XGBoost) for mass land price appraisal in Seoul, South Korea. The models were constructed based on a set of variables primarily focused on land use and zoning conditions. The authors underscored the impressive performance of both algorithms, particularly XGBoost. However, a notable limitation of their study was the indirect estimation of land values for constructed sites used for model training and testing. This estimation was achieved by deducting the reconstruction and depreciation costs from the property price, potentially introducing uncertainty into the input data. Also, while the authors employed grid search for hyperparameter tuning, they utilized a fixed number of five features without providing a rationale for their decision. Carranza et al. (2022) later directed their attention to evaluating the performance of RF, Quantile RF (QRF) and GB models for mass land valuation based on the land values of 68,000 samples in the City of Fortaleza, Brazil. Following the development of models with tuned hyperparameters, the authors concluded that QRF exhibited superior performance for mass land valuation. Nevertheless, the study was constrained by its focus solely on geographic factors and the lack of specification regarding feature selection mechanisms, representing key limitations.

Furthermore, DL has demonstrated remarkable capabilities in estimation and prediction practices, such as housing rate (Zhou et al., 2019), house price (Zhan et al., 2020), asset price (Chen et al., 2023) and crude oil (Zhao et al., 2017) estimations. Most such studies focus on predictions based on time series analysis, mainly using Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM), or combining them with other DL methods (Hu et al., 2021). A study by Yu et al. (2018) could be an example of such methodologies specifically for land valuation. The authors made house price predictions using time series data and value-related features through LSTM and Convolution Neural Networks (CNNs), respectively. The results indicated better performance of the CNN-based model developed on different features affecting land value, but the final accuracy was somewhat compromised due to the limited number of variables, prompting the authors to advocate for the inclusion of additional factors to enhance accuracy.

However, the concept of price estimation using time series analysis differs from developing AVMs for mass valuation of real estate assets, which relies on a multitude of independent value-related factors to estimate the value as a dependent variable. DL applications for such purposes are mainly based on employing Deep Neural Networks (DNNs), as reported by Jiang and Shen (2019) and Zhan et al. (2020) for the valuation of constructed properties. Nevertheless, research specifically focused on mass land valuation using DL is scarce in the literature. Among these few studies, Li et al. (2019) compared DNN with HPM and GWR for urban land price estimation in Shenzhen, China, demonstrating superior performance by DNN for commercial and industrial lands. Hou et al. (2019) also validated the efficacy of DNN-based AVMs for land price estimation in Shenzhen, China. Ai et al. (2020) explored the potential of the Deep Belief Network (DBN) for land valuation in Chengdu, China, by converting textual value-related features into visual features and employing DBN for appraising urban residential land prices. Yamada et al. (2020) also attempted to develop a hybrid model based on visual feature extraction using CNN and integrating them to a set of five textual features (land area and four locational features) through a Multilayer Perceptron (MLP)-based AVM for mass land valuation in three cities of Japan. The output of the proposed hybrid model was associated with high accuracy, but the applied textual variables were limited, and the study had no specific feature selection procedure. Additionally, the primary limitation observed in all reviewed studies focusing on DL-based land valuation is the absence of comparisons between the performance of DNN and advanced ML techniques such as RF and XGBoost in mass land valuation.

Hence, there persists a significant research gap in the development and comparative evaluation of advanced ML/DL-based AVMs for accurate mass land valuation. While previous studies in different parts of the world have made strides in this domain, there remains room for improvement in customizing different models to address the unique challenges of mass land valuation. Many existing studies are constrained by limited ground truth dataset sizes, the scope of considered features, and, more importantly, a lack of robust feature selection procedures. To address this research gap, a complex research methodology is followed in this paper: First, preparing a comprehensive set of physical, geographical, socio-economic, environmental, legal and planning features affecting land value; Second, developing and comparing four ML and DL-based AVMs by applying extensive feature selection and hyperparameter tuning procedures; Finally, mass land valuation using the model demonstrating the best performance. In addition to considering the most comprehensive dataset used to develop automated land valuation systems, our innovation also lies in the meticulous integration of multiple feature selection methods. This approach aims to create a synergistic process that identifies key features contributing to the highest accuracy for each model. In the realm of mass land valuation, where a myriad of factors can influence land prices, the conventional approaches to feature selection are algorithm-specific and can overlook nuanced interactions between features (Kuzudisli et al., 2023). So, this paper adopts a novel strategy to rank the importance of different features using various ML models and evaluate the performance of all potential feature combinations. This method allows us to identify feature sets consistently leading to the best performance for each valuation method. The development of such mature AVMs holds promise for addressing challenges within housing systems, particularly in combating the global housing crisis. By producing more accurate estimates of land values, these models can inform policy decisions and interventions aimed at alleviating housing affordability issues and promoting sustainable urban development. Strategies targeting supply and demand dynamics, taxation systems, mortgage and lending practices, as well as land use planning and construction regulations, stand to benefit from the insights provided by improved land valuation models. This holistic approach to addressing housing challenges can contribute to fostering healthier housing systems, not only in Australia but also in other nations grappling with similar issues worldwide.

2. Materials and methods

2.1. Study area

As previously mentioned, it is necessary to establish reliable mass land valuation systems in Australia. Among Australia's capital cities, Melbourne Metropolitan, with about 5 million people, has had the largest growth (up by 806,800 people) between 2011 and 2021 (ABS, 2022). Melbourne, the capital of Victoria, spans approximately 10,000 square kilometers (km) and comprises 31 Local Government Areas (LGAs). It experiences significant spatial inequality in terms of income and mobility, with considerable variations in the distribution of activities such as job opportunities, private car ownership and public transport usage patterns (Saberi et al., 2017). According to the Real Estate Institute of Victoria (REIV), the median land price per meter in the Melbourne Metropolitan has increased by 48 % between 2014 and 2019 (REIV, 2019). These three issues of population growth, spatial inequality and continuing increase in the land price can not only intensify the importance of mass estimation of land prices in the area but also complicate the automatic land valuation process. In this study, the mass land valuation is carried out inside 19 LGAs of the Melbourne Metropolitan, including the city of Melbourne and 18 LGAs around it, as shown in Fig. 2. This is due to the access to ground truth data in these LGAs, which will be further explained in the next section.

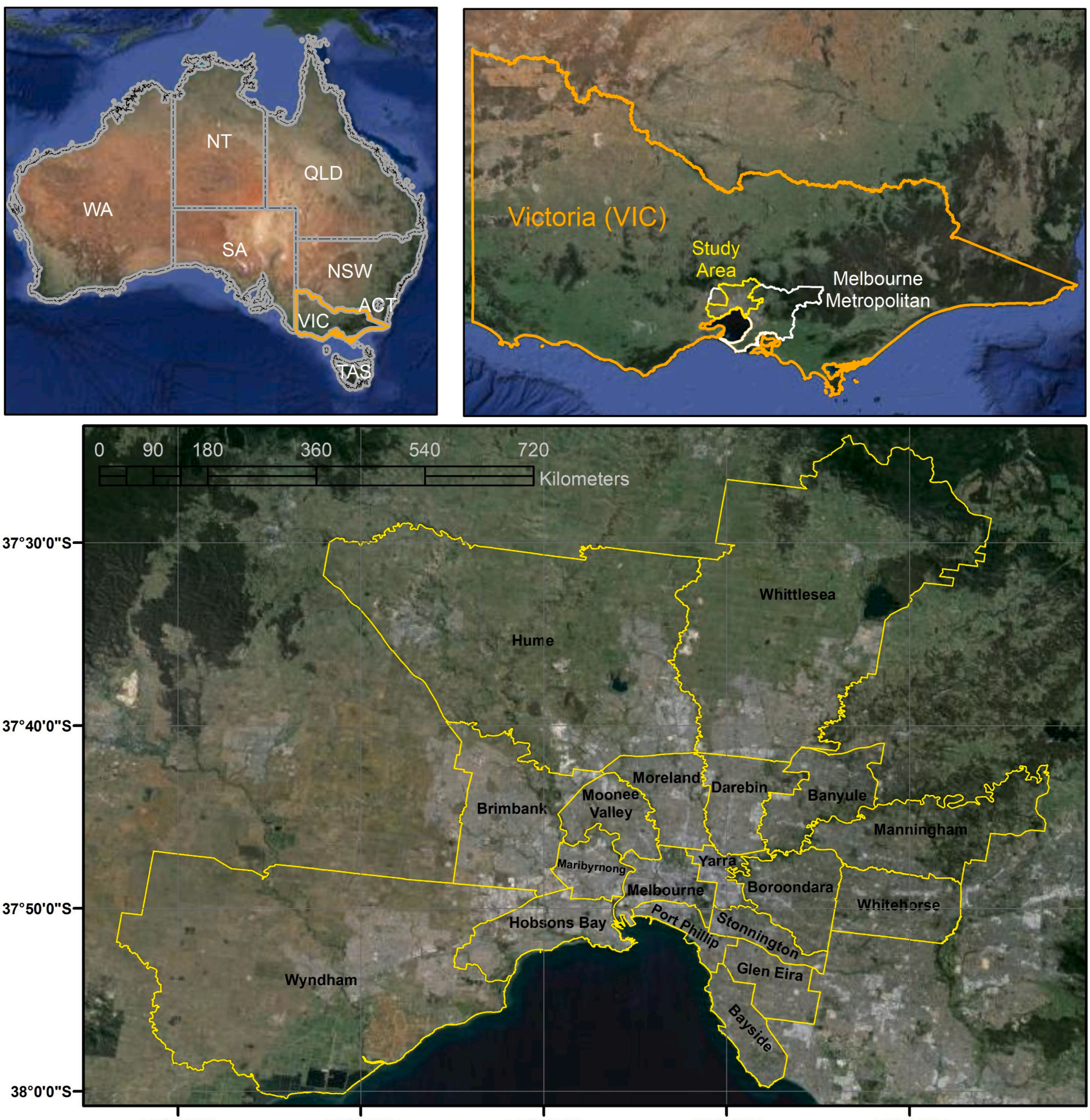

Fig. 2. Study area: 19 Local Government Areas (LGAs) inside the Melbourne Metropolitan Area, Victoria, Australia.

2.2. Data on land value

To ensure the reliability of ML models for estimating land prices in the study area, access to a trustworthy dataset is essential. The Valuer-General Victoria (VGV), as the independent authority on property valuations in the state of Victoria, provided us with a dataset on Site Value (SV) for both vacant and constructed properties. The SV refers to the value of a land without any added structures or developments such as buildings (The-State-Revenue-Office-Victoria, 2023). This dataset is used as the ground truth data for the development of the models. It covers properties randomly distributed across the 19 mentioned LGAs of the Melbourne Metropolitan area and pertains to the reference year 2022.

VGV is responsible for valuing properties and land within the state, employing a comprehensive and rigorous valuation methodology. This ensures data accuracy and reliability for various purposes, including tax assessment, urban planning and real estate market management. VGV conducts annual valuations in compliance with the Valuation of Land Act 1960 (State-Valuation-of-Land-legislation-across-Australia, 2023). Their valuation process initiates with conducting a detailed environmental scan to understand requirements, systems, and resources and address any identified issues from previous valuations. Data collection, property inspections, analysis and modeling are then followed. These involve property inspections, data updates, collection of rental and commercial evidence, analysis of sales and leases, creation of look-up tables and the confirmation of valuation models using Valuation Best Practice Specifications Guidelines (VBPSG) compliant valuation system (DELWP, 2022). The VGV employs a hybrid valuation methodology that

Table 1
List of potential factors affecting land value included in this study, along with their relevance and spatial resolution.

	Factor	Relevance to land valuation	Spatial resolution
1	Area	Larger parcels of land typically have more significant development potential and may command higher prices.	Parcel level
2	Shape (convexity of each land parcel)	The shape of a land parcel can affect its usability and attractiveness for development, and regularly shaped parcels may be more desirable.	Parcel level
3 & 4	Elevation and slope	The topography of a land parcel can influence its suitability for development. Flat or gently sloping terrain may be preferred for construction projects, while steep slopes may limit development options.	The mean value in each parcel based on a Digital Elevation Model (DEM) with 10 m resolution
5 to 14	Latitude, longitude, and distances to Central Business District (CBD), sustenance amenities, shopping centers, higher level education centers, health centers, childcares and kindergartens, natural landscapes and water bodies	Geographic and locational features, as well as proximity to urban centers, commercial hubs and different amenities, often correlate with higher land values due to increased accessibility and economic opportunities and enhanced livability and convenience.	Parcel level (for the accessibility-related factors: average distances of each parcel from nearby Points of Interest (PoIs))
15	Local Government Area (LGA)	Administrative boundaries can impact land use regulations, zoning policies and infrastructure development, thereby affecting land values.	LGA level (presence of the parcels in the LGAs)
16	Locality (suburb)	Specific neighborhoods may have unique characteristics or amenities that attract higher demand and command higher prices.	Suburb level (presence of the parcels in the suburbs)
17	Distance to public transportation	Proximity to public transportation can influence land values by increasing accessibility and reducing commuting times.	Parcel level (average distance of each parcel from nearby stations)
18	Road Type	Access to transportation networks and road infrastructure can impact land values.	Parcel level (extracted from each parcel address)
19	Walkability	The walkability of a neighborhood, based on its walking paths, can affect livability.	Suburb level
20	Population density	Areas with higher population densities may experience greater demand for land.	Australian Statistical Areas Level 1 (SA1)
21 to 23	Employment rate, job opportunities and Gross Regional Product (GRP)	Economic stability, job opportunities, economic productivity and prosperity of an area influence land values by attracting residents and businesses and influencing investment patterns.	Australian Statistical Areas Level 2 (SA2), SA1 and LGA level, respectively
24	Mortgage rate	Interest rates on mortgages can affect housing affordability and, consequently, land values.	SA1
25	Ethnicity	The ethnic composition may influence neighborhood preferences and social dynamics.	SA1
26	Income	Household income levels can impact purchasing power and housing affordability.	SA1
27 & 28	Crime: criminal activities and offensive incidents	Security and safety concerns can affect the desirability of an area.	Parcel level (average distances of parcels from nearby crime incidents)
29	Crash	Areas with lower crash rates may be perceived as safer and more attractive.	Parcel level (average distances of parcels from nearby crash incidents)
30 & 31	Temperature and rainfall	In metropolitans, where urban growth occurs in large areas of the earth's surface, the climatic features can vary in different city regions, impacting people's preferences.	Based on maps with 2.5 km and 5 km resolutions for temperature and rainfall, respectively
32	Green vegetation: NDVI	Access to green spaces can enhance an area's aesthetic appeal and quality of life.	Mean NDVI in each parcel (10 m resolution NDVI map)
33	Air Quality	Air quality can influence health outcomes and residents' perceptions of an area.	Interpolated map based on data from stations within and around the study area
34 & 35	Land use and zoning	Land use regulations and zoning ordinances can restrict or dictate the types of development allowed in a particular area.	Land use and zoning maps of the study area
36 & 37	Primary and secondary school zones	School proximity affects land values due to the impact of education on public housing decisions.	School zone maps of the study area

combines manual assessments of benchmark properties with generalized valuations for other properties in the region. Experienced valuers conduct detailed on-site inspections of benchmark properties to ensure precision and accuracy in valuations. The selection of benchmark properties is carefully designed to represent a diverse range of real estate, including various property types, locations and land features. This thorough and systematic approach ensures the accuracy and reliability of the data provided by the VGV (DELWP, 2022; State-Valuation-of-Land-legislation-across-Australia, 2023). The dataset, rooted in a thorough valuation process, is instrumental in this study's research and the development of the AVMs.

2.3. Land valuation factors

Identifying the influential factors of land values and establishing a spatial database on them is the backbone of any land valuation process using AVMs (Ma et al., 2020; Zhang et al., 2021). Accordingly, the literature was reviewed to compile a comprehensive list of factors that can contribute to the land price estimation. Many of the factors considered by the scholars are related to geography and location (Carranza et al., 2022; Derdouri & Murayama, 2020; Zhang et al., 2021). There are other studies that have focused on factors from the social, economic, land use and planning domains (Kim et al., 2021; Sampathkumar et al., 2015). Considering the used features in the literature, as well as existing gaps in previous studies regarding covering environmental factors, which this study assumes can contribute to the process of mass land valuation, this research establishes a comprehensive set of factors. A total of 37 factors categorized into five groups of physical, geographical, socio-economic, environmental, and legal and planning outlined in Table 1 are used. The required spatial data on the different features were received from different sources, such as Victoria's Department of Environment, Land, Water and Planning (DELWP), Open Street Map (OSM), the Walk Score, Australian Bureau of Statistics (ABS), Australian Urban Research Infrastructure Network (AURIN), the REMPLAN, Victoria's Department of Transport and Planning, Crime Statistics Agency (CSA) of Victoria, Australian Bureau of Meteorology and the Environment Protection Authority Victoria (EPA). For the green vegetation, the maximum annual Normalized Difference Vegetation Index (NDVI) layer of the study area is produced based on Sentinel-2 satellite data from 1 January 2021 to 31 December 2021 through the Google Earth Engine (GEE) platform. All the procedures with regard to the preparation of the features and joining the relevant values to the land polygons are carried out using the different tools provided in Esri ArcMap 10.8.1 and Quantum Geographic Information System (QGIS) 3.22.16.

In addition to providing a list of factors included in this study, Table 1 also presents the reason for choosing the factors and their spatial resolutions. Table 2 also presents descriptive statistics, including minimum (Min), maximum (Max), mean, median and standard deviation (SD), for the numerical factors considered in this study. These statistical variables provide an overview of the distribution and characteristics of the valuation factors.

2.4. Appraisal methods

In this study, three methods of SVR, RF and XGBoost as the most compatible ML techniques for developing AVMs introduced in the literature, as well as DNNs as more complex models than ANNs to handle non-linear relationships between a large number of features, are considered. Four AVMs are developed and compared to find a method with the best performance for mass land valuation in the study area using the previously introduced features. The programming is conducted in R (R-Core-Team, 2023) and RStudio (RStudio-Team, 2023) using “e1071”, “randomForest”, “xgboost”, “keras” packages. Besides, the specifications of the computer system used for training, testing, assessment and final land valuation in the study are as follows: 11th Gen Intel(R) Core(TM) i7-1165G7 2.80 GHz CPU, 16 GB DDR4-3200 RAM and Intel Iris Xe Graphics GPU.

2.4.1. Support Vector Regression (SVR)

Support Vector Machine (SVM), which is based on Vapnik's statistical learning theory, is mainly used for classification purposes (Vapnik, 1999). The algorithm has been altered to handle regression problems, resulting in Support Vector Regression (SVR). SVR utilizes kernel functions to map input features into a higher-dimensional space, aiming to find a function that closely fits the data while avoiding overfitting. The optimization involves solving a quadratic problem to determine the decision function. SVR is effective in capturing non-linear relationships

Table 2
Descriptive statistics of numerical valuation factors.

Variable	Unit	Min	Max	Mean	Median	SD
Area	Square meter	0.57	1,538,311.00	1176.44	559.65	18,187.81
Convexity	–	0.03	1.00	0.99	1.00	0.05
Elevation	Meter	0.00	144.95	44.98	41.95	29.23
Slope	Degrees	0.00	34.04	1.83	1.01	2.22
Dist.to.CBD	Meter	0.00	47,155.34	9958.25	9818.95	4582.98
Dist.to.Sust	Meter	2.76	9687.95	945.17	852.83	537.07
Dist.to.Shop	Meter	103.40	11,576.46	1972.86	1917.06	750.51
Dist.to.Uni	Meter	7.68	32,098.14	2708.26	2524.38	1399.89
Dist.to.Health	Meter	75.11	11,357.89	1613.34	1468.75	804.51
Dist.to.Childcare	Meter	246.94	7215.00	905.47	847.21	331.04
Dist.to.PTV	Meter	7.49	12,154.22	355.45	321.58	196.49
Dist.to.Landscape	Meter	0.00	1069.00	148.69	120.46	127.87
Dist.to.Water	Meter	0.00	3367.56	879.48	786.24	539.63
Walkability	–	2.00	97.00	64.44	66.00	14.35
Population	–	0.00	2355.00	463.82	456.00	168.57
Employment	–	0.00	100.00	74.84	77.51	8.24
GRP	Billion $	2.23	96.62	10.74	8.20	12.30
Mortgage	$/month	0.00	9999.00	2337.95	2200.00	749.46
Income	$/weekly	0.00	16,250.00	960.16	963.00	299.77
Crash	Meter	10.88	2122.16	281.97	261.01	147.16
Crime.Criminal	Events/100,000 population	2054.60	16,427.50	5728.70	5213.70	2287.03
Crime.Offense	Events/100,000 population	2911.10	22,504.20	7667.08	6770.90	3174.23
Rainfall	Milli meter	456.98	823.21	592.20	591.75	61.17
Temperature	Celsius (°C)	0.00	15.30	14.82	14.99	1.40
Air.Quality	PM2.5	5.14	5.82	5.66	5.67	0.10
NDVI	–	0.14	0.77	0.47	0.47	0.08

in the data (Astudillo et al., 2020; Ma et al., 2020).

2.4.2. Random forests (RF)

In a regression problem, a decision tree operates by dividing the dataset into smaller subsets through a recursive process based on the value of a feature with the aim of minimizing the variance of the target variable at each split. The decision tree is constructed in a top-down fashion, where the tree is built from the root node down to the leaf nodes. At each node of the decision tree, the algorithm chooses the feature and the split value that minimizes the variance of the target variable. The algorithm continues splitting the data until it reaches a stopping criterion, such as a maximum depth or a minimum number of instances per leaf node (Soltani et al., 2022). Although it is relatively simple to develop and interpret a single decision tree, this method can often overfit the training data and may not generalize well to new data. In order to mitigate these deficiencies, ensemble techniques that apply multiple weak learning models to create one optimal predictive model are employed (Jafary et al., 2022). RF is an ensemble learning method that combines multiple decision trees to improve generalization performance. Through bagging and feature selection, RF builds diverse trees, reducing overfitting and enhancing stability. Each tree is constructed by recursively splitting the data based on selected features, and the final prediction is an average of predictions from all trees. RF is known for its robustness and mitigating overfitting issues (Ho et al., 2021; Soltani et al., 2022; Wu et al., 2021; Xue & Yao, 2022).

2.4.3. XGBoost

Boosting is another ensemble learning method to deal with the shortcomings of the decision tree models. Unlike the parallel creation of models in bagging, boosting combines weak models sequentially and trains each model to correct the errors of the previous model. Gradient Boosting (GB) is a boosting method that is capable of reducing the residuals of the previously trained model and establishing a new model in the direction of the gradient that further reduces the residuals (Almaslukh, 2020; Ho et al., 2021; Zulkifley et al., 2020). XGBoost is a method developed based on GB but employs a more regularized model formulation to improve the generalization capabilities and performance of the model (Peng et al., 2019). XGBoost iteratively adds decision trees to the model, optimizing the objective function through gradient descent. It controls the step size of updates using a learning rate, enhancing convergence and performance (Iwai & Hamagami, 2022; Li et al., 2021; Peng et al., 2019).

2.4.4. Deep neural network (DNN)

At their most basic levels, ANNs consist of three layers: an input layer, a hidden layer and an output layer. The architecture of the ANN, including the number of layers, the number of neurons per layer and the activation functions used, can vary depending on the complexity of the problem and the amount of data available. To solve a regression problem using an ANN, the model is trained on a labeled dataset consisting of input features and their corresponding target values. During training, the model modifies its weights and biases in response to the errors between the predicted and the actual outputs. This task is iterated numerous times until the model converges to an optimal set of weights and biases that are capable of minimizing the error (Abidoye & Chan, 2017; Mujeeb et al., 2019).

DNN is a form of ANN that comprises numerous hidden layers, making it capable of learning more complex relationships between the independent features and the target variable. DNN has several advantages over traditional neural networks for regression problems. DNNs are more capable of learning complex representations of the input data, have higher accuracy, are more robust to overfitting and can benefit from transfer learning, making them a more suitable choice for regression problems compared to traditional neural networks (Sze et al., 2017).

2.5. Preprocessing

Before training ML algorithms, some preprocessing steps are required in order to increase the robustness of the models and improve their performance. This can include cleaning the data, encoding, scaling and data splitting (Soltani et al., 2022). This paper follows the below preprocessing steps accordingly:

- The data cleaning step for the development of the models in this study is highly relevant to the 37 considered factors and the ground truth data received from VGV. Indeed, after the calculation of all the factors in each land polygon in the study area, a spatial dataset is created. This dataset is then joined to the spatial layer of the SV values provided by VGV to extract the values related to all factors in each sample with relevant land values. Subsequently, any possible duplications and lack of data in each of the factors are identified and removed from the dataset.
- After data cleaning, the One-Hot Encoding technique is used to encode categorical variables like locality, road type and ethnicity to numerical variables. In this encoding scheme, each unique category or label is mapped to a binary value, and each binary digit (bit) represents the presence or absence of a particular category.
- For feature scaling, both Min-Max scaling method of normalization and standardization are employed and compared to determine the most suitable approach based on the specific characteristics of the dataset and the requirements of the ML algorithm being used. Min-Max scaling involves transforming the input features into a specific range, typically between 0 and 1. On the other hand, standardization involves transforming the data to have a mean of 0 and a standard deviation of 1.
- Finally, for data splitting, a stratified sampling approach is employed. While stratified sampling is traditionally associated with categorical variables, its application to regression problems, especially when the response variable deviates from normality (i.e., positively skewed), is acknowledged in the literature (Boehmke & Greenwell, 2019). Here, the dataset is stratified based on quantiles of the SV distribution. This segmentation enables us to create strata that capture the variability in SV, ensuring a proportional representation of different SV ranges in both the training and test sets. By maintaining a similar distribution of the dependent variable in both sets, we aim to enhance the generalizability and robustness of our models. In this study, 0.75 of the input dataset is used for training, and the rest for testing the models.

2.6. Feature selection

XGBoost and RF both have the ability to rank the features based on their importance. RF feature selection is mainly based on Mean Decrease Accuracy (MDA) or Mean Decrease Gini (MDG) metrics. MDA is estimated based on the importance of each feature by calculating the decrease in accuracy when that feature is removed from the model. MDG is also achieved by calculating the total reduction in Gini impurity of each feature over all the trees in the forest. The features with the highest MDA or MDG scores are considered the most important variables (Hong et al., 2016; Ma et al., 2020). XGBoost commonly uses the gain to calculate feature importance. The gain represents the average gain in training loss that is achieved when a particular feature is used for splitting a node. The higher the gain, the more important the feature is considered (Chen et al., 2020; Li et al., 2022). Moreover, Recursive Feature Elimination (RFE)-SVM is an algorithm that works by repeatedly training an SVM on a subset of features and eliminating the least important features until a desired number of features is reached. The importance of each feature is determined by the SVM's weights, which are used to rank the features in order of importance (Cai et al., 2018; Dhal & Azad, 2022).

To optimize the performance of RF, XGBoost and SVR in mass land valuation within the study area, we apply RF, XGBoost and RFE-SVM feature importance ranking algorithms, respectively. For running each of these three estimation models, the columns in the dataset are ranked based on the importance identified by each of the corresponding feature importance ranking algorithms. Subsequently, all possible ranked datasets with varying feature counts ($n = 2$ to 37) are created to later assess and identify the feature sets that lead to the best performance for each valuation method. For the DNN method, a similar approach of assessing different datasets based on ranked features is followed, but the features are ranked based on all three feature selection algorithms of RF, XGBoost and RFE-SVM to select the ranked feature set with the best performance.

2.7. Hyperparameter tuning

In parameter tuning, the goal is to find the optimal set of hyperparameters that will result in the best performance on a validation set (Boehmke & Greenwell, 2019). The hyperparameter tuning process in this study is characterized by a meticulous exploration of potential hyperparameter values for each model. A grid search approach is employed, wherein a comprehensive grid of hyperparameter combinations is defined, and each model is systematically evaluated for all possible combinations within this grid (Soltani et al., 2022). Although it can be a time-consuming and resource-intensive task to find the optimal set of hyperparameters, it could be justifiable for an extensive mass land valuation project that does not require real-time processing. In this study, the models are tuned through the following steps.

- For SVR, these parameters are tuned:
- o The kernel.
- o Gamma (a hyperparameter that controls the width of the kernel).
- o Cost (C) that determines the degree of regularization in the model.
- o Epsilon.
- For RF, these parameters are tuned:
- o The number of trees in the forest.
- o The number of features to consider at any given split, known as "m_{try}".
- o Node size.
- For XGBoost, these parameters are tuned:
- o Number of trees.
- o Learning rate (eta).
- o Maximum depth.
- o Subsample that controls the percentage of samples used for each tree.
- o The percentage of features used for each tree.
- The following approaches are followed to fine-tune DNN:
- o Modifying the model capacity that involves adjusting the number of layers and nodes.
- o Implementing batch normalization.
- o Applying regularization techniques.
- o Adjusting the learning rate (Boehmke & Greenwell, 2019).

This hyperparameter tuning process is intricately linked to the earlier feature selection step to ensure a robust and optimal model construction. Initially, three importance ranking models—RF, XGBoost and RFE-SVM—are meticulously developed using a grid search hyperparameter tuning technique. This initial model development phase involves utilizing all 37 features, enabling the identification of feature ranks based on the best performance achieved by each model.

Subsequently, the land valuation models—SVR, RF, XGBoost and DNN—are crafted with a profound integration of grid search hyperparameter tuning and corresponding feature subsets ranging from 2 to 37 features. Each model is systematically executed using various subsets within the defined grid of hyperparameter values, coupled with the different feature sets identified through the corresponding feature importance ranking. Simultaneously, these models are rigorously evaluated, enabling the identification of the best possible combination of features and relevant hyperparameter values. This simultaneous evaluation of diverse feature sets and hyperparameter configurations is pivotal for pinpointing combinations that yield optimal performance.

2.8. Performance metrics

Different statistical metrics have been proposed in the literature for evaluating the performance of models developed for solving regression problems. Among them, this paper utilizes three widely used metrics of coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE) and normalized Root Mean Square Error (nRMSE).

- R^2 is often used to measure the amount of variation in the dependent variable that can be predictable from the independent variable(s). It ranges between 0 and 1, and a higher R^2 refers to better modeling performance (Teang & Lu, 2021).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}$$

where n is the number of samples, y_i is the actual value, $\widehat{y}_i$ is the estimated value, and $\overline{y}$ is the mean of the ground truth data.

- MAPE is another metric that is commonly used for assessing the accuracy of predictions by a regression-based model. It measures the average percentage difference between the predicted values and the actual values. Lower values of MAPE indicate better performance of the model (Carranza et al., 2022).

$$\mathrm{MAPE} = n^{-1} \sum_{i=1}^{n} \left| \frac{y_i - \widehat{y}_i}{y_i} \right|$$

- Root Mean Square Error (RMSE) measures the average deviation of the estimated values from the ground truth values (Yilmazer & Kocaman, 2020). However, the RMSE value depends on the scale of the variable being predicted. To overcome this issue, the nRMSE is often used, which scales the RMSE by a measure of the variability of the observed variable. A model's performance is considered better when its nRMSE values are lower (Carranza et al., 2022).

$$\mathrm{nRMSE} = \sqrt{n^{-1} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2} \Big/ \overline{y}$$

Fig. 3 represents the whole process followed in this research for mass land valuation in the study area. The research is carried out in three phases: data collection on the ground truth data and basic data for valuation features, feature set preparation using spatial analysis, and model development and evaluation.

3. Results

3.1. Dataset preparation

The data received from VGV was cleaned, and land values (SVs) for 26,700 land parcels were extracted to be used as ground truth data. Table 3 presents summary statistics of the land values in this cleaned ground truth dataset. The first row is based on the land values for different land parcels, irrespective of their size, while the second row is based on the land values per square meter (m^2) for the sample parcels (the land value of each parcel divided by its area). Fig. 4 represents the

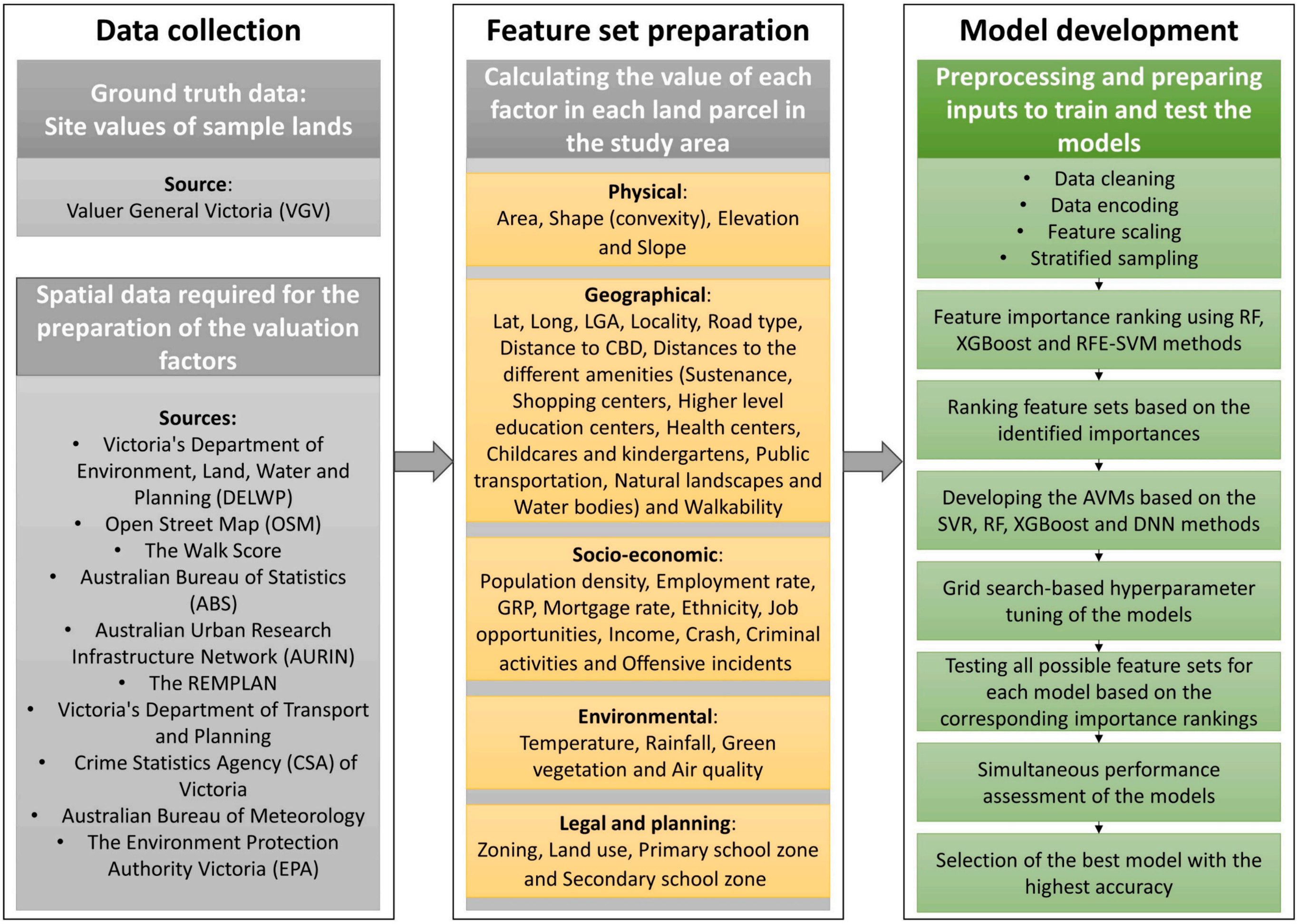

Fig. 3. The flowchart of the research process.

Table 3
Summary statistics of cleaned ground truth data based on VGV site values (values are in AUD).

	Minimum	Maximum	Median	Mean	Std Dev
Land value	1050	72,000,000	875,000	1,156,617	1,348,127
Land value per m^2	2	34,273	1880	2399	1969

spatial distribution of land values per parcel in the cleaned ground truth dataset. Fig. 5 also shows the distribution of land values per m2 for the different parcels in the ground truth data. Values in the table and figures are in Australian Dollars (AUD).

Additionally, a foundational spatial dataset was generated by computing relevant values for the considered 37 features across all land polygons in the study area, totaling approximately 1.1 million polygons. Then, a subset of the whole dataset was created containing the 26,700 parcels with their corresponding values for the 37 features and SVs from the VGV ground truth data. This subset was used to train and test the AVMs, with 75 % of the data allocated for training and 25 % for testing. Prior to AVM development, the dataset underwent data cleaning, encoding and stratified splitting processes.

3.2. Feature selection and model tuning

Next, in order to select the feature sets that lead to the highest accuracies for each model, the feature importance ranking was conducted using RF, XGBoost and RFE-SVM methods. Fig. 6 presents the ranking of the features based on the normalized values of their importance computed through these three models. The ranking of the RF is based on the average normalized value of MDA and MDG for each feature. The prepared dataset in the previous step was then ranked based on these rankings to three datasets for creating the AVMs. The significant differences in the rankings of the importance of different features indicate the completely different structures of the ML models.

Among the top 15 features identified by each feature importance ranking algorithm, it becomes evident that certain factors, such as area, distance to CBD and latitude, play pivotal roles across multiple models. The significance of the area lies in its representation of land size impact on valuation within the study area, where diverse neighborhoods exhibit varying spatial expanse. Proximity to the CBD also emerges as a key factor, reflecting accessibility to economic hubs and capturing the influence of urban development radiating from the city center. Finally, considering the geographical layout of Melbourne Metropolitan, where coastal areas are situated to the south, the latitude gains heightened significance. Coastal proximity often carries intrinsic value, influencing factors such as climate, aesthetics and recreational opportunities. Another paramount feature that emerges prominently in the analyses that were carried out is land use, which holds the top rank as identified by the RFE-SVM method. This underscores the pivotal role of land use in the valuation process within the study area. The diverse functions and activities associated with different land uses contribute significantly to the nuanced valuation of properties. In addition, findings highlight the sustained importance of accessibility-related factors across various algorithms. Notably, factors such as distance to public transportation, universities and natural landscapes continue to exhibit substantial

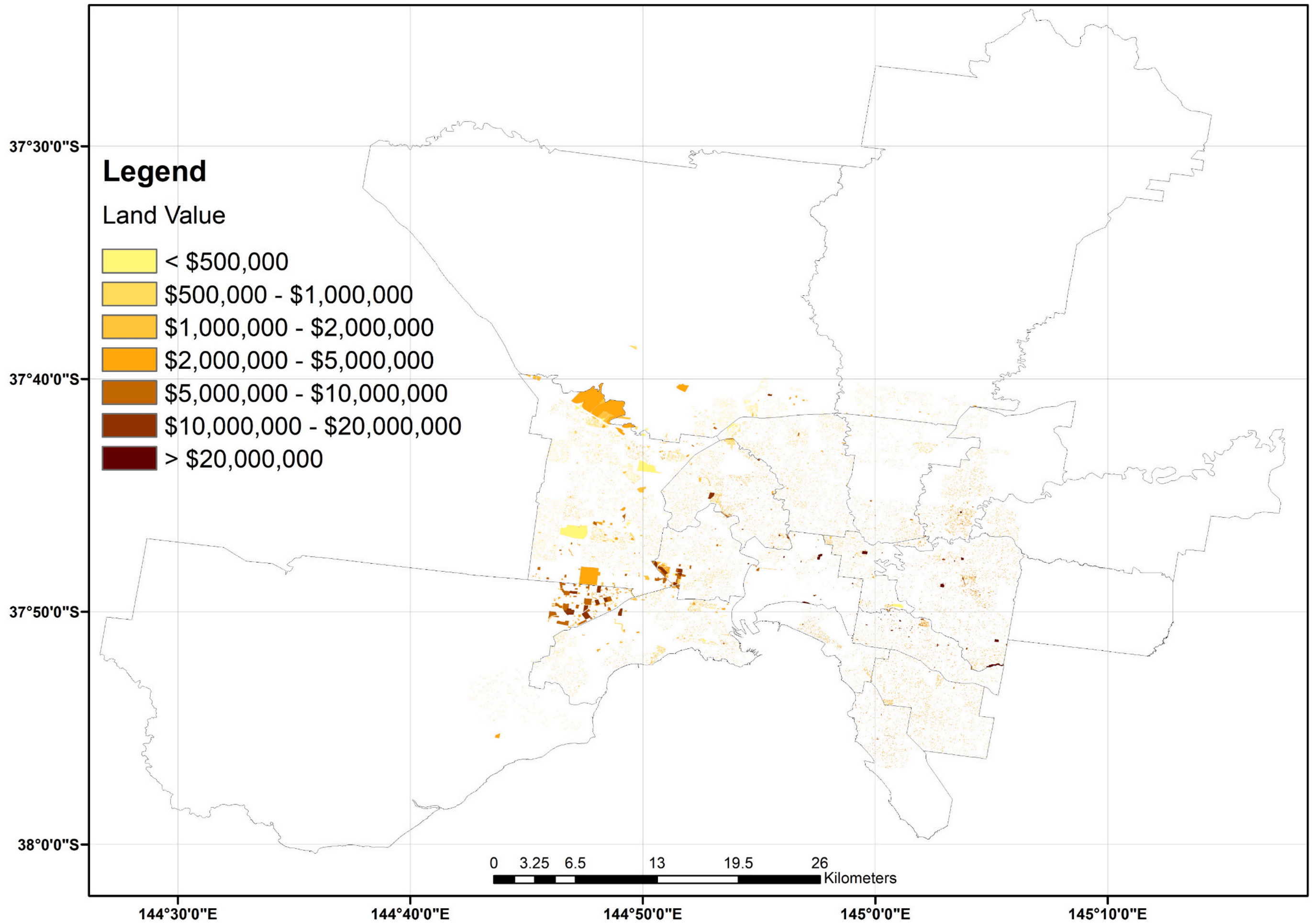

Fig. 4. Map of land values of ground truth land parcels (a total value for each land parcel in AUD).

importance. The significance of accessibility-related features aligns with the dynamic urban landscape of the study area. The proximity to public transportation hubs is crucial, reflecting the emphasis on efficient commuting in the bustling city. The presence of universities underscores the educational opportunities available in certain areas, contributing to their attractiveness and, subsequently, their valuation. Moreover, the importance of natural landscapes speaks to the value placed on green spaces and environmental considerations, reflecting the preferences of residents in the study area.

In the next step, the four considered methods in this study were trained using the ranked datasets. SVR, RF and XGBoost were applied to the datasets ranked based on RFE-SVM, RF and XGBoost, respectively. DNN was also run on all three datasets ranked through the three models to identify a ranking that has the highest compatibility with DNNs. For each model and dataset, two important series of model training and evaluation were carried out to attain the optimal methods.

- Each algorithm was recursively run and assessed on all possible sub-datasets with n ranked features ($n = 2$ to 37) to select the feature set that is associated with the best performance.
- Each model was recursively trained and assessed through different sets of pertinent hyperparameters using the grid search method. Accordingly, the best combinations of the hyperparameters that give rise to the best performance of each model were identified.

Accordingly, the SVR had the best performance using the RBF kernel based on the first 21 features ranked using the RFE-SVM method. For the RF, the best performance was achieved using the first 13 features ranked using itself. XGBoost also performed best based on the first 18 features ranked using itself. Finally, for the DNN, different architectures, batch normalization, regularization techniques and learning rate adjustment were pursued to find the optimal model. Accordingly, a DNN with five hidden layers based on a feature set with the 30 first features ranked through the RFE-SVM method was associated with the best performance. In this optimal DNN, the first hidden layer has 1024 nodes, and the subsequent layers have 512, 256, 128 and 64 nodes, respectively. Additionally, Table 4 presents detailed information regarding the hyperparameters that yielded the highest accuracy in identifying the feature importance rankings using all 37 features across three ranking models of RFE-SVM, RF and XGBoost. It also includes the hyperparameters that achieved the highest accuracy for each ML-based valuation model (i.e., SVR, RF and XGBoost) corresponding to the feature set that demonstrated the highest accuracy.

3.3. Performance comparison of the methods

A comparison between the final results of the four methods in terms of the different metrics is presented in Table 5. According to the considered metrics, the XGBoost model performed better on training and test data through almost all metrics. Hence, this model is selected in this study as the ML-based algorithm for mass land valuation. In the context of mass land valuation, the decision to select XGBoost as the optimal model in this study is underpinned by careful consideration of different aspects. Despite showing signs of overfitting, as a difference in performance between the train and test datasets (Montesinos López et al., 2022), XGBoost consistently outperforms other models on critical

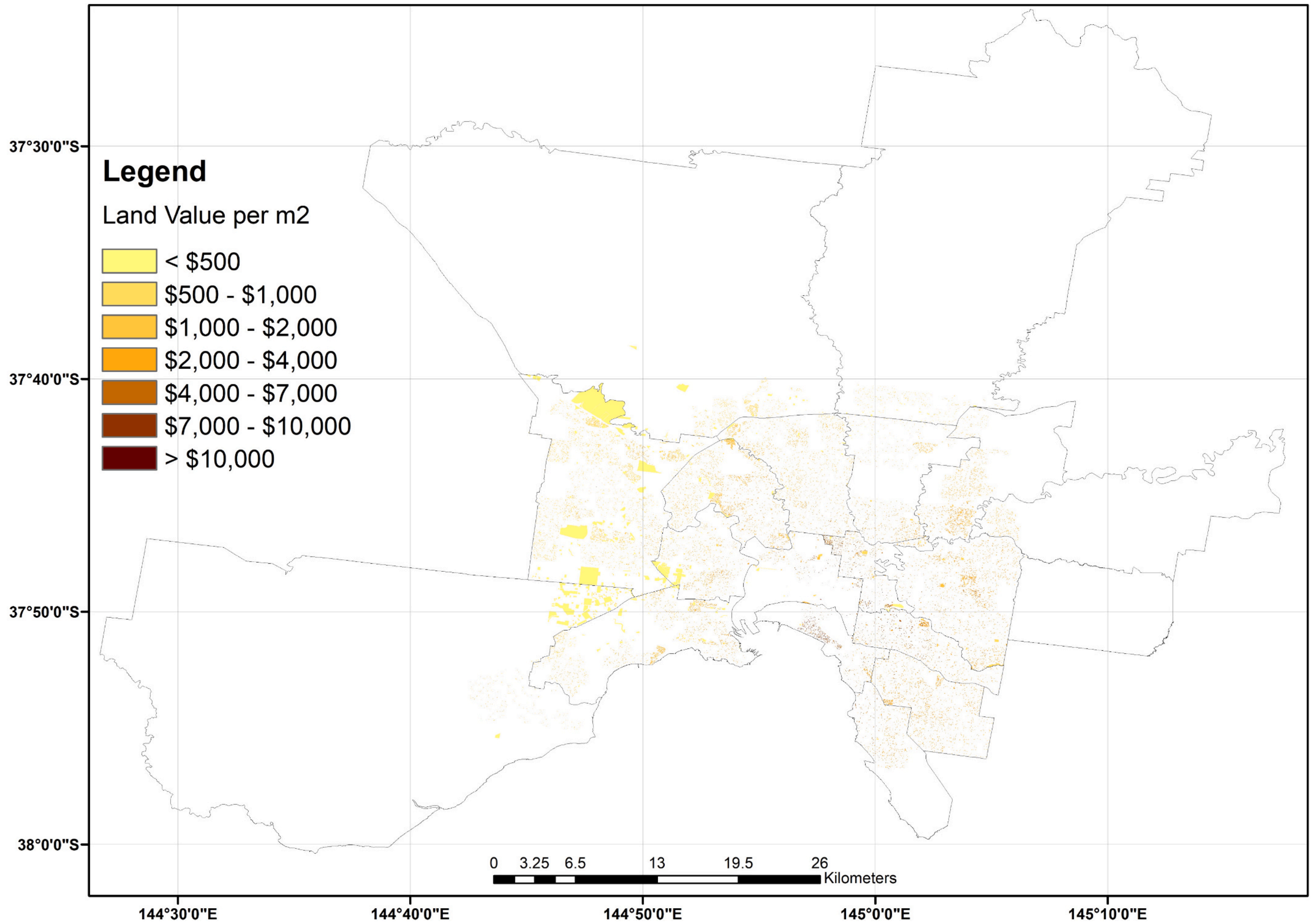

Fig. 5. Map of the value of one square meter of land per parcel in the ground truth data (values are in AUD).

evaluation metrics when subjected to rigorous testing on previously unseen data. In addition, scholars often posit overfitting as a phenomenon occurring when models exhibit low accuracies for new samples (test data) (Kuhn & Johnson, 2013); however, XGBoost, in this instance, consistently demonstrates outstanding accuracies on the test data. The emphasis here lies in prioritizing the model's performance in real-world scenarios, where XGBoost showcases remarkable accuracy in predicting land values. The subtle overfitting observed in XGBoost is acknowledged, but this trade-off is deemed acceptable given the substantial gains in predictive power (Mehta et al., 2019). To address concerns about overfitting, rigorous hyperparameter tuning and consideration of regularization techniques were employed, showcasing a commitment to refining the model's generalization ability (Santos & Papa, 2022).

The lower accuracy of the DNN model in comparison to the other ML methods, especially the tree-based methods of XGBoost and RF, also aligns with some other studies comparing DNNs with ensembled tree-based methods for handling regression tasks and tabular data. Such studies highlight that despite tremendous advancements in using DL methods for classification tasks based on texts and images, ML models may still outperform DL methods in certain scenarios involving tabular data and regression problems (El Bilali et al., 2023; Grinsztajn et al., 2022; Huber et al., 2022; Zamani Joharestani et al., 2019).

Visual comparisons of the performance of the different methods have also been presented through scatter plots of actual values vs predicted values and scatter plots of the residuals in Fig. 7 and Fig. 8, respectively. In Fig. 7, actual values are plotted on the x-axis and predicted values on the y-axis. The red line in each plot represents a linear regression line that shows the relationship between the actual and predicted values. Upon examining the plots of the different models in this figure, it is observed that the slopes of the lines related to RF and XGBoost predictions are closer to 1, indicating the better performance of these two models. In other words, the steeper slopes of the lines for these two models suggest a stronger relationship between the actual and predicted values. Furthermore, upon comparing the plots of RF and XGBoost, it is evident that the points in the XGBoost plot are more tightly clustered around the line, signifying that the XGBoost method outperforms the RF method. Moreover, using the scatter plots of the residuals presented in Fig. 8, it is possible to evaluate the performance of the different models by examining the distribution of errors. Accordingly, again, for the XGBoost, the residuals are closer to the zero-line compared to the other methods. These visual comparisons between the performance of the different models confirm the assessment of them using the utilized metrics.

Table 6 also provides insights into the runtime performance of various models, with XGBoost demonstrating notably faster performance compared to the other models. While it's important to note that runtime is not a critical factor in selecting the optimal model for mass land valuation, as this task does not typically require real-time computations, the accelerated performance of XGBoost underscores its efficiency and computational capabilities.

3.4. Final land valuation maps

The optimal XGBoost model, developed based on the previously mentioned selected features and tuned hyperparameters, was employed to estimate the land values of the whole parcels within the study area,

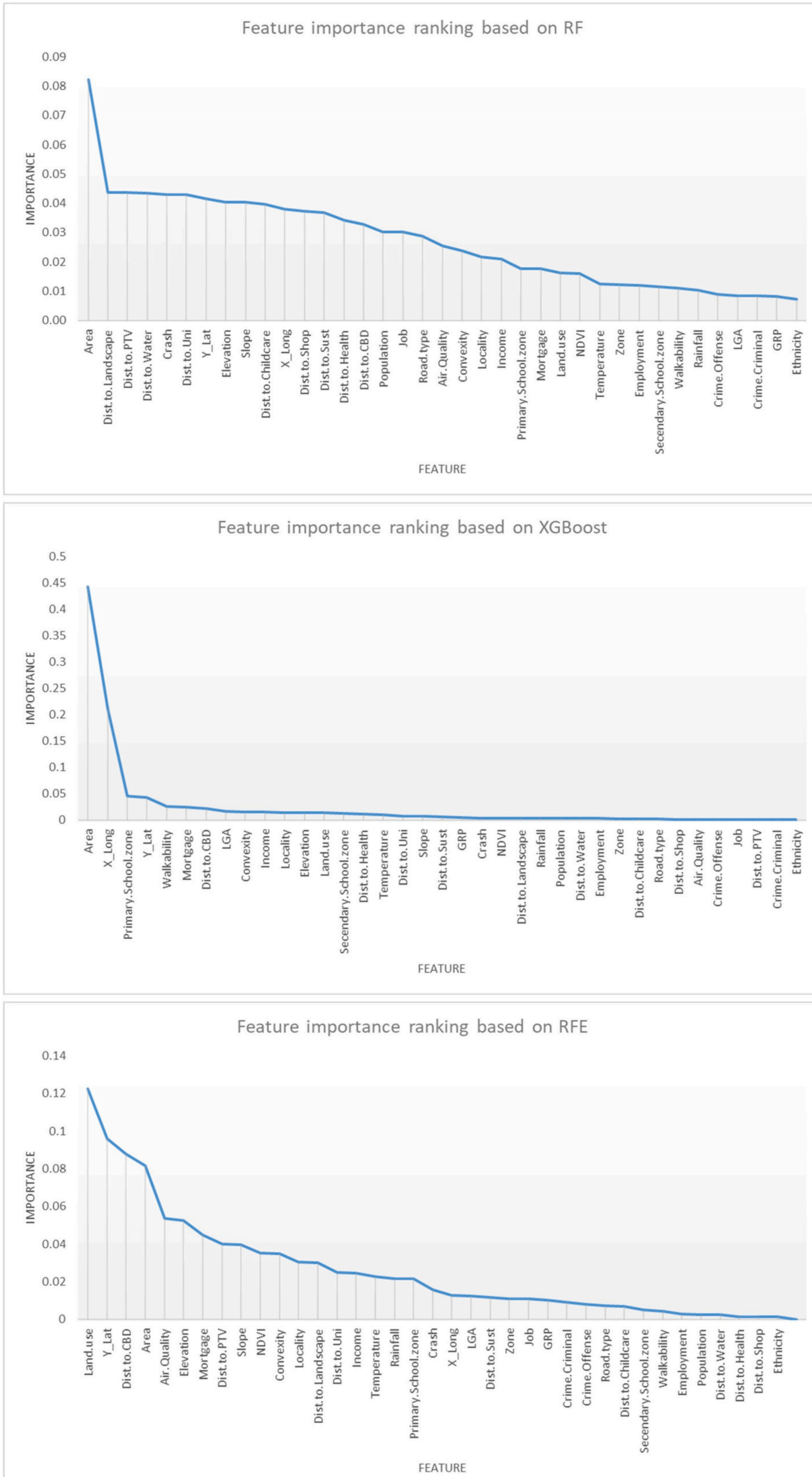

Fig. 6. Results of ranking the importance of features using RF, XGBoost and RFE-SVM methods.

Table 4
Optimal hyperparameters for the different feature importance ranking and valuation models.

Hyperparameter	Feature importance ranking	ML-based valuation
	RFE-SVM	SVR
The kernel	Radial	Radial
Gamma	0.07	0.03
Cost	7	7
Epsilon	0.1	0.1
	RF	RF
Number of trees	300	500
m_{try}	10	10
Node size	9	8
	XGBoost	XGBoost
Number of trees	500	500
eta	0.26	0.3
Maximum depth	6	6
Subsample ratio of training samples	1	1
Subsample ratio of features	1	1

Table 5
Results of the four methods considered for mass land valuation.

Method	SVR	RF	XGBoost	DNN
Training data				
R^2	0.674	0.996	0.999	0.647
MAPE	0.25	0.028	0.046	0.593
nRMSE	0.766	0.076	0.037	0.776
Test data				
R^2	0.649	0.701	**0.862**	0.611
MAPE	0.477	0.166	**0.139**	0.573
nRMSE	0.436	0.406	**0.281**	0.48

totaling approximately 1.1 million polygons. Summary statistics of the estimated land values across the entire study area are presented in Table 7. The first row displays land values for different land parcels regardless of their size, while the second row showcases the land values per m^2 for all different parcels within the area. Fig. 9 illustrates the spatial distribution of land values per parcel throughout the study area, reflecting the final estimations. Fig. 10 also depicts the distribution of land values per m^2 for all parcels within the study data. All values in the table and figures are denoted in Australian Dollars (AUD). Due to reduced urban density in the marginal suburbs within the study area, coupled with significantly larger parcel sizes, certain areas—such as those depicted in the northeastern regions—exhibit notably high land prices in Fig. 9. Consequently, Fig. 10, structured to reflect land prices per m^2, can provide a more descriptive representation of the spatial patterns of land prices in the study area as determined by this research.

In addition, given that land valuation in Australia often considers recent transactions in comparable markets at the administrative level of locality or suburb, we computed the mean value of one m^2 of land parcels for each suburb within the study area (as shown in Fig. 11). Accordingly, ten suburbs of Middle Park, South Melbourne, Fitzroy, Toorak, Windsor, Prahran, Collingwood, Cremorne, Princes Hill and Armadale were among the suburbs associated with the highest land value per m^2 based on this study's estimations.

4. Discussions and conclusions

Access to accurate land prices is crucial for various aspects such as taxation, land resource allocation, real estate market management and urban development and planning. However, manual valuation by individual experts on a large scale is not only time-consuming but also expensive. Therefore, there is a growing necessity to adopt automated methods, particularly AVMs, to address these challenges efficiently. The primary objective of this study was to contribute to global efforts in

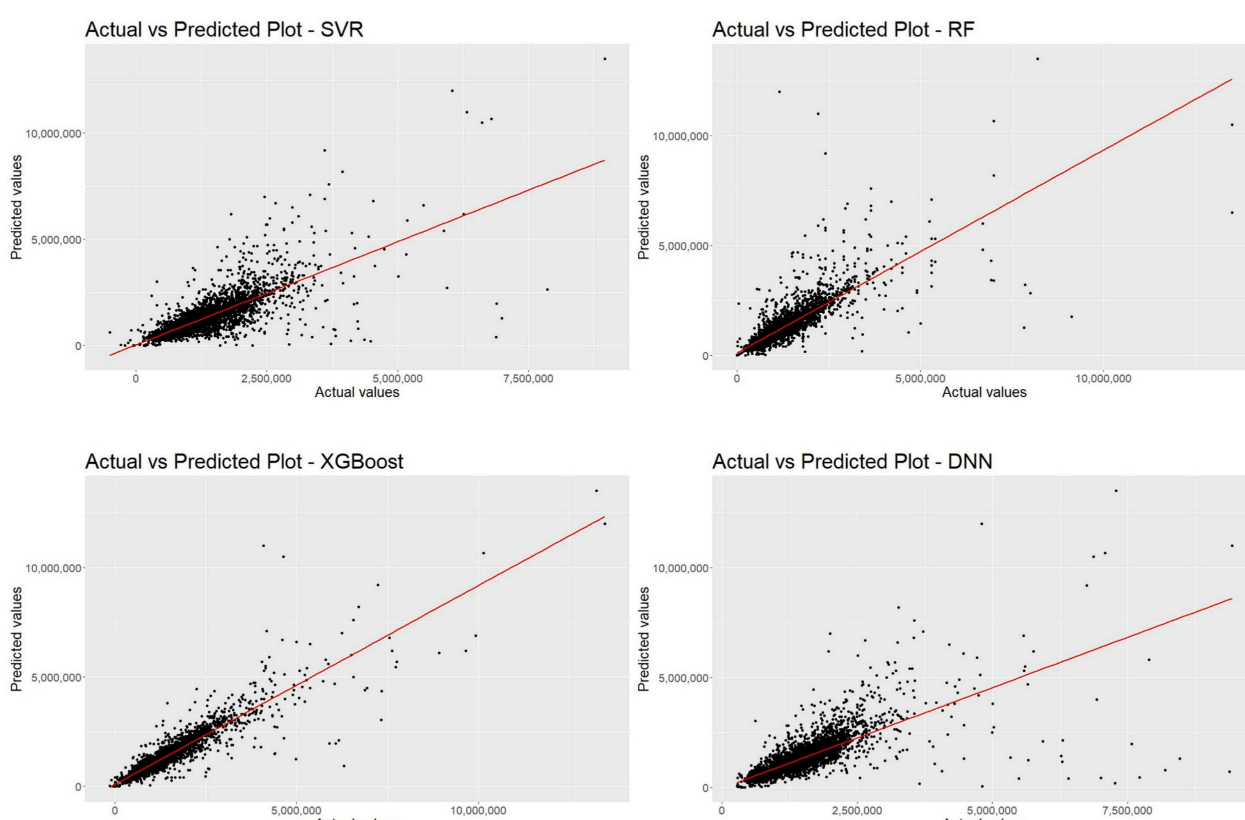

Fig. 7. Scatter plots of actual values vs predicted values for each algorithm.

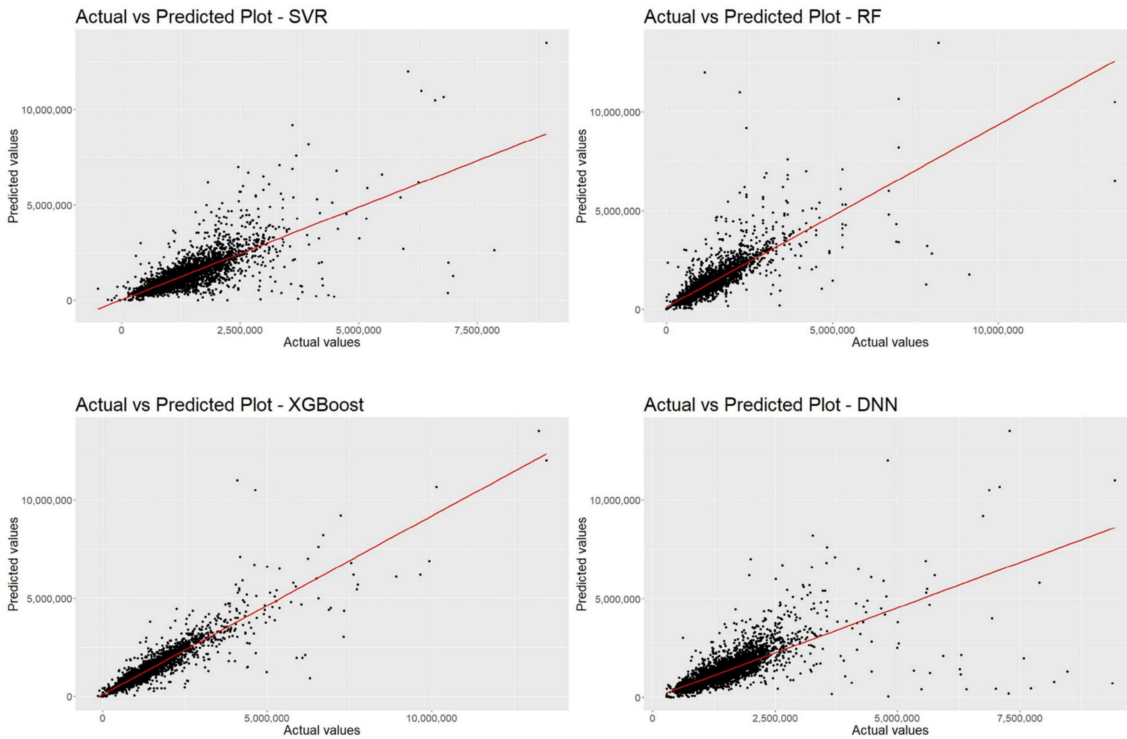

Fig. 8. Scatter plots of the residuals based on different models.

Table 6
Running time of different models.

Model		Runtime (mm:ss)
The speed of each tuned model for training and making estimations on both the training and test sets when runs on the corresponding feature set leading to the highest accuracy	SVR	12:56
	RF	05:06
	XGBoost	00:07
	DNN	10:15
The speed of the selected model to run on the whole parcels in the study area	XGBoost	00:01

Table 7
Summary statistics of mass land valuation in the study area based on the selected model (AVM developed using XGBoost) (values are in AUD).

	Minimum	Maximum	Median	Mean	Std Dev
Land value	1060	71,969,208	923,735	1,388,305	2,216,842
Land value per m^2	1	3,434,383	1751	2308	5287

developing accurate AVMs for land valuation systems using ML and DL technologies. These systems play a vital role in facilitating informed decision-making processes aligned with sustainable development goals and enhancing the quality of life, especially in the housing sector. By providing more precise valuation datasets for real estate assets, decision-makers can implement better housing planning and policies, leading to improved affordability and equitable urban development (Carranza et al., 2022; Soltani et al., 2022). The following subsections will discuss the innovative methodology applied in this study and its technical achievements, along with study implications, limitations and sources of uncertainty, and potential avenues for future research in the field.

4.1. Methodological discussion

This study significantly contributes to the scientific literature by embracing an extensive array of factors compared to previous research in developing AVMs for land valuation. We meticulously curated a comprehensive set of 37 potential determinants of land price, categorized into physical, geographical, socio-economic, environmental, and legal and planning aspects. This broad feature set enabled a holistic assessment of factors influencing land values, surpassing the limitations of studies that focus solely on specific domains or overlook crucial variables.

Moreover, our innovative feature selection process sets this study apart from conventional practices in other relevant studies. While most studies ignore the feature selection task or use a specific feature selection method to automatically select features without considering their impact on model performance, we adopted a more rigorous approach. The variability in feature rankings across different models and scenarios, as noted by Zhang et al. (2021), prompted us to follow recommendations by Pudjihartono et al. (2022) that applying multiple and step-wise feature selection methods can be associated with more accurate results despite heavy computations. After ranking features based on importance analysis using RFE-SVM, RF and XGBoost models, we evaluated all possible feature sets to select those leading to the best performance for each model. This exhaustive process, integrated with grid search-based hyperparameter tuning, justified its time-consuming nature by achieving a high level of accuracy, which is crucial for non-real-time land price estimation requiring periodic repetition.

Although our study encompasses unique aspects that distinguish it from prior research, we find consistency in the importance of certain features across various studies in the field. For instance, our findings align with previous studies that emphasize the critical importance of factors such as land area (Ma et al., 2020), land use patterns (Derdouri & Murayama, 2020; Kim et al., 2021) and proximity to water bodies (Zhang et al., 2021) in land valuation using ML techniques. This paper also notes that environmental factors such as temperature can contribute to a more accurate estimation of land prices in large study areas where such parameters differ from one place to another place.

Comparative analysis with previous research also highlights the superior performance of our selected model in terms of accuracy rates and

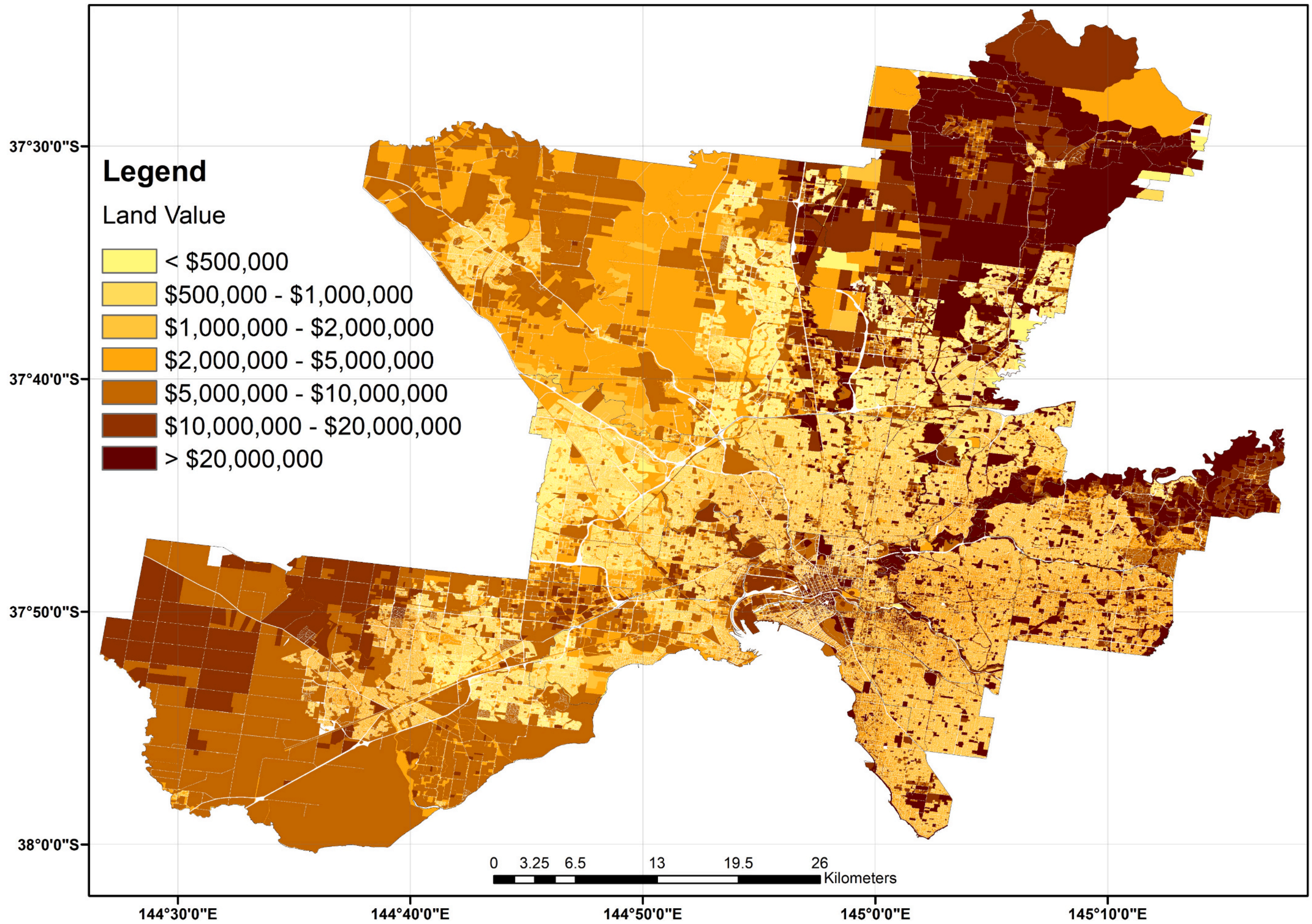

Fig. 9. Map of land values in the study area based on the selected AVM developed using the XGBoost technique (values are in AUD).

model robustness. While studies like those by Sampathkumar et al. (2015), Derdouri and Murayama (2020), Zhang et al. (2021) and Carranza et al. (2022) demonstrated notable results using ML techniques in mass land valuation, our study surpasses these benchmarks with a higher accuracy in terms of the considered performance metrics. Furthermore, our study's selection of XGBoost as the optimal ML-based algorithm for land valuation resonates with the growing body of literature advocating for ensemble tree-based methods due to their ability to capture complex interactions and high-level representations in valuation tasks (Gao et al., 2022; Guliker et al., 2022; Kim et al., 2021; Zaki et al., 2022). It should also be noted that the use of a reliable dataset on land values obtained from VGV for training and testing the models was crucial in achieving high accuracy in mass land valuation in this study.

4.2. Study implications

The findings of this study carry significant practical implications, particularly concerning housing affordability issues in the study area. Through the accurate estimation of land values using advanced ML techniques, we have mapped spatial patterns in land values across a large region within the Melbourne Metropolitan area, directly impacting the housing sector. This information holds crucial value for policymakers, urban planners and stakeholders involved in addressing housing affordability challenges. Identifying areas with higher land values provides valuable insights for targeted interventions, such as affordable housing initiatives, land use policies and urban development strategies. By understanding these spatial patterns, stakeholders can work towards creating more equitable and sustainable housing systems, ultimately benefiting residents and communities affected by housing challenges.

Our study contributes to fostering a fair housing landscape, aligning with strategies proposed by experts to address housing crises (Local-Valuers-Australia, 2023). For instance, our insights can support initiatives like fast-tracking home supply in desirable locations and streamlining planning processes. Furthermore, our outputs can assist urban planners in assessing the impact of infrastructure projects on property values, prioritizing community needs and promoting inclusive urban development. Policymakers can also leverage our data to strategically allocate resources, monitor the effectiveness of affordability measures and enhance housing affordability over time.

4.3. Study limitations and sources of uncertainty

While this study aimed to provide mass land valuation for approximately 1.1 million land parcels in 19 LGAs of the Melbourne Metropolitan area, it is essential to recognize the inherent limitations and sources of uncertainty in the methodology employed. One notable limitation pertains to the absence of land sales data and certain market-related indices, which are typically used in AVMs. This research acknowledges the importance of these factors for accurate land valuation. However, there are specific challenges and constraints that led to their exclusion from this study.

Property or land valuation in real-world settings usually involves the integration of recent transactions of similar properties/lands in the same geographical area, as well as other market-related indicators, such as day on market, price change and clearance rate. The study area encompasses a large number of Statistical Area 1 (SA1) and SA2 (suburbs)

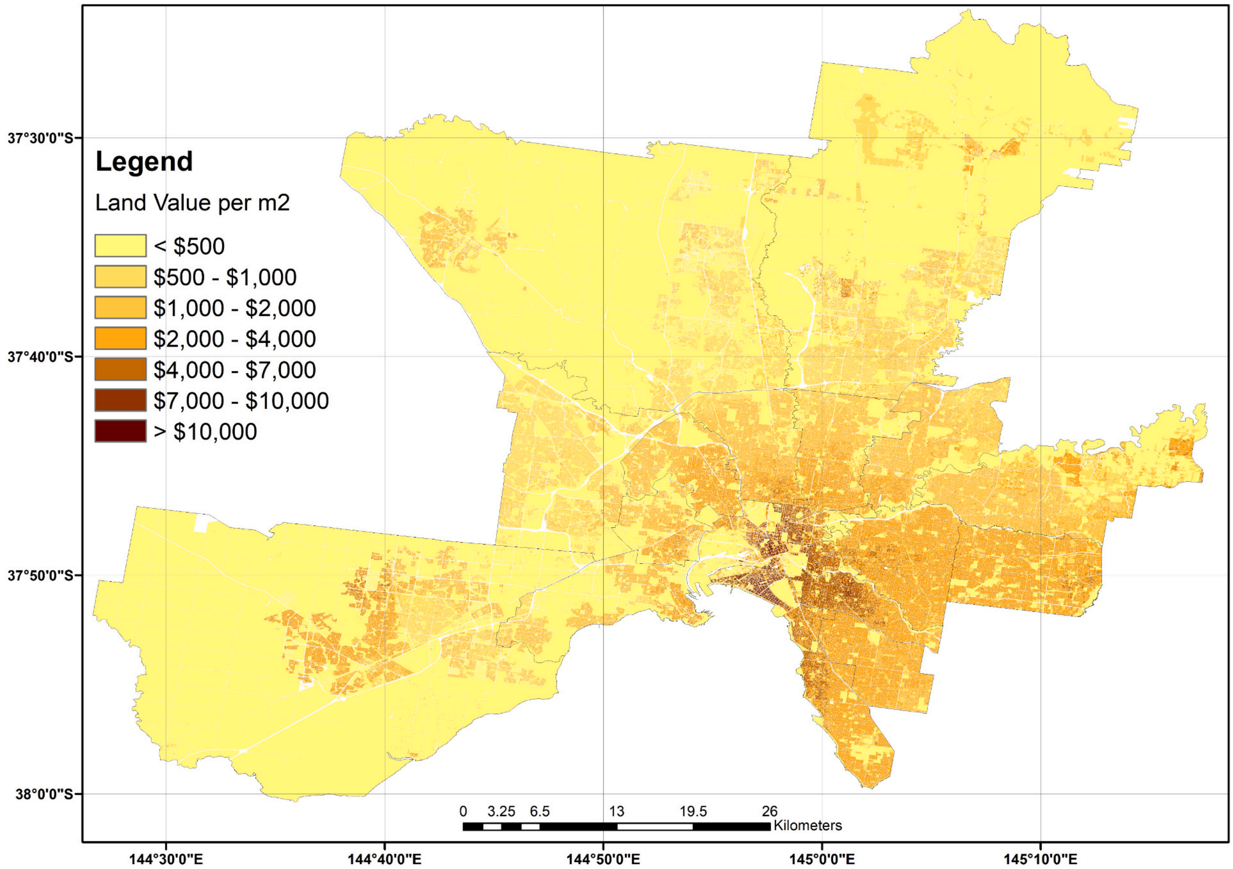

Fig. 10. Map of the value of one square meter of land per parcel in the study area based on the selected AVM developed using the XGBoost technique (values are in AUD).

polygons, totaling 6652 and 215, respectively. In an ideal scenario, incorporating transaction data at such granular levels would be imperative. Unfortunately, the number of land sales transactions available for this study was insufficient to derive meaningful insights or to calculate market indices that are usually based on the median or average of recent transactions. Moreover, access to such data, even if it existed, proved to be challenging within the scope and timeframe of this research. Investigating land transactions presents distinct challenges compared to the transactions of constructed properties, which commonly have a higher frequency of sales. The scarcity of land transactions complicates the incorporation of market-related data into studies focused on developing AVMs for land valuation, unlike studies that concentrate on the mass valuation of constructed properties. While our predictive models were designed to make mass valuations based on various factors, it is essential to recognize that the models are rooted in historical data. Consequently, the ability of these models to predict land values outside the temporal range of the available transaction data may be constrained. It is worth noting that real-world land values can be subject to fluctuations that are not entirely accounted for within the models.

The absence of recent land sales data can also be related to another source of uncertainty in this study. The current study uses the SVs received from VGV as the ground truth data for training and testing the AVMs in the sample land parcels. Again, in an ideal scenario, the best option for training and testing the AVMs must be based on the latest transactions on sample lands. As discussed above, access to large amounts of land transactions for a specific time period, which is mainly annual for property valuation purposes, was not possible. That is why the data received from VGV for 2022 was considered as an alternative solution. As the VGV follows the process of a hybrid valuation methodology, combining manual assessments of benchmark properties with generalization to a broader set of properties, this could be another source of uncertainty for the outputs of this paper. The hybrid approach involves valuers conducting detailed on-site inspections of selected benchmark properties to derive precise valuations. These benchmark properties represent a cross-section of the real estate market, accounting for different property types, geographical locations, and land characteristics. This process also involves making assumptions and modeling, which may introduce variations in the accuracy of valuations across different property types. Despite these limitations, the dataset from the Valuer General is considered reliable for the purpose of this study because the VGV maintains rigorous standards in data collection and valuation processes and the dataset is regularly updated to reflect property changes, ensuring its accuracy and currency.

Furthermore, it is important to note that the subtle overfitting observed in the XGBoost model, despite rigorous hyperparameter tuning and consideration of regularization techniques, may still pose potential impacts on predictions using new data, which warrants cautious interpretation of the model's outputs in practical applications.

4.4. Future research

Although each study may have specific characteristics based on the area under investigation, our comprehensive feature set and robust feature selection algorithm can serve as a valuable reference for other researchers. Most of the features considered in our study are independent of the study area and can be applied in diverse geographical contexts worldwide, enhancing the generalizability and applicability of our findings to land valuation studies globally.

Such a methodology for other areas at national and international levels can be followed by researchers, relevant governmental organizations and industry-based actors. Especially, in terms of the study area, the VGV undertakes annual revaluations. The applied methodology in

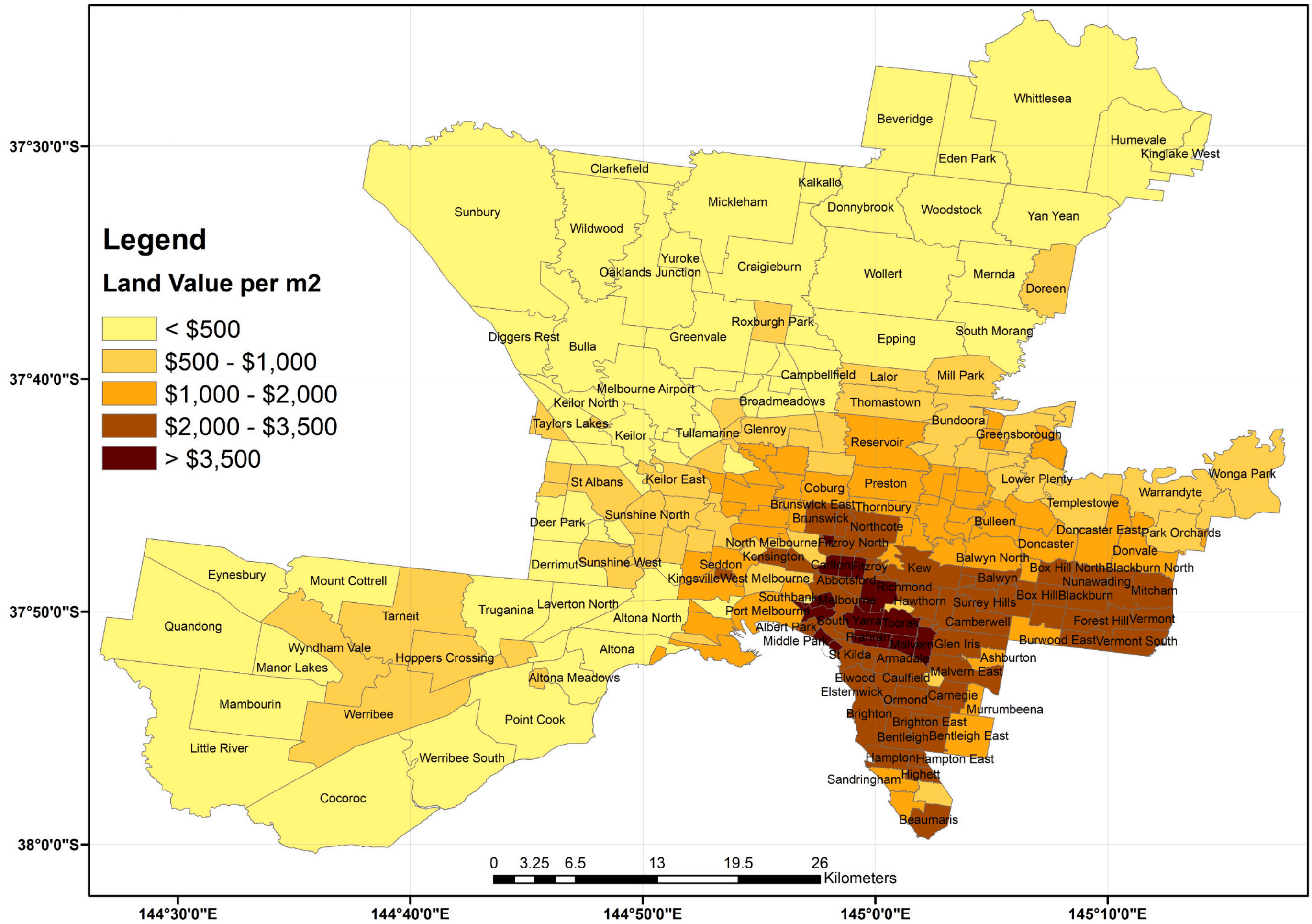

Fig. 11. Map of the mean values of one square meter of land parcels in each suburb (values are in AUD).

this project can contribute to their activities on mass valuation to increase the accuracy of the land value estimations and decrease the required time and cost for revaluations. Furthermore, future work in the field can focus on two main subjects:

- Using computer vision and DL methods, especially CNNs, to extract some useful features from visual data that could be mixed with the other driving factors of land value introduced in this paper for a possible increase in the accuracy of the AVMs.
- Time-series analysis of some factors may also contribute to the better performance of the models since temporal variations of some variables may affect their impact on the land price estimations.

CRediT authorship contribution statement

Peyman Jafary: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Davood Shojaei:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Abbas Rajabifard:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization. **Tuan Ngo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

Peyman Jafary reports financial support was provided by Building 4.0 CRC.

Data availability

The authors do not have permission to share data.

Acknowledgements

This research is supported by Building 4.0 CRC. The support of the Commonwealth of Australia through the Cooperative Research Centre Programme is acknowledged. The authors also thank the Valuer-General Victoria, Australia, for providing a dataset on Site Value (SV) of the sample properties in the study area.

References

Abidoye, R. B., & Chan, A. P. C. (2017). Artificial neural network in property valuation: Application framework and research trend. *Property Management, 35*, 554–571.

ABS. (2022). *Regional population: Statistics about the population for Australia's capital cities and regions*. Australian Bureau of Statistics (ABS).

Ai, H., Liu, Q., Jiang, Y., & He, J. (2020). Urban residential land Price appraisal via quantifying impact factors based on deep belief networks. In *Proceedings of the 2020 12th international conference on machine learning and computing* (pp. 29–33). Shenzhen, China: Association for Computing Machinery.

Almaslukh, B. (2020). A gradient boosting method for effective prediction of housing prices in complex real estate systems. In *2020 International Conference on Technologies and Applications of Artificial Intelligence (TAAI)* (pp. 217–222).

ANZ-CoreLogic. (2023). *Housing affordability report*. Australia and New Zealand Banking Group Limited (ANZ).
Astudillo, G., Carrasco, R., Fernández-Campusano, C., & Chacón, M. (2020). Copper price prediction using support vector regression technique. In *, vol. 10. Applied sciences* (p. 6648).
Boehmke, B., & Greenwell, B. M. (2019). *Hands-on machine learning with R*. CRC Press.
Cai, J., Luo, J., Wang, S., & Yang, S. (2018). Feature selection in machine learning: A new perspective. *Neurocomputing, 300*, 70–79.
Carranza, J. P., Piumetto, M. A., Lucca, C. M., & Da Silva, E. (2022). Mass appraisal as affordable public policy: Open data and machine learning for mapping urban land values. *Land Use Policy, 119*, Article 106211.
Chen, C., Zhang, Q., Yu, B., Yu, Z., Lawrence, P. J., Ma, Q., & Zhang, Y. (2020). Improving protein-protein interactions prediction accuracy using XGBoost feature selection and stacked ensemble classifier. *Computers in Biology and Medicine, 123*, Article 103899.
Chen, L., Pelger, M., & Zhu, J. (2023). Deep learning in asset pricing. *Management Science, 70*, 714–750.
Codosero Rodas, J. M., Naranjo Gómez, J. M., Castanho, R. A., & Cabezas, J. (2018). Land valuation sustainable model of urban planning development: A case study in Badajoz, Spain. *Sustainability, 10*, 1450.
Crosby, H., Damoulas, T., Caton, A., Davis, P., Porto de Albuquerque, J., & Jarvis, S. A. (2018). Road distance and travel time for an improved house price kriging predictor. *Geo-spatial Information Science, 21*, 185–194.
DELWP. (2022). *2023 valuation best practice specifications guidelines*. Department of Environment, Land, Water and Planning (DELWP) - The Victorian Government.
Demetriou, D. (2016). The assessment of land valuation in land consolidation schemes: The need for a new land valuation framework. *Land Use Policy, 54*, 487–498.
Demetriou, D. (2018). Automating the land valuation process carried out in land consolidation schemes. *Land Use Policy, 75*, 21–32.
Deng, F., & Huang, Y. (2004). Uneven land reform and urban sprawl in China: The case of Beijing. *Progress in Planning, 61*, 211–236.
Derdouri, A., & Murayama, Y. (2020). A comparative study of land price estimation and mapping using regression kriging and machine learning algorithms across Fukushima prefecture, Japan. *Journal of Geographical Sciences, 30*, 794–822.
Dhal, P., & Azad, C. (2022). A comprehensive survey on feature selection in the various fields of machine learning. *Applied Intelligence, 52*, 4543–4581.
El Bilali, A., Abdeslam, T., Ayoub, N., Lamane, H., Ezzaouini, M. A., & Elbeltagi, A. (2023). An interpretable machine learning approach based on DNN, SVR, Extra Tree, and XGBoost models for predicting daily pan evaporation. *Journal of Environmental Management, 327*, Article 116890.
Gao, Q., Shi, V., Pettit, C., & Han, H. (2022). Property valuation using machine learning algorithms on statistical areas in Greater Sydney, Australia. *Land Use Policy, 123*, Article 106409.
Goundar, S., Maharaj, K., Kumar, A., & Bhardwaj, A. (2021). Property valuation using linear regression and random Forest algorithm. *International Journal of System Dynamics Applications, 10*, 1–16.
Grinsztajn, L., Oyallon, E., & Varoquaux, G. (2022). Why do tree-based models still outperform deep learning on typical tabular data? *Advances in Neural Information Processing Systems, 35*, 507–520.
Guliker, E., Folmer, E., & van Sinderen, M. (2022). Spatial determinants of real estate appraisals in The Netherlands: A machine learning approach. *ISPRS International Journal of Geo-Information, 11*.
Hardin, H. (2023). Breaking the immigration taboo: Canada needs to reduce immigration dramatically until the housing crisis is resolved, especially in Vancouver. *Inroads: A Journal of Opinion*, 159–178.
Ho, W. K. O., Tang, B.-S., & Wong, S. W. (2021). Predicting property prices with machine learning algorithms. *Journal of Property Research, 38*, 48–70.
Hong, H., Xiaoling, G., & Hua, Y. (2016). Variable selection using mean decrease accuracy and mean decrease Gini based on random Forest. In *2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS)* (pp. 219–224).
Hong, J., Choi, H. H., & Kim, W.-S. (2020). A house price valuation based on the random forest approach: The mass appraisal of residential property in South Korea. *International Journal of Strategic Property Management, 24*, 140–152.
Hou, A., Liu, J., Tao, Y., Jiang, S., Li, K., Zheng, Z., … Li, J. (2019). Land price assesment based on deep neural network. In *IGARSS 2019–2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 3053–3056).
Hu, S., Cheng, Q., Wang, L., & Xu, D. (2013). Modeling land price distribution using multifractal IDW interpolation and fractal filtering method. *Landscape and Urban Planning, 110*, 25–35.
Hu, S., Yang, S., Li, W., Zhang, C., & Xu, F. (2016). Spatially non-stationary relationships between urban residential land price and impact factors in Wuhan city, China. *Applied Geography, 68*, 48–56.
Hu, Z., Zhao, Y., & Khushi, M. (2021). A survey of forex and stock Price prediction using deep learning. *Applied System Innovation, 4*.
Huber, F., Yushchenko, A., Stratmann, B., & Steinhage, V. (2022). Extreme gradient boosting for yield estimation compared with deep learning approaches. *Computers and Electronics in Agriculture, 202*, Article 107346.
Inoue, R., Kigoshi, N., & Shimizu, E. (2007). Visualization of spatial distribution and temporal change of land prices for residential use in Tokyo 23 wards using spatio-temporal kriging. In *, 63. Proceedings of 10th International Conference on Computers in Urban Planning and Urban Management* (pp. 1–11).
Iwai, K., & Hamagami, T. (2022). A new XGBoost inference with boundary conditions in real estate price prediction. *IEEJ Transactions on Electrical and Electronic Engineering, 17*, 1613–1619.
Jafary, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2022). A framework to integrate BIM with artificial intelligence and machine learning-based property valuation methods. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, X-4/W2-2022*, 129–136.
Jafary, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2024). BIM and real estate valuation: Challenges, potentials and lessons for future directions. *Engineering Construction and Architectural Management, 31*, 1642–1677.
Jiang, Z., & Shen, G. (2019). Prediction of house Price based on The Back propagation neural network in The Keras deep learning framework. In *2019 6th international conference on systems and informatics (ICSAI)* (pp. 1408-1412).
Jiao, L., & Liu, Y. (2012). Analyzing the spatial autocorrelation of regional urban datum land price. *Geo-spatial Information Science, 15*, 263–269.
Kim, B., & Kim, T. (2016). A study on estimation of land value using spatial statistics: Focusing on real transaction land prices in Korea. *Sustainability, 8*, 203.
Kim, J., Won, J., Kim, H., & Heo, J. (2021). Machine-learning-based prediction of land prices in Seoul, South Korea. *Sustainability, 13*, 13088.
Kok, N., Monkkonen, P., & Quigley, J. M. (2014). Land use regulations and the value of land and housing: An intra-metropolitan analysis. *Journal of Urban Economics, 81*, 136–148.
Krause, A., & Bitter, C. (2012). Spatial econometrics, land values and sustainability: Trends in real estate valuation research. *Cities, 29*, S19–S25.
Kuhn, M., & Johnson, K. (2013). Over-fitting and model tuning. In M. Kuhn, & K. Johnson (Eds.), *Applied predictive modeling* (pp. 61–92). New York, NY: Springer New York.
Kuzudisli, C., Bakir-Gungor, B., Bulut, N., Qaqish, B., & Yousef, M. (2023). Review of feature selection approaches based on grouping of features. *PeerJ, 11*, Article e15666.
Lakševics, K., Franz, Y., Haase, A., Nasya, B., Patti, D., Reeger, U., Raubiško, I., Schmidt, A., & Šuvajevs, A. (2023). The permanent regime of temporary solutions: Housing of forced migrants in Europe as a policy challenge. *European Urban and Regional Studies, 31*, 81–87.
Li, H., Huang, X., & Li, X. (2019). Urban land price assessment based on GIS and deep learning. In *IGARSS 2019–2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 935–938).
Li, H., Shi, L., Gao, W., Zhang, Z., Zhang, L., Zhao, Y., & Wang, G. (2022). dPromoter-XGBoost: Detecting promoters and strength by combining multiple descriptors and feature selection using XGBoost. *Methods, 204*, 215–222.
Li, S., Jiang, Y., Ke, S., Nie, K., & Wu, C. (2021). Understanding the effects of influential factors on housing prices by combining extreme gradient boosting and a hedonic Price model (XGBoost-HPM). *Land, 10*.
Lima, V. (2024). Pandemic housing policies: Mitigation strategies and protection of rights. *Housing and Society, 51*, 34–49.
Local-Valuers-Australia. (2023). *Addressing Australia's housing crisis effectively*. Local Valuers Australia.
Louati, A., Lahyani, R., Aldaej, A., Aldumaykhi, A., & Otai, S. (2022). Price forecasting for real estate using machine learning: A case study on Riyadh city. *Concurrency and Computation: Practice and Experience, 34*, Article e6748.
Ma, J., Cheng, J. C. P., Jiang, F., Chen, W., & Zhang, J. (2020). Analyzing driving factors of land values in urban scale based on big data and non-linear machine learning techniques. *Land Use Policy, 94*, Article 104537.
Mangioni, V. (2014). Land value taxation and the valuation of land in Australia. *Nordic Journal of Surveying and Real Estate Research, 10*, 82–98.
Mehta, P., Bukov, M., Wang, C.-H., Day, A. G. R., Richardson, C., Fisher, C. K., & Schwab, D. J. (2019). A high-bias, low-variance introduction to machine learning for physicists. *Physics Reports, 810*, 1–124.
Mete, M. O., & Yomralioglu, T. (2021). Implementation of serverless cloud GIS platform for land valuation. *International Journal of Digital Earth, 14*, 836–850.
Montesinos López, O. A., Montesinos López, A., & Crossa, J. (2022). Overfitting, model tuning, and evaluation of prediction performance. In *Multivariate statistical machine learning methods for genomic prediction* (pp. 109–139). Springer.
Mujeeb, S., Javaid, N., Ilahi, M., Wadud, Z., Ishmanov, F., & Afzal, M. K. (2019). Deep long short-term memory: A new Price and load forecasting scheme for big data in smart cities. *Sustainability, 11*.
OECD. (2023). Housing prices. In O. f. E. C.-o. a. D. (OECD) (Ed.).
Pawson, H., Martin, C., Aminpour, F., Gibb, K., & Foye, C. (2022). *COVID-19: Housing market impacts and housing policy responses-An international review*. Australian Council of Social Service.
Peng, Z., Huang, Q., & Han, Y. (2019). Model research on forecast of second-hand house price in Chengdu based on XGboost algorithm. In *2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT)* (pp. 168–172).
PEXA. (2023). *Australia's housing crisis - uncovering the real causes* (vol. 2023). Australia: Property Exchange Australia (PEXA).
Pudjihartono, N., Fadason, T., Kempa-Liehr, A. W., & O'Sullivan, J. M. (2022). A review of feature selection methods for machine learning-based disease risk prediction. *Frontiers in Bioinformatics, 2*, Article 927312.
R-Core-Team. (2023). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.
REIV. (2019). *Melbourne land values skyrocket over 5 years*. The Real Estate Institute of Victoria (REIV).
RStudio-Team. (2023). *RStudio: Integrated development environment for R*. Boston, MA: RStudio, PBC.
Saberi, M., Wu, H., Amoh-Gyimah, R., Smith, J., & Arunachalam, D. (2017). Measuring housing and transportation affordability: A case study of Melbourne, Australia. *Journal of Transport Geography, 65*, 134–146.
Saiz, A. (2023). *The global housing affordability crisis: Policy options and strategies*. MIT Center for Real Estate Research Paper.

Sampathkumar, V., Santhi, M. H., & Vanjinathan, J. (2015). Forecasting the land price using statistical and neural network software. *Procedia Computer Science, 57*, 112–121.

Santos, C. F. G. D., & Papa, J. P. (2022). Avoiding overfitting: A survey on regularization methods for convolutional neural networks. *ACM Computing Surveys (CSUR), 54*, 1–25.

Silveira, P., & Dentinho, T. P. (2018). A spatial interaction model with land use and land value. *Cities, 78*, 60–66.

Soltani, A., Heydari, M., Aghaei, F., & Pettit, C. J. (2022). Housing price prediction incorporating spatio-temporal dependency into machine learning algorithms. *Cities, 131*, Article 103941.

State-Valuation-of-Land-legislation-across-Australia. (2023). Valuation of Land Act 1960. In *Valuation of Land Act 1960 No. 6653 of 1960 Authorised Version incorporating amendments as at 1 July 2023*.

Sze, V., Chen, Y. H., Yang, T. J., & Emer, J. S. (2017). Efficient processing of deep neural networks: A tutorial and survey. *Proceedings of the IEEE, 105*, 2295–2329.

Teang, K., & Lu, Y. (2021). *Property valuation by machine learning and hedonic pricing models : A case study on Swedish residential property*. Unpublished Student thesis.

Tezcan, A., Büyüktaş, K., & Akkaya Aslan, Ş. T. (2020). A multi-criteria model for land valuation in the land consolidation. *Land Use Policy, 95*, Article 104572.

The-State-Revenue-Office-Victoria. (2023). Land valuations. In.

Tsutsumi, M., Shimada, A., & Murakami, D. (2011). Land price maps of Tokyo Metropolitan Area. *Procedia - Social and Behavioral Sciences, 21*, 193–202.

Vapnik, V. (1999). *The nature of statistical learning theory*. New York, USA: Springer science & business media.

Wang, W. (2022). Rethinking local government perceptions of Land Value Capture in land marketization: The lens of dominant consideration(s) in interest-balancing acts. *Cities, 122*, Article 103528.

Wu, R., Wang, J., Zhang, D., & Wang, S. (2021). Identifying different types of urban land use dynamics using Point-of-interest (POI) and Random Forest algorithm: The case of Huizhou, China. *Cities, 114*, Article 103202.

Xue, F., & Yao, E. (2022). Adopting a random forest approach to model household residential relocation behavior. *Cities, 125*, Article 103625.

Yalpir, S., & Unel, F. B. (2017). Use of spatial analysis methods in land appraisal; Konya example. In *5th International Symposium on Innovative Technologies in Engineering and Science (ISITES2017)* (pp. 1573–1582). Baku, Azerbaijan.

Yamada, S., Yamasaki, S., Okuno, T., Harada, K., Sasaki, Y., & Onizuka, M. (2020). Are satellite images effective for estimating land prices on deep neural network models?. In *2020 21st IEEE International Conference on Mobile Data Management (MDM)* (pp. 304–309).

Yilmazer, S., & Kocaman, S. (2020). A mass appraisal assessment study using machine learning based on multiple regression and random forest. *Land Use Policy, 99*, Article 104889.

Yu, L., Jiao, C., Xin, H., Wang, Y., & Wang, K. (2018). Prediction on housing price based on deep learning. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 12*, 90–99.

Zaki, J., Nayyar, A., Dalal, S., & Ali, Z. H. (2022). House price prediction using hedonic pricing model and machine learning techniques. *Concurrency and Computation: Practice and Experience, 34*, Article e7342.

Zamani Joharestani, M., Cao, C., Ni, X., Bashir, B., & Talebiesfandarani, S. (2019). PM2.5 prediction based on random Forest, XGBoost, and deep learning using multisource remote sensing data. *Atmosphere, 10*.

Zhan, C., Wu, Z., Liu, Y., Xie, Z., & Chen, W. (2020). Housing prices prediction with deep learning: An application for the real estate market in Taiwan. In *, vol. 1. 2020 IEEE 18th International Conference on Industrial Informatics (INDIN)* (pp. 719–724).

Zhang, P., Hu, S., Li, W., Zhang, C., Yang, S., & Qu, S. (2021). Modeling fine-scale residential land price distribution: An experimental study using open data and machine learning. *Applied Geography, 129*, Article 102442.

Zhao, Y., Li, J., & Yu, L. (2017). A deep learning ensemble approach for crude oil price forecasting. *Energy Economics, 66*, 9–16.

Zhou, X., Tong, W., & Li, D. (2019). Modeling housing rent in the Atlanta metropolitan area using textual information and deep learning. *ISPRS International Journal of Geo-Information, 8*.

Zulkifley, N., Rahman, S., Nor Hasbiah, U., & Ibrahim, I. (2020). House price prediction using a machine learning model: A survey of literature. *International Journal of Modern Education and Computer Science, 12*, 46–54.