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FORECASTING PANDEMIC-INDUCED CHANGES IN REAL ESTATE MARKET VALUES THROUGH MACHINE LEARNING APPROACHES

Adile Gülsüm ULUCAN [1], Aslı BOZDAĞ [1], Murat KARAKOYUN [2], Tansu ALKAN [1,3*]

[1] *Department of Geomatics Engineering, Niğde Ömer Halisdemir University, Niğde, Türkiye*
[2] *Department of Computer Engineering, Necmettin Erbakan University, Konya, Türkiye*
[3] *Institute of Science, Necmettin Erbakan University, Konya, Türkiye*

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Abstract. In this study, a new temporal segmentation method is used to forecasting the real estate market based on the structural and spatial attributes of 676 houses in Niğde, Türkiye, from the years 2019 to 2022. Artificial Neural Networks (ANN), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbours (KNN) were employed for model development and comparative performance analysis. According to the results, the ANN model that used temporal variables showed the most successful performance by achieving the highest R^2 for 2019 (1. period: 0.979, 2. period: 0.990, 3. period: 0.914, 4. period: 0.831) and 2022 (1. period: 0.971, 2. period: 0.975, 3. period: 0.586, 4. period: 0.896) scores. Additionally, the COD values (5%–10%) and PRD values (0.98 to 1.03) remained within the acceptable range, further validating the model's reliability. RF model showed more effective performance than other models by achieving the highest R^2: 0.510 for 2019 and R^2: 0.509 for 2022 when temporal variables were excluded. These findings highlight the importance of integrating time-sensitive parameters into valuation models to improve forecast accuracy and robustness. The study offers a replicable, flexible methodology for crisis-responsive valuation, providing valuable insights for policymakers, investors, and urban planners aiming to mitigate risks and enhance resilience in real estate market decision-making.

Keywords: real estate valuation, pandemic, valuation criteria, time modelling, geographic information system, machine learning techniques.

* Corresponding author. E-mail: *tansualkan93@gmail.com*

1. Introduction

1.1. General background

Real estate valuation plays a central role across a broad spectrum, ranging from optimizing individual investments to determining corporate strategies and developing public policies. This discipline performs a critical function in diverse contexts, including tax transactions, expropriation processes, credit evaluations, property appraisals, structural improvements, land arrangements, and urban development (Aydınoğlu et al., 2023; Erdem, 2018). Accurately determining the value of real estate requires a multidimensional analytical process that goes beyond superficial assessments of spatial and structural features. In this regard, it is essential to address systematically and holistically the criteria encompassing the spatial, structural, historical, social, cultural, and environmental aspects of the property (Demirel et al., 2018; Yağmahan, 2019). Traditional valuation approaches often focus exclusively on static elements of these criteria, inadequately accounting for the dynamic variables that characterize modern real estate markets. However, the complex structure of contemporary markets is shaped by extraordinary circumstances, including rapidly increasing urbanization, evolving economic investments, global pandemics, and political conflicts. These extraordinary factors precipitate radical changes in real estate markets, significantly affecting not only market mechanisms but also the value dynamics of individual properties. For instance, economic restructuring and escalating environmental crises have profoundly disrupted the continuity and stability of market conditions, exposing the limitations of traditional valuation methods. In this context, integrating dynamic variables into real estate valuation processes becomes imperative. The time dimension emerges as an indispensable analytical tool for understanding changing market conditions and evaluating the impacts of extraordinary events. Systematically incorporating dynamic parameters allows for detailed analysis of periodic market fluctuations and predictions of future trends. Such an approach facilitates the development of analytical models that enhance the flexibility, adaptability, and contextual sensitivity of real estate valuation processes.

Various methods have been developed to enhance the accuracy and impartiality of real estate valuation. Traditional approaches have relied on systematic comparison techniques that use scoring principles to evaluate properties. However, most of these methods are based on static parameters, which fail to reflect market dynamics adequately (Uşak, 2019; Yağmahan, 2019). To address these deficiencies, Multi-Criteria Decision Making (MCDM) techniques have been introduced. MCDM methods have enhanced local-level comparison processes by incorporating expert input and assigning weights to criteria (Alkan & Durduran, 2020; Demirel et al., 2018; Yomralıoğlu et al., 2022). Nevertheless, these approaches often struggle to adapt to rapid market changes. At this point, advanced technologies such as Geographic Information Systems (GIS) and Machine Learning Techniques (MLT) have introduced a new paradigm in real estate valuation. GIS has deepened valuation processes by enabling detailed analyses of spatial and environmental factors while visualizing the positions and dynamics of properties within their geographical contexts (Başer et al., 2016; Özgüven & Erenoğlu, 2020; Sesli, 2015). MLT, on the other hand, surpasses traditional methods by processing large datasets, modeling complex variable relationships, and predicting dynamic market conditions. When integrated with GIS, these technologies play a critical role in understanding the complexities of contemporary markets, offering higher accuracy, flexibility, and innovative perspectives in real estate valuation processes.

Machine learning techniques have gained prominence in scientific and practical applications due to their ability to simultaneously evaluate multidimensional and independent criteria in real estate valuation. These techniques analyze extensive and complex datasets to produce highly accurate, future-oriented predictions, providing more objective, efficient, and comprehensive evaluations compared to traditional methods. The primary aim of Machine Learning Algorithms (MLAs) is to effectively process information from existing datasets and optimize model performance using selected algorithms (Pekel, 2018). Each algorithm employs distinct mathematical approaches to develop problem-specific solutions, resulting in varying levels of success. This methodological flexibility, coupled with the ability to address non-linear data relationships, has established machine learning as an essential tool for managing dynamic and complex data structures in real estate valuation. A review of the literature reveals several commonly employed machine learning approaches in real estate valuation. For instance, the k-nearest neighbors algorithm has been utilized by Moosavi (2017), Baldominos et al. (2018), and Alkan et al. (2023); the random forest algorithm has been applied by Dimopoulos and Bakas (2019), Yilmazer and Kocaman (2020), Kucklick et al. (2021), Tchuente and Nyawa (2022), and Mora-Garcia et al. (2022); support vector machines have been examined by Savaş (2019), Pai and Wang (2020) and, Louati et al. (2022); neural networks have been investigated by Bilgilioğlu (2018), Tabar et al. (2021), Lee (2022), Xu and Zhang (2022), Barut and Bilgin (2023), Karthika et al. (2024), and Kütük (2024); and regression trees have been addressed by Baldominos et al. (2018), Pai and Wang (2020), and Chou et al. (2022). Additionally, an increasing body of research focuses on the real estate valuation process during the COVID-19 pandemic, emphasizing the application of MLAs (Hoesli & Malle, 2022; Mora-Garcia et al., 2022; Ngoc et al., 2020).

Global extraordinary processes that have disrupted economic and social structures have led to significant changes in real estate valuation methods. These processes have exposed the limitations of traditional valuation approaches that rely solely on spatial and structural elements, underscoring the need for comprehensive and dynamic models. Particularly, the social and economic transformations of recent years have emphasized the importance of considering temporal variations in real estate valuation, necessitating the development of new methodological frameworks.

This study aims to address the need to understand dynamic market conditions by systematically integrating the concept of "temporal variability" into real estate valuation processes. Seeking to overcome the limitations of traditional approaches, this research proposes a multidimensional modeling framework that incorporates not only spatial and structural elements but also temporal interactions. In this context, a phase-based segmentation method has been developed, treating time as a central structural component rather than a static variable, to analyse how market behaviour changes during crises. This temporal segmentation, divided into four phases, pre-pandemic, early pandemic, adaptation, and recovery, enables a deeper understanding of market fluctuations and allows for a comparative assessment of the performance of machine learning algorithms across different phases. This original approach is particularly valuable in testing the adaptability of valuation models during extraordinary events such as pandemics and highlights both the theoretical and practical contributions of time-sensitive analytical methods.

The research evaluates the effects of temporal and spatial dynamics on the real estate market using advanced analytical methods. Both quantitative and qualitative elements are modeled by integrating MLAs with GIS. This approach leverages various machine learning techniques, including Artificial Neural Networks (ANN), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN), to transform extensive datasets into meaningful insights through multivariate analysis. Among these methods, ANN exhibit a strong ability to model complex interactions, while RF stands out for its robust generalization across datasets. The comparative performance of these algorithms was assessed over datasets segmented by specific periods, with statistical metrics used to validate the reliability of the results.

The findings of this study highlight the importance of time-sensitive methodologies in addressing the limitations of traditional approaches, offering an innovative perspective to the existing literature. The proposed methodological framework enables the modeling of real estate market dynamics shaped by extraordinary events, such as pandemics, and large-scale transformations, including environmental changes and economic crises. This research aims to serve as a methodological foundation for future studies, providing a valuable resource for policymakers and market stakeholders.

In conclusion, this study demonstrates that artificial intelligence–based methods can produce reliable and accurate predictions for future-oriented analyses and modeling processes. The findings emphasize the importance of integrating the temporal dimension, particularly in monitoring processes influenced by dynamic external factors. This comprehensive approach, which accounts for temporal variability and external complexity, enhances predictive accuracy and fosters a deeper understanding of multidimensional and dynamic parameters in real estate valuation. By elucidating how extraordinary events, such as pandemics, affect property value dynamics, this study contributes to the development of an innovative and adaptive valuation model.

1.2. Literature review

The rapid evolution of artificial intelligence and machine learning techniques has profoundly transformed real estate valuation research, shifting the field away from conventional rule-based models toward data-driven, dynamic prediction systems. Traditional valuation models, such as hedonic regression and repeat-sales approaches, have served as the theoretical backbone for decades (Calainho et al., 2024). However, these models are constrained by linear assumptions, limited responsiveness to non-linear relationships, and an inability to reflect phase-dependent fluctuations caused by external shocks. In response to these limitations, a growing body of research has embraced machine learning as a more adaptable and predictive alternative. Tekouabou et al. (2024) emphasize that despite the rising interest in artificial intelligence-driven valuation frameworks, most studies still rely on small datasets and shallow models, limiting both performance and generalizability.

Recent empirical studies have further advanced the methodological discourse. For example, Hernes et al. (2024) investigated the applicability of multiple regression, RF and ANN in valuing investment land in Poland. Their findings highlight ANN's predictive superiority, particularly in underdeveloped markets with limited transaction data, while stressing the necessity for structured datasets to enhance model performance. Tapia et al. (2025), through a comparative study in Santiago, Chile, demonstrated that incorporating visual and spatial data using convolutional neural networks significantly improves valuation accuracy. Calainho et al. (2024) contributed to index-based valuation by integrating machine learning into chained hedonic models, showing that model-agnostic methods can capture non-linear trends more effectively than ordinary least squares. Beyond model performance, the evolution of machine learning in real estate has introduced new paradigms in conceptual design. Rodriguez-Serrano (2025) proposed a prototype-based learning framework that incorporates the human-like principle of direct comparison while retaining explainability and non-linear modeling capabilities. This approach not only enhances transparency but also enables segmentation through representative prototypes, offering a scalable and interpretable alternative to conventional black-box algorithms.

Broader discussions around artificial intelligence in real estate suggest expanding the analytical scope of valuation beyond pricing. A persistent limitation in current valuation studies is the underutilization of temporal dynamics. Time is often treated as a static or peripheral input, thereby overlooking its critical role in shaping market behaviours during disruptive events such as pandemics, environmental crises, or geopolitical shifts. As Mora-Garcia et al. (2022) highlight, price elasticity and volatility are rarely uniform across time, and models lacking temporal segmentation fall short in adapting to these transitions.

In summary, the literature confirms a paradigm shift from static to adaptive valuation frameworks and from linear to nonlinear, interpretable machine learning methodologies. However, limitations in temporal awareness, explainability, and geographic scalability continue to restrict the practical and academic potential of current models. By introducing a temporally segmented, explainable, and spatially scalable methodology, the present study contributes a robust and forward-looking approach to real estate valuation in volatile conditions.

Table 1 provides a structured comparison of these key contributions, summarizing their input parameters, machine learning techniques, and contextual focus. It underscores the need for models that incorporate temporal segmentation, spatial diversity, and algorithmic comparability.

Table 1 provides a comprehensive summary of contemporary studies utilizing modern methodologies in real estate valuation. The table categorizes prior research based on the reference authors, the types of parameters considered, and the machine learning techniques employed. A diverse range of parameters is evident across the studies, including structural, spatial, legal, local, and economic characteristics. Many machine learning techniques have been applied in these studies. This comparative overview highlights the evolving landscape of real estate valuation methodologies, showcasing how different models have been utilized to analyse market dynamics across varying datasets and conditions. Moreover, there is a notable body of research employing contemporary methodologies to assess the relationship between the pandemic and property valuation. One such noteworthy study is that of Mora-Garcia et al. (2022), in which they undertook an in-depth analysis of the pandemic's impact on the real estate valuation process using machine learning techniques. Within their study, Mora-Garcia et al. (2022) specifically focus on the identification of optimal MLAs for predicting house prices in Alicante, Spain, while concurrently assessing the influence of the COVID-19 pandemic on these property valuations.

This study aims to evaluate the efficacy of machine learning techniques in forecasting market dynamics and managing real estate market processes during the pandemic. It makes a valuable contribution to the existing literature by conducting valuation on a large urban scale and incorporating the temporal dimension into the modeling process.

Table 1. Studies conducted with modern methods

Reference	Parameters	Machine learning techniques
Park and Bae (2015)	Structural data, public school rating, and mortgage rate data	C4.5, RIPPER, and Naive Bayes
Baldominos et al. (2018)	Structural and spatial features	K-Nearest Neighbors, Multilayer Perceptron, Regression Tree Ensembles, and Support Vector Regression
Dimopoulos and Bakas (2019)	Structural and spatial data	Random Forest and Regression Analysis
Pai and Wang (2020)	Structural and spatial data	Support Vector Machines, Classification and Regression Trees, General Regression in Neural Networks, and Back Propagation Neural Networks
Louati et al. (2022)	Structural and spatial features	Decision Tree, Random Forest, and Linear Regression
Tchuente and Nyawa (2022)	Structural and spatial data	Artificial Neural Network, Random Forest, K-Nearest Neighbors, Linear Regression, Support Vector Machine, Adaptive Boosting and Gradient Boosting
Chou et al. (2022)	Structural and spatial data	Artificial Neural Networks, Support Vector Machine, Classification and Regression Tree (CART), and Linear Regression
Gao et al. (2022)	Structural data, spatial data, and property data	Linear Regression Model, Support Vector Regression, Tree-Based Model, Gradient Augmentation Based Model, and Neural Networks
Mora-Garcia et al. (2022)	Structural data, spatial data, and time data	Gradient Boosting Regressor, Extreme Gradient Boosting, Light Gradient Boosting Machine, Bagging Random Forest, and Extra Trees Regressor
Iban (2023)	Price management, neighborhood categorical, physical feature, topographical features, spatial characteristics	Random Forest, XGboost, LightGBM, and Gradient Boosting
Aydınoğlu et al. (2023)	Parcel features, environmental features, independent section features	Multiple Linear Regression, Generalised Linear Models, Support Vector Machines, Decision Trees, and Random Forest
Barut and Bilgin (2023)	Structural and spatial data	KNIME Platform, Artificial Neural Networks, and Polynomial Regression
Baur et al. (2023)	Legal features, structural features, spatial features, local features	Linear Regression, Support Vector Regression, Random Forest, and Gradient Boosting Algorithm (Lightgbm)
Alkan et al. (2023)	Structural and spatial data	Support Vector Machines, K-Nearest Neighbors, and Random Forest
Calainho et al. (2024)	Structural features, spatial features, local features, and economic features	Ordinary Least Squares, Extreme Gradient Boosting Tree, Support Vector Regression, Neural Networks Using Model Averaging, and Cubist
Sharma et al. (2024)	Structural and economic features	XGBoost
Zhao (2024)	Time series data and structural features	ARIMA, Random Forest
Genc et al. (2025)	Structural, locational and demographic features	Linear Regression, Random Forest, Support Vector Machine, Regression Trees, Gaussian Process Regression, Artificial Neural Network, Least-Squares Boosting
Hoxha (2025)	Structural and spatial features	Linear Regression, Decision Trees, K-Nearest Neighbors, Support Vector Regression
In this study	Structural data, spatial data, and time data	Random Forest, Decision Tree, K-Nearest Neighbors, and Artificial Neural Network

2. Material and method

2.1. Study area: Niğde and its representativeness

Niğde is situated in the Central Anatolia Region of Turkey (Figure 1). In 2022, its population stood at 365,419, with 60% living in urban areas and 40% in rural settlements. This demographic structure makes Niğde a valuable setting for examining how the pandemic has influenced real estate markets that encompass both urban and rural characteristics. Being a mid-sized city, Niğde allows for clearer observation of external factors such as health crises and policy changes compared to large metropolises where multiple overlapping dynamics may obscure specific trends.

The local economy primarily relies on agriculture and small-scale industries, providing a relatively self-contained environment to assess how extraordinary conditions like

Figure 1. Niğde city study area

COVID-19 shape demand, pricing, and other market behaviors. Niğde's moderate scale, combined with relatively accessible data, enables a citywide structural and spatial evaluation of the ways in which pandemic-related factors affect property valuation. Although Niğde's demographic and economic attributes do not represent all regions, these findings can still offer insights, particularly for other mid-sized cities in Central Anatolia with similar characteristics. However, caution is advised when extending the conclusions to significantly larger urban centers or areas with markedly different socioeconomic profiles.

2.2. Data sets

The data collection phase was meticulously structured to ensure comprehensive temporal, structural, and spatial coverage. Data were gathered in alignment with predefined criteria and time periods to facilitate crisis-sensitive modeling. The inclusion of both pre- and post-pandemic datasets enables a comparative longitudinal assessment, which is critical for understanding shifts in valuation dynamics.

In the city of Niğde, the acquisition of data to elucidate the changes in real estate values during the pandemic unfolded systematically, comprising three key stages:

- Data Compilation and Limitations: Data for Niğde's real estate market was collected from online sources for two distinct periods, 2019 (pre-pandemic) and 2022 (post-pandemic), resulting in 338 property records per year. Hence, a total of 676 records was assembled, each encompassing structural attributes such as floor area (m^2), floor number, heating system, association fees, room count, building age, bathroom count, credit eligibility, and façade characteristics. These data were filtered to include only consistent and verified entries, ensuring a high-quality dataset.

  Despite the careful selection process, the sample size remains relatively limited, which may constrain the statistical power and generalizability of the findings. The data reflect Niğde-specific conditions, and results should therefore be interpreted with prudence, especially when considering applicability to other cities or regions with different demographic or economic contexts. Future research could enhance

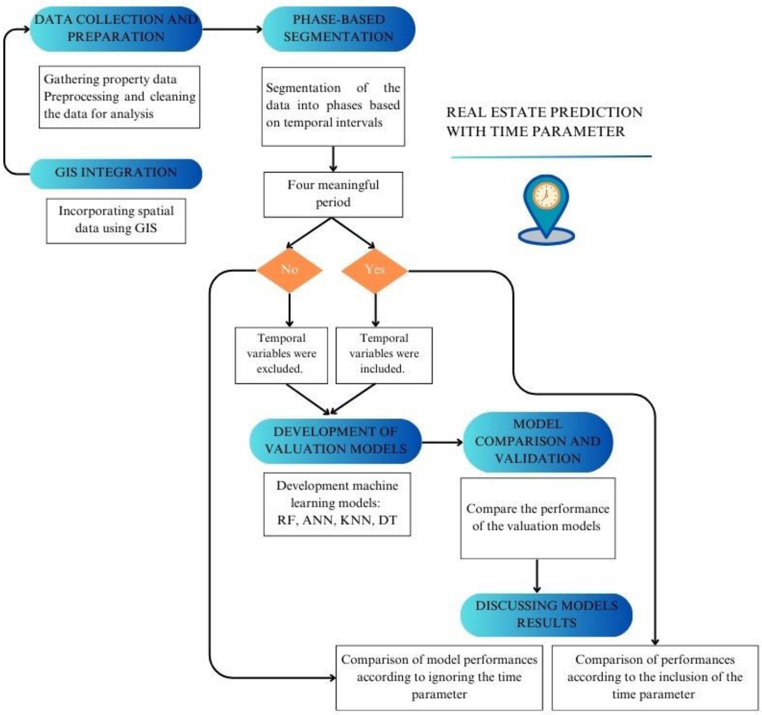

Figure 2. Workflow of the data collection and preparation process

the reliability of these results by incorporating larger datasets or encompassing multiple mid-sized cities with comparable characteristics. Figure 2 illustrates the overall data collection and preparation workflow employed in the study, including acquisition, cleaning, and integration stages. The diagram outlines each stage in the dataset development process, from raw data acquisition to temporal segmentation and final integration into machine learning models.

- Spatial Analysis: In the spatial analysis process conducted using ArcGIS 10.7 software, buffer and near analyses were applied to evaluate the relationship between real estate properties and environmental or locational factors. Buffer analyses were used to examine how properties are positioned within specific distances of key spatial components (e.g., educational institutions, healthcare facilities, commercial areas). Near analyses, on the other hand, calculated the direct distances of each property to these factors, providing a more detailed model of spatial dependencies. Through these methods, the locational attributes of properties were integrated into the spatial dataset, enhancing the overall accuracy of the valuation model.

Figure 3 visualizes the implementation process and results of the spatial analyses. This figure illustrates the distances of properties from essential spatial elements such as educational institutions, healthcare facilities, government offices, socio-cultural areas, sports facilities, industrial zones, afforestation areas, and commercial districts. The color scales and density distributions in the maps represent the accessibility levels of properties to these factors and their spatial dependencies. These analyses scientifically reveal how property values are shaped by environmental factors and highlight the significance of spatial components in real estate valuation processes.

- Incorporating the Temporal Dimension: To evaluate the pandemic's impact more dynamically, the dataset was segmented into distinct time periods to reflect variations in policy measures, public sentiment, and overall pandemic severity. Some effects emerged rapidly, whereas others became apparent over time, underscoring the significance of adopting a longitudinal perspective. This temporal segmentation allowed for an in-depth analysis of how property valuations evolved during and following critical pandemic milestones such as lockdowns, reopening phases, and policy announcements.

Finally, although Niğde's mid-sized market structure provides a manageable study, it does not capture the full range of economic or cultural variables present in larger metropolitan areas. The findings thus offer an empirical basis for understanding pandemic-induced changes in a mid-sized city, with potential relevance to regions sharing similar scale and characteristics, but they should be extrapolated to vastly different contexts with caution.

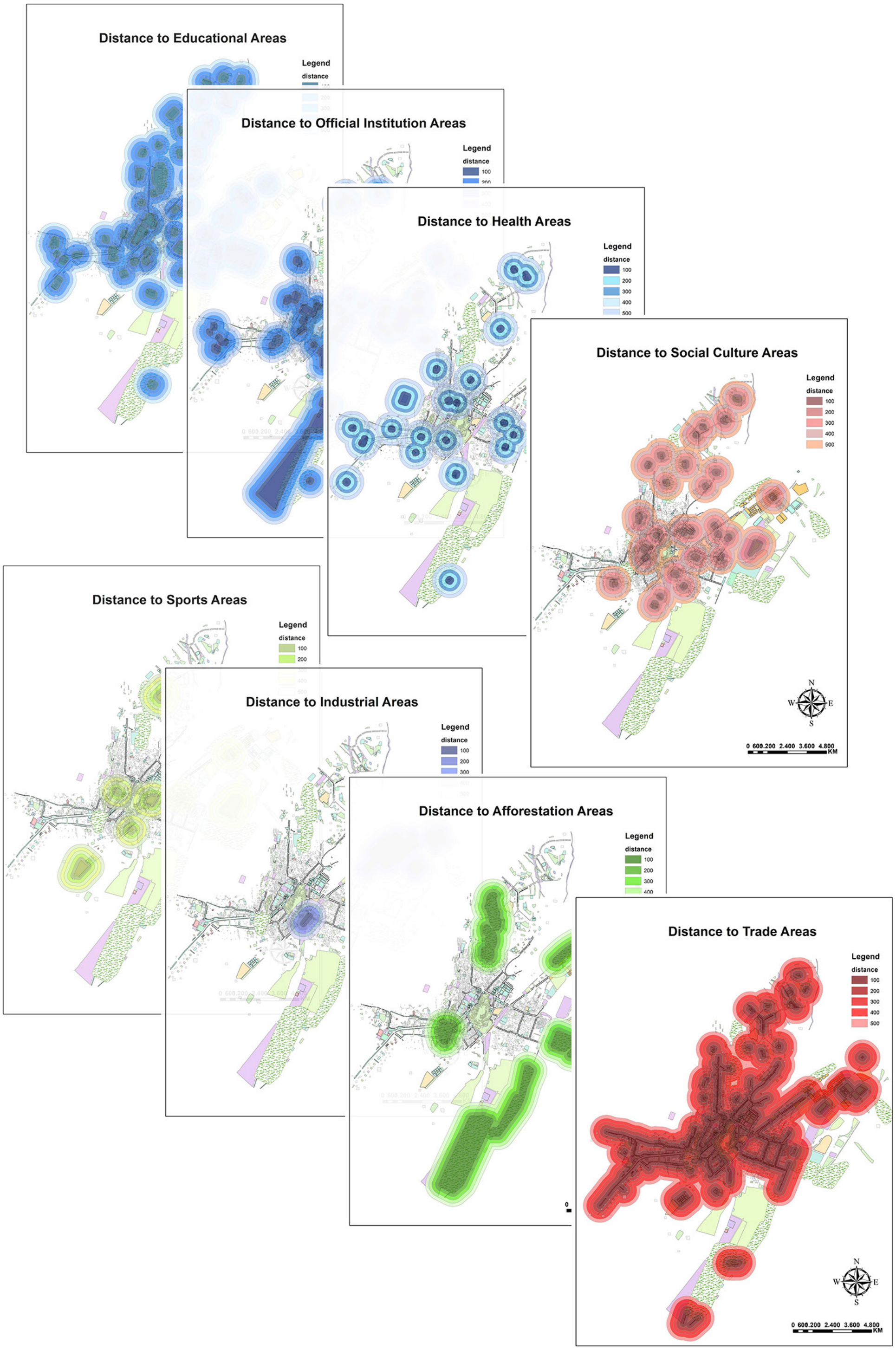

Figure 3. Spatial analyses of the real estate

2.3. Method

In this study, MLAs, specifically RF, DT, KNN, and ANN were employed for a comprehensive real estate valuation analysis focused on the impact of the pandemic in Niğde city. The modeling process encompassed data from the years 2019 and 2022, considering the structural and spatial attributes of 676 real estate properties, in addition to the time parameter. To elaborate further, the initial step involved modeling the time parameter about other independent variables within the dataset. Subsequently, the entire dataset underwent modeling using machine learning techniques. The methodological framework of this study is visually depicted in Figure 4.

The applied methodology is very important for managers to monitor trends in the real estate market with artificial

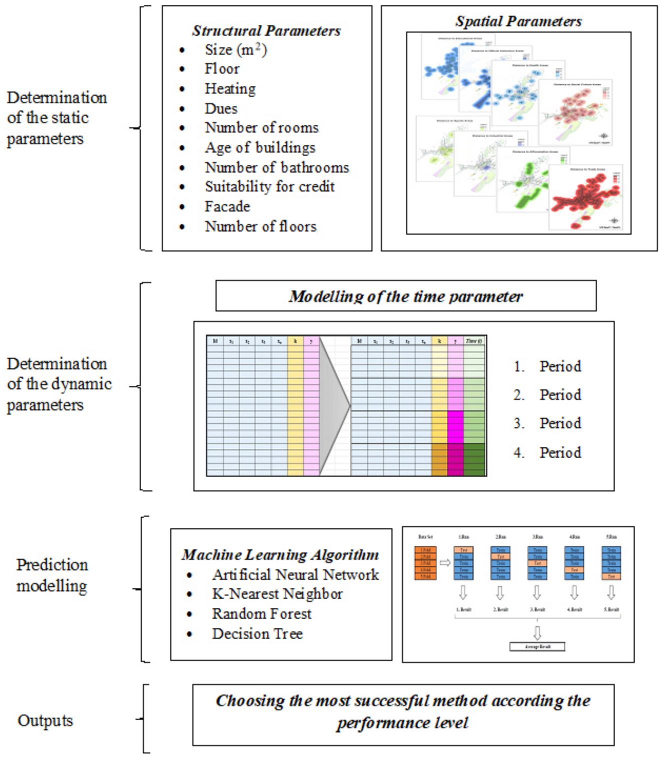

Figure 4. The methodological approach of the study

intelligence, to conduct competition and risk analysis, and to objectively analyse the effects by evaluating them temporally in adverse and extraordinary situations such as pandemics, economic crises, earthquakes and wars. Thus, local governments can adapt to changes in the market, plan infrastructure projects and zoned land demands correctly, and create planning strategies for the prevention of regional inequalities and sustainable development of cities.

2.3.1. Modelling the time parameter

In this study, the modelling of the time parameter involved a two-step process. First, the independent variables, which include the structural and spatial characteristics of the real estate properties, were scored and subsequently normalized. These normalized independent variables are denoted as x_1, x_2, ..., x_n. The algebraic total score for each real estate's normalized independent variable is represented as k (Equation 1). The study then proceeded to compute the average of these k values (Equation 2) and the average market value (Equation 3). These averages were then juxtaposed with the normalized independent variables and market values of each real estate, resulting in categorization based on the respective time periods of sale.

In this study, the time parameter is categorized into four distinct periods based on the k value, which represents the characteristics and market values of real estate (Figure 5). These periods correspond to different market phases: pre-pandemic, early pandemic, adaptation, and recovery. Each phase is defined according to its economic characteristics and validated through fluctuations observed in structural trends and market values.

The pre-pandemic period reflects stable market conditions with low volatility. The early pandemic phase captures abrupt price fluctuations and heightened uncertainty. The adaptation phase represents the market's adjustment to new conditions, characterized by shifts in demand and evolving buyer preferences. Finally, the recovery phase signifies a return to relative stability as economic confidence is restored. These classifications were determined by analysing how market trends evolved over time, ensuring alignment with real-world economic shifts rather than arbitrary date ranges.

The indices used and Equations (1), (2) and (3) are expressed as follows:

$$\sum_{i=1}^{n} x_n = k; \tag{1}$$

$$\frac{\sum_{i=1}^{n} k}{n} = m; \tag{2}$$

$$\frac{\sum_{i=1}^{n} y_n}{n} = p, \tag{3}$$

where x_1, x_2, ..., x_n is normalized independent variables representing the structural and spatial characteristics of each real estate unit; k is the algebraic total score of the normalized independent variables for a single real estate unit. It is calculated by summing all x_j values and represents the

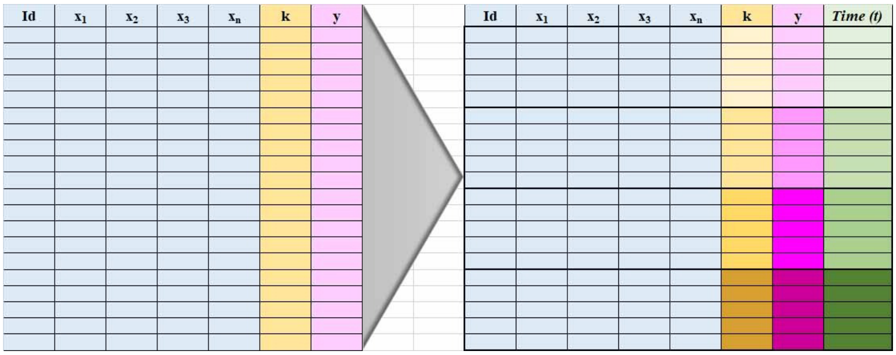

Figure 5. Categorization of the time period

combined property profile; y_n is the market value (dependent variable) of the n-th real estate unit; m is the number of real estate units within a specific time period. It is used to calculate averages of scores and values; p is the total market value of all real estate units within a given time period. $p = \sum y$; n is the total number of independent variables (criteria) included in the model.

2.3.2. Modelling of value estimation

Random forest algorithm

The RF algorithm is a machine learning algorithm among ensemble-based classification methods (Mursalin et al., 2017). This algorithm is aimed to determine the class with the best discrimination ability in a random feature subset (Alkan et al., 2023). In the working principle of the RF algorithm, firstly, more than one decision tree is created, and the result is produced by taking the average values in these decision trees. The trained "*k*" trees are incorporated into an RF algorithm model, as expressed in Equation (4) (Chen et al., 2016).

$$H\left(X,\theta_j\right)=\sum h_i\left(x,\theta_j\right),\left(j=1,2,\ldots,m\right)k_i=0. \qquad (4)$$

In Equation (4), $H(X, \theta_j)$ is a meta–Decision Tree classifier (Salman & Aksoy, 2022). While x represents the input feature vector of the training dataset, θ_j is a uniformly distributed and independent random vector that determines the growth process of the tree. The RF algorithm is formed because of the combination of "*k*" independently randomly generated decision trees (Salman & Aksoy, 2022). Each of the samples belonging to the test dataset is predicted by the decision trees forming the forest. Classification is performed according to the prediction results obtained from these trees (Chen et al., 2016).

K-nearest neighbors algorithm

The KNN algorithm was developed by Cover and Hart in 1967 with their "Nearest Neighbors Pattern Classification" studies (Dilki & Başar, 2020; Hu et al., 2016). The KNN algorithm is a versatile algorithm widely used in the literature and used in classification and regression problems based on lazy learning (Yao & Ruzzo, 2006).

The working principle of the KNN algorithm is to calculate and compare the distance between new data points of an unknown class and other data in the training set to classify them (Tang et al., 2023). According to the calculated distance and comparison, the most appropriate class is determined for the unclassified data. In the process of classifying each new data, the entire training set is treated as a classifier by going back to the raw training data (Dilki & Başar, 2020).

The number of neighbors (k), distance criterion and weighting method are effective and important parameters in the performance of the KNN algorithm.

In the KNN algorithm, classification is performed depending on the value of the k parameter (Taşcı & Onan, 2016). Here, the class value k depends on the size and structure of the data, but for k = 1, only the class with the nearest neighbor is assigned, while the number k can be up to n classes. In a classification up to n classes, all data in the data set are considered. If the class value is too large than it should be, the data that are not very similar are included in the same group and the accuracy value decreases. If the class value is smaller than it should be, some possible classes are excluded, and the class accuracy decreases (Dilki & Başar, 2020). For this reason, in determining the number of k neighbors, a distance criterion should be used to calculate the distance between the new data with an unknown class and the other data in the training set.

Euclidean distance given in Equation (5) is frequently used to calculate the distances of neighborhoods (Güvenç et al., 2021; Hu et al., 2016; Zamri et al., 2022).

$$d\left(x,y\right)=\sqrt{\sum_{i=1}^{n}\left(x_1-y_1\right)^2}. \qquad (5)$$

Decision tree algorithm

Decision trees are fundamental data mining algorithms utilized in classification, pattern recognition, and regression models (Demirel, 2019; Kavzoğlu & Çölkesen, 2010). The fundamental architecture of a DT comprises three key components: a node containing the data, internal nodes (branches), and terminal nodes (leaves). The classification process in decision trees encompasses two primary stages:

training and classification. During the training phase, the model is developed by subjecting it to the classification method using a training dataset. The tree structure is established based on this training data, and a series of inquiries are posed regarding the data. The DT formulates decision rules in response to the answers to these inquiries. This process continues until nodes and leaves without branches are identified (Foody, 1995). Subsequently, test data are employed to assess the accuracy of the model learned with the training data (Demirel, 2019). The test data enters through the root of the tree and traverses to lower nodes according to the test results, continuing until they reach a leaf node (Kavzoğlu & Çölkesen, 2010).

The pivotal stage in decision trees lies in determining the quality, criterion, or attribute that will guide this classification, essentially defining the branching structure within the tree. The absence of a new discriminative criterion hinders the formation of new branches. To create new branches and segregate sub-datasets, fresh discriminative criteria must be identified. Various criteria have been proposed to address this issue, including information gain (Cover & Thomas, 1991) and information gain ratio (Quinlan, 1993), Gini index (Akçetin & Çelik, 2014; Breiman et al., 1984), Towing rule (Breiman et al., 1984), and Chi-Square contingency table statistic (Mingers, 1989). These criteria help determine which distinguishing attribute or criterion will shape the branching and structure of the tree.

Artificial neural networks

Artificial neural networks represent a computational model, both mathematically and graphically, within a computer environment. They draw inspiration from the structure and functioning of neurons in the human brain, including the interconnections and working mechanisms of these neurons (Boğar & Özsüt Boğar, 2017; Jain et al., 1996; Kunt, 2014). The architecture of an ANN comprises several key components, namely inputs, weights, a summation function, an activation function, and an output. Inputs represent external information received by the artificial neural cell, while weights determine the influence and significance of these inputs on the cell's functioning. The summation function computes the net input to the cell, and the activation function, also known as the efficiency, threshold, or transfer function, transforms the results of the summation function into an output. The output of the cell is the value determined by the activation function (Boğar & Özsüt Boğar, 2017; Öztemel, 2003). A mathematical representation of an artificial neural network model is depicted in Figure 6.

Figure 6 illustrates the mathematical model of an artificial neuron, depicting the relationship between input values, weight coefficients, the summation function, the activation function, and the final output. The figure visually represents how input signals are weighted by corresponding coefficients, summed, and processed through an activation function after subtracting a threshold value. This process determines whether the neuron activates and transmits the signal further in the network. The diagram effectively demonstrates the computational mechanism underlying

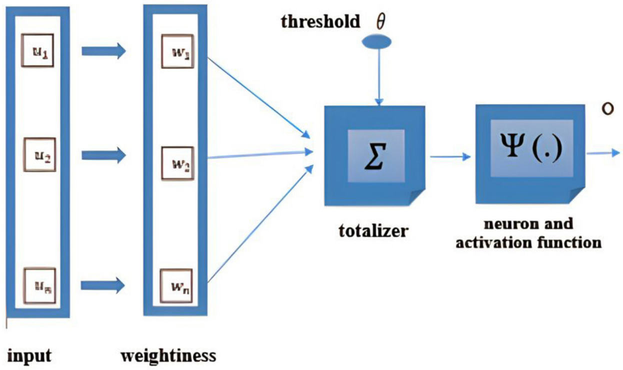

Figure 6. Mathematical model of the neuron (Fırat & Güngör, 2004)

artificial neural networks, aligning with the mathematical expressions provided in Equations (6) and (7).

$$S = w_1 \cdot u_1 + w_2 \cdot u_2 + w_3 \cdot u_3 + \ldots + w_n \cdot u_n - \theta = \sum_{i=1}^{n} w_i \cdot u_i - \theta. \tag{6}$$

$$O = \Psi(S). \tag{7}$$

According to these equations, S is the total function; u_i is the input function; w_i is the weighting factor; O is the output function; $\Psi(S)$ is the activation function; θ is the threshold value.

Each neuron acts as a simple trigger by switching on or off according to the level and change of the input signal (Fırat & Güngör, 2004). While these processes are taking place, neurons weigh the input information process them in a function and give the output. Other neurons connected to the cell receive this output as input information. In this way, the ANN algorithm consists of two stages: learning and testing.

2.3.3. Model training and testing

The dataset employed for assessing the performance of MLAs was partitioned into training and test data subsets. This data division was executed in four distinct periods within the year, with each period evaluated independently. Given the limited volume of data within each period, a direct data split at a fixed ratio (e.g., training: 75% and test: 25% or training: 80% and test: 20%) would result in suboptimal training and subsequently lead to reduced testing performance. Hence, in this study, the k-fold cross-validation approach was adopted. This approach afforded each sample in the dataset the opportunity to partake in both the training and testing phases. In this study, a value of 5 was chosen as the number of folds. The operational concept of the cross-validation approach is graphically depicted in Figure 7.

As depicted in Figure 7, in the first iteration, the first fold is assigned as the test set, while the remaining folds are used for training. In the second iteration, the second fold becomes the test set, with the rest used for training. This process continues for five iterations, ensuring that each subset is utilized for testing at least once. In the figure, arrows and color-coded sections visually represent

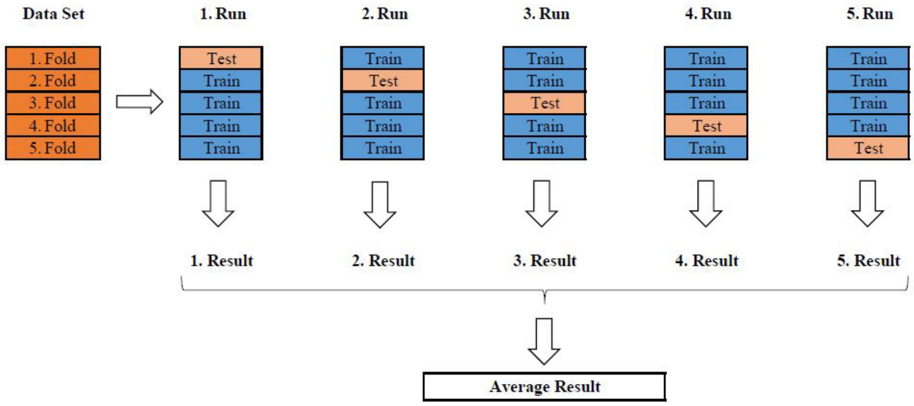

Figure 7. Working principle of cross-validation

how training and test sets change in each iteration. This visualization clearly presents the fundamental principles of cross-validation, illustrating how the dataset is managed and how the validation process operates systematically.

In the process of cross-validation, the dataset is partitioned into equal segments based on the predetermined number of folds. Subsequently, the algorithm is executed iteratively, with each segment serving as the test data while the remaining segments (k-1 in total) constitute the training data. Performance metrics are recorded for each of the test segments. Ultimately, the overall algorithmic performance is derived by calculating the average of the successes achieved across all test segments. This cross-validation approach was consistently applied across four distinct algorithms, all operating under identical conditions.

After the data were separated according to the cross-validation principle, the specific parameters of the algorithms were adjusted. In the ANN method, the number of iterations was set as 250, the number of neurons in the hidden layer was set as 40, and the activation function was set as ReLu. In the RF method, the number of trees was set to 10 and the depth was set to 5. In another method, the KNN algorithm, the number of nearest neighbors (k) parameter was set to 5 and Euclidean distance was used as the similarity criterion. In our last method, the DT approach, the minimum number of nodes in a leaf was determined as 2.

2.3.4. Performance metrics for predictions

In the study, R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) metrics were used. R^2 is a performance measure that measures how successful the model built with training data is on test data. MAE represents the average of the absolute differences between actual values and predicted values. RMSE, one of the most widely used performance measures, is a metric that measures the magnitude of the error between the model-predicted values and the actual values by finding the difference between them. R^2, MAE, and RMSE equations are given in Equations (8), (9), and (10) respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2}; \tag{8}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|; \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}. \tag{10}$$

In the equations, y_i represents the actual values, $\hat{y}_i$ represents the predicted values, and n represents the number of data points.

In addition, COD and PRD metrics defined by IAAO were also used in the study to determine model performances. COD measures how consistent the valuation model's predictions are with actual values. COD represents the ratio of the standard deviation of the predicted values to the actual value. In areas with homogeneous houses with similar characteristics, COD should be between 5%–10% (International Association of Assessing Officers [IAAO], 2013). In areas with heterogeneous houses with different characteristics, the COD value should be between 5%–15% (IAAO, 2013). PRD is a metric that expresses the difference between the prices predicted by a valuation model and the actual prices in percentage terms. PRDs should be between 0.98 and 1.03 (IAAO, 2013). The COD value is given in Equation (11) and the equations giving the PRD value are given in Equations (12) and (13).

$$COD = \frac{100}{m} x \left(\frac{\sum_{i=1}^{n} \left| \frac{y_i}{\hat{y}_i} - m \right|}{n-1} \right); \tag{11}$$

$$m = median\left(y_i / \hat{y}_i\right); \tag{12}$$

$$PRD = \frac{mean\left(y_i / \hat{y}_i\right)}{\sum_{i=1}^{n} y_i / \sum_{i=1}^{n} \hat{y}_i}. \tag{13}$$

Error and error rate are fundamental concepts employed to assess the performance of machine learning models. Error, in this context, signifies the disparity between the predicted outcome generated by a machine-learning model and the corresponding actual outcome. Essentially, the greater the discrepancy between the model's predicted result and the actual result, the more substantial the error. On the other hand, the error rate represents the proportion of accurate predictions made by the model. It is computed as the ratio of incorrect predictions to the total number of correct predictions.

3. Results and discussion

In the study, the results of the actual and predicted values for the years 2019 and 2022 are examined using four different algorithms (RF, DT, K NN, ANN) according to the inclusion and exclusion of the time parameter (in the form of periods) in the modelling. Success metrics, error, and error rates were calculated and compared.

3.1. Comparison of performances according to the inclusion of the time parameter in the modelling

The results of the models used for 2019 and 2022 and the actual and predicted values for 4 periods are compared in Figure 8. This figure enables a clear assessment of how each model captures market dynamics across different time frames and how prediction accuracy varies over time. Notably, the degree of overlap between predicted and actual values highlights the impact of temporal segmentation on model performance.

The models used and the performance metrics for the periods are shown in Table 2.

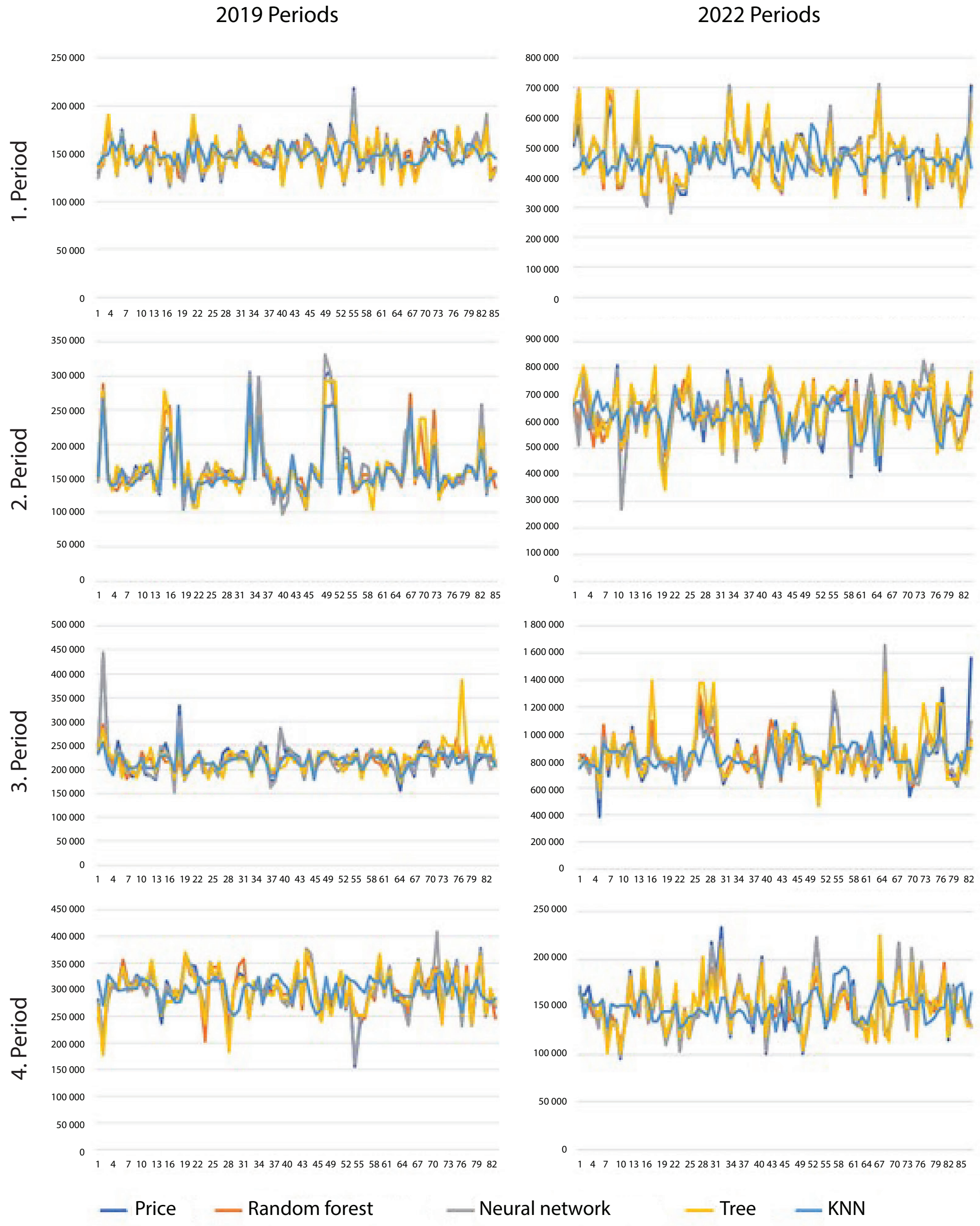

Figure 8. Results of actual and predicted values for the periods of 2019 and 2022

Table 2. Models and performance metrics used for the years 2019 and 2022

Periods	Metrics	2019				2022			
		RF	ANN	DT	KNN	RF	ANN	DT	KNN
1. Period	MAE	6100	1945	6582	13181	19636	11234	23648	86248
	RMSE	8006	2679	8660	17627	29031	15323	36326	104787
	R^2	0.808	0.979	0.775	0.069	0.897	0.971	0.838	–0.344
	COD	9.131	6.344	9.454	8.898	4.056	7.527	4.861	18.286
	PRD	1.000	1.000	1.000	1.001	1.000	1.001	1.003	1.010
2. Period	MAE	14044	2359	16014	11301	39038	13216	45313	83157
	RMSE	19766	4527	24024	16811	52042	16927	59675	103428
	R^2	0.807	0.990	0.716	0.861	0.763	0.975	0.689	0.066
	COD	8.137	6.414	9.405	6.558	6.440	7.175	7.440	12.987
	PRD	0.998	1.001	1.005	0.993	0.996	1.000	1.002	1.004
3. Period	MAE	15752	8364	20914	16088	73328	54402	87925	122014
	RMSE	26408	10522	34074	27035	127618	113502	152003	165327
	R^2	0.460	0.914	0.101	0.434	0.477	0.586	0.257	0.122
	COD	7.085	8.927	8.997	7.228	8.597	5.852	9.673	14.902
	PRD	0.998	1.002	1.005	0.998	1.002	1.002	1.014	1.003
4. Period	MAE	13211	9024	13214	32986	91689	50083	99947	235662
	RMSE	19591	16716	18548	41925	130871	90701	139626	298243
	R^2	0.768	0.831	0.792	–0.061	0.784	0.896	0.754	–0.124
	COD	4.615	7.952	4.682	11.259	5.959	8.242	6.471	16.043
	PRD	1.001	1.001	1.002	1.003	0.997	1.001	1.001	1.007

Table 3. Errors and errors rates

Year	Period	RF		ANN		DT		KNN	
		Error	Error rate (%)	Error	Error rate (%)	Error	Error rate (%)	Error	Error rate (%)
2019	1	6100	4.07	1945	1.33	6582	4.40	13181	9.02
	2	14044	8.16	2359	1.41	16014	9.60	11301	6.40
	3	15752	6.69	8364	3.82	20914	9.05	16088	6.87
	4	13211	4.92	9024	3.08	13214	4.91	32986	11.85
2022	1	19636	4.25	11234	2.51	23648	5.00	86248	19.13
	2	39038	7.06	13216	2.19	45313	8.09	83157	14.32
	3	73328	8.42	54402	6.10	87925	10.10	122014	14.67
	4	91689	6.03	50083	3.39	99947	6.57	235662	15.60

Table 2 shows the real estate market value prediction performance of RF, ANN, DT and KNN algorithms for four different periods in 2019 and 2022. The MAE, RMSE, R^2, COD and PRD values calculated for each period were compared in terms of the models' predictive power, stability and sensitivity to distribution.

According to the results, the ANN model showed the most successful performance by achieving the highest R^2 scores with the lowest MAE and RMSE values in both 2019 and 2022. Additionally, the COD values (5%–10%) and PRD values (0.98 to 1.03) remained within the acceptable range, further validating the model's reliability.

Among the applied methods, the neural network-based approach demonstrated superior performance in all periods. This success can be attributed to the following factors:

- Capturing complex relationships: The deep learning structure effectively models intricate connections between structural and spatial data, allowing for a more comprehensive real estate valuation.
- Strong generalization ability: When trained with large datasets, neural networks produce highly generalizable results, enhancing accuracy in large-scale real estate valuation studies.

The error and error rates for the models used and the period slices are shown in Table 3.

Table 3 shows the errors and error rates of four different machine learning models in 2019 and 2022 when predicting real estate prices. The error indicates the difference between the model's predicted result and the actual result, while the error rate indicates the proportion of correct predictions made by the model.

The analysis reveals that the ANN model had the lowest error and error rates compared to other models in all periods of both years. In all periods of 2019 and 2022, the ANN model displayed an impressive performance by keeping the error rate between 1.33% and 6.10%. The KNN model, on the other hand, stands out with its high error rates (the highest was 19.13%) and large error values, especially in 2022. Although the RF and DT models generally produced more consistent and balanced results, neither model could achieve the high accuracy and low error rates offered by the ANN model.

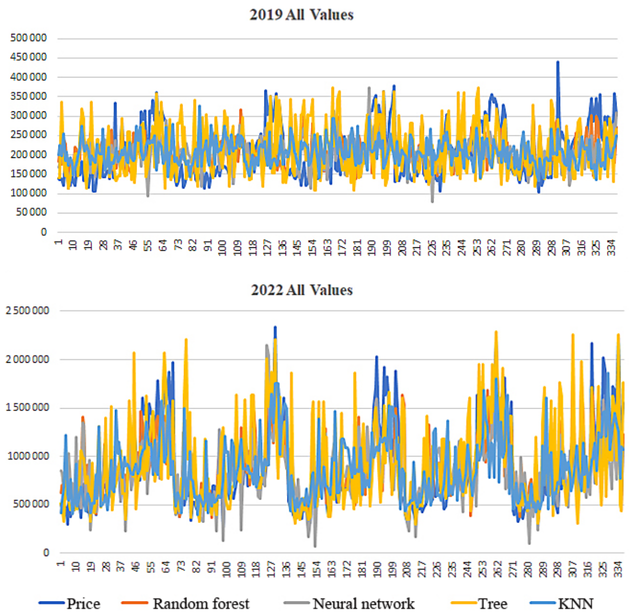

Figure 9. Results of actual and predicted values covering 2019 and all of 2022

3.2. Comparison of model performances according to ignoring the time parameter

For 2019 and 2022, the results of the actual and predicted values for the modelling performed without using a period to cover all years are compared in Figure 9. The figure illustrates how the models responded to market dynamics and to what extent the predicted values aligned with actual prices. It is observed that market fluctuations in 2022 were more pronounced compared to 2019, highlighting the variability of the pandemic's impact on the real estate market over time and how model performance varied across different periods.

The performance metrics for the models used and the modelling performed for all years are compared in Table 4.

According to Figure 9 and Table 4, RF is the most successful algorithm in terms of success metrics (R^2 = 0.510, COD = 27.213, PRD = 1.017) when the real estate value estimates for 2019 are evaluated according to all year data and the time parameter is ignored.

According to Figure 9 and Table 4, RF is the most successful algorithm in terms of success metrics (R^2 = 0.509, COD = 27.145, PRD = 1.009) when the real estate value estimates for 2022 are evaluated according to all year data and the time parameter is ignored.

According to Table 4, the reasons for the success of the RF algorithm in the data set covering the year scale compared to other algorithms can be expressed as follows. RF is a holistic method created by combining multiple decision trees. This means that it has a better generalization ability and a lower variance thanks to the combination

Table 4. Models and performance metrics used for the full dataset for 2019 and 2022

Year	Metrics	RF	ANN	DT	KNN
2019	MAE	53510	50492	63603	58804
	RMSE	66808	61135	82755	72614
	R^2	0.510	0.205	–0.456	–0.121
	COD	27.213	25.181	32.058	30.303
	PRD	1.017	1.009	1.077	1.019
2022	MAE	235637	276126	280543	251523
	RMSE	310506	348349	406310	335301
	R^2	0.509	0.382	0.159	0.427
	COD	27.145	37.607	30.084	29.129
	PRD	1.009	0.996	1.082	1.011

Table 5. Errors and error rates

Year	RF		ANN		DT		KNN	
	Error	Error rate (%)	Error	Error rate (%)	Error	Error rate (%)	Error	Error rate (%)
2019	53510	27.44	50492	26.11	63603	33.25	58804	29.81
2022	235637	30.25	276126	34.79	280543	35.44	251523	32.05

of multiple trees. It also provides a good model fit while minimizing the overfitting problem. For this reason, when examined as a whole year, the generalization ability and minimization of the fit problem make the RF algorithm successful compared to other algorithms.

The error and error rates for the models used and the modelling performed for all years are shown in Table 5.

According to Table 5, when the whole data set is analysed on a year scale; it is seen that ANN has the least error rate for 2019, and the RF algorithm has the least error rate for 2022.

3.3. Evaluation of model results within the scope of literature

In this study, real estate valuation is performed using various machine learning based algorithms, and especially ANN and RF models stand out with their high performance. Real estate valuation studies in the literature using machine learning algorithms were analysed and a comparison was made between this study and the literature. Factors such as normalisation of data, exchange rate differences and timing of data collection affect the values, and the R^2 metric is less affected by these factors compared to other metrics (Genc et al., 2025). For this reason, the results obtained using the R^2 metric are compared with the literature.

In the study, when the temporal variable is included in the model, the highest accuracy was obtained with the ANN algorithm in 2019 (R^2; 1st period: 0.979, 2nd period: 0.990, 3rd period: 0.914, 4th period: 0.831) and 2022 (R^2; 1st period: 0.971, 2nd period: 0.975, 3rd period: 0.586, 4th period: 0.896). In the scenario where the temporal variable is not included in the model, the most successful result was obtained with the RF algorithm in 2019 (R^2: 0.510) and 2022 (R^2: 0.509).

When similar studies in the literature are examined, Chou et al. (2022) (R^2: 0.948), Türkan et al. (2023) (R^2: 0.849) and Genc et al. (2025) (R^2: 0.669) values were reported for the ANN model. For the RF model, Alkan et al. (2023) (R^2: 0.696), Aydınoğlu et al. (2023) (R^2: 0.284) and Genc et al. (2025) (R^2: 0.724) values were reported. In this context, when the R^2 values obtained in our study are evaluated in terms of both ANN and RF models, they reveal that they exhibit comparable performance to many studies in the literature, and even higher in some states. When a general evaluation is made, it can be said that the proposed models give quite satisfactory results, especially in scenarios where the effect of the temporal variable is taken into consideration.

In recent years, there has been a surge in research examining the repercussions of the pandemic on the real estate sector within the literature. These studies encompass predictions regarding investor and household behaviors, the strategic planning of future construction investments, and the enhancement of professional knowledge and skills within the real estate sector while supporting its workforce (Grybauskas et al., 2021; Kaklauskas et al., 2021; Ngoc et al., 2020).

Among these studies, Ngoc et al. (2020) investigated the opportunities and challenges confronting real estate brokerage companies in Vietnam following the COVID-19 pandemic. This research sheds light on the prevailing circumstances of the pandemic, pinpointing opportunities and challenges that are present within the real estate brokerage market. The proposed solutions include companies transitioning to online channels, implementing digital marketing strategies, and reducing operational costs.

Kaklauskas et al. (2021) aimed to explore the emerging changes within the real estate market, formulate guidelines for real estate development, and identify key trends. The research outcomes illustrate that the COVID-19 pandemic has influenced investor behavior across various property types, resulting in shifts in investment strategies.

In their study, Grybauskas et al. (2021) examined the impact of the COVID-19 pandemic on the real estate sector, particularly focusing on the factors influencing apartment prices. By utilizing a dataset derived from property advertisements in the city of Vilnius, they applied 15 distinct machine learning models, with the XGB (Extreme Gradient Boosting) model producing the most accurate results. The variable TOM emerged as the most influential and consistent factor in predicting price revisions. This study underscores the significance of investors and households considering TOM values when assessing the real estate market and formulating their future investment plans.

Differing from the studies in the literature, Mora-Garcia et al. (2022) aimed to identify the best MLAs for predicting house prices in Alicante (Spain) in 2022 and to evaluate the impact of the pandemic on house prices. Through extensive datasets, they assessed the performance of ensemble learning algorithms, including Gradient Boosting Regressor, Extreme Gradient Boosting, Light Gradient Boosting Machine, Random Forest, and Extra-Trees Regressor. Consequently, this study not only identifies the top-performing MLAs for predicting house prices but also measures the influence of the COVID-19 pandemic on house prices.

This study constitutes a significant contribution to the existing literature by distinguishing itself through its focus on a mass city scale and the modelling of the time parameter at this level. In general, the findings derived from the analyses conducted within the purview of this research underscore the impact of incorporating the dynamic element of time as a parameter. These effects are outlined below:

- Segmentation of time into distinct periods has enhanced the precision and granularity of the modelling process, particularly concerning performance metrics.
- By evaluating each period individually, market conditions and period-specific factors receive more thorough consideration.
- This approach has proven advantageous in facilitating a deeper understanding of variations and periodic influences between different time segments, rendering the real estate valuation process more robust and current.
- When the time parameter is considered, particularly in the analysis of phenomena like pandemics

and other atypical forecasting processes, it has been demonstrated that the ANN algorithm can be effectively employed while adhering to established success metrics.

- Furthermore, it has come to light that the RF algorithm can deliver successful outcomes, particularly when undertaking mass valuation procedures within expansive regions such as the city of Niğde.

4. Conclusions

This study presents an innovative framework for real estate valuation by integrating dynamic temporal segmentation with machine learning algorithms, offering significant theoretical and practical contributions. The complex and volatile nature of real estate markets, particularly during extraordinary events such as pandemics, is effectively captured through temporal segmentation. This approach addresses the limitations of static models by analysing the dynamic market impacts observed across different time periods.

To achieve this, a dataset comprising real estate transactions from 2019 (pre-pandemic) and 2022 (post-pandemic) was utilized, totaling 676 property records. Machine learning techniques, including RF, DT, KNN, and ANN, were employed to assess real estate values across these periods. For 2019 and 2022, ANN is the algorithm with the most successful R^2 value in all periods. In addition, according to this model, all COD values (5%–10%) and PRD values (0.98 to 1.03) were found to be in the appropriate range. The comparison of valuation models before and after the pandemic provided insights into how temporal segmentation influences prediction accuracy, highlighting the evolving dynamics of the real estate market.

The results demonstrate that the ANN algorithm performs optimally when temporal segmentation has been implemented showcasing its superiority in modeling nonlinear interactions and capturing evolving market dynamics. The COD and PRD values further support their performance, as they fall within acceptable ranges established in the literature. In contrast, without temporal segmentation, the RF algorithm exhibits superior generalization, underscoring the importance of algorithm selection based on data structure. When temporal segmentation is integrated, overall model performance improves significantly, highlighting the necessity of incorporating time-sensitive data into predictive models.

Beyond methodological advancement, the practical implications of this research are equally compelling. Temporal segmentation enables stakeholders to make time-specific decisions based on data-driven foresight rather than retrospective assumptions. Policymakers can utilize phase-based models to develop responsive property tax regimes, zoning adjustments, or crisis subsidies. Investors may leverage such models to detect undervalued properties during early disruption phases or to time market entry and exit more strategically. For urban planners and local governments, the ability to track market sentiment and value shifts over time enhances long-term sustainability planning and crisis resilience.

From a theoretical standpoint, this study repositions time as an essential structural dimension in real estate modeling. Traditional valuation frameworks have long acknowledged spatial, structural, and economic variables, but have struggled to operationalize time beyond simple trend coefficients. The segmentation technique proposed here enables time to function as a dynamic index of market evolution, revealing behavioural patterns otherwise obscured by aggregated datasets. This marks a theoretical shift toward more agile and temporally responsive valuation systems that can adapt to complex, phase-dependent conditions.

Considering the study's findings and methodological contributions, several potential avenues for future enhancement are also acknowledged. The dataset, limited to two key years (2019 and 2022), enabled a clear comparison between pre- and post-crisis dynamics. However, applying the framework to high-frequency, multi-year datasets (e.g., quarterly or monthly) could further improve its predictive sensitivity and temporal granularity. The selection of Niğde as a study area provides an intentional contrast to studies focusing on metropolitan regions. As a mid-sized, economically balanced city with limited speculative pricing, Niğde offers a controlled environment in which valuation shifts can be more directly attributed to extraordinary events, rather than the complex noise of global capital flows or infrastructural megaprojects. This design choice allows the methodology to be more transferable to other secondary urban centres, which represent a significant but underexplored portion of the global property market. Indeed, the generalizability of this framework to similar cities in developing economies fills a key gap in valuation literature, which has historically prioritized primary urban cores.

While the study compared four established machine learning algorithms (ANN, RF, DT, KNN), future research could explore advanced ensemble models to further enhance performance. Additionally, integrating macroeconomic indicators, such as interest rates, unemployment, or housing price indices, would add contextual depth to the model's predictive capacity. Taken together, these future directions not only extend the academic relevance of the study but also reinforce its potential applicability in real-world domains, including adaptive tax policies, crisis-driven planning, and sustainable urban development strategies.

In conclusion, this study provides a robust and forward-looking framework for real estate valuation, one that responds to both theoretical and practical demands of an increasingly volatile market landscape. By embedding temporal segmentation into the heart of the modeling architecture, and by rigorously comparing machine learning algorithm performance across dynamic phases, this research transcends traditional limitations and paves the way for more adaptable, transparent, and accurate valuation systems. The findings not only reaffirm the value of machine learning in real estate analysis but also establish time as a critical axis of valuation, with wide-reaching implications for academia, policy, and industry alike.

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Author contributions

Adile Gülsüm Ulucan contributed to data collection and analysis, design of methodology, drafting and revising the manuscript. Aslı Bozdağ contributed to design of methodology, drafting and revising the manuscript and interpretation of results. Murat Karakoyun contributed to design of methodology. Tansu Alkan contributed to revising the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

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