IJER
ISSN: 2757-959X

INTERNATIONAL JOURNAL OF ECONOMIC AND ADMINISTRATIVE ACADEMIC RESEARCH

Available online, ISSN: 2757-959X | https://dergipark.org.tr/tr/pub/ijerdergisi | Economic and Administrative Academic Research

COMPARING THE PERFORMANCE OF ENSEMBLE LEARNING ALGORITHMS IN PREDICTING LAND PRICES

Enes FİLİZ *[a]

**Corresponding Author*

ARTICLEINFO

Research Article

Received : 02/12/2025
Accepted : 18/03/2026

Keywords:
Land price,
prediction model,
ensemble learning algorithm,
Istanbul

ABSTRACT

Economic developments around the world influence every aspect of life and have a significant impact on economic conditions. The volatility of economic conditions encourages countries and individuals to make sound investments. In this context, land has become a very popular investment vehicle in recent years. It serves as a very important economic indicator for countries and individuals. As the importance of land has increased, its prices have risen in parallel. Since important investment tools such as houses and cars have become necessities rather than investments for people, they are now looking for new investment tools. Analyzing changes in land prices and making predictions for the future serves as a guide for investors and those who want to own property. Land prices are a concept that varies according to many factors. It reflects not only property ownership but also economic and social conditions. In this context, the study focuses on predicting land prices in Istanbul in the future. Additive Regression and Random Committee ensemble learning algorithms were used to measure the performance of the prediction models. Furthermore, the variables affecting land prices were determined using the Chi-Squared feature selection algorithm. The analysis revealed that the Random Committee ensemble learning algorithm yielded more successful results than the Additive regression ensemble learning algorithm. The effective variables land prices were found to be 'Price per square meter', 'Square meter', and 'Credit status'.

Uluslararasi İktisadi Ve İdari Akademik Araştırmalar Dergisi, 6(1), 2026, 65-79

ARSA FİYATLARININ TAHMİNİNDE TOPLULUK ÖĞRENME ALGORİTMALARININ PERFORMANSLARININ KARŞILAŞTIRILMASI

MAKALE BİLGİSİ
Araştırma Makalesi

Geliş :02/12/2025
Kabul : 18/03/2026

Anahtar Kelimeler:
Arsa fiyatı,
tahmin modeli,
topluluk öğrenme algoritması,
İstanbul

ÖZ

Dünya üzerindeki ekonomik gelişmeler hayatın her alanını etkilediği gibi ekonomik durumları da yüksek seviyede etkilemektedir. Ekonomik durumların bu denli hareketli olması ülkeleri ve insanları doğru yatırım yapmaya yönlendirmektedir. Bu doğrultuda arsa, son yıllarda çok popüler bir yatırım aracı haline dönüşmüştür. Ülkeler ve insanlar için çok önemli bir ekonomik gösterge durumundadır. Arsanın önemi bu kadar artmışken fiyatları da paralel olarak artmaktadır. Ev, araba gibi önemli yatırım araçları artık insanlar için yatırımdan ziyade ihtiyaç haline geldiğinden beri, artık insanlar yeni yatırım araçları aramaktadır. Arsa fiyatlarının değişimini incelemek, geleceğe yönelik tahminler yapmak yatırımcılar ve bir yer sahibi olmak isteyenler için yol gösterici durumundadır. Arsa fiyatları, birçok faktöre göre değişkenlik gösteren bir kavramdır. Sadece bir mülkiyet olarak değil hem ekonomik hem de sosyal durumu göstermektedir. Bu bağlamda çalışmada, İstanbul ili arsa fiyatlarının geleceğe yönelik tahmin modellerine odaklanılmıştır. Tahmin modellerinin performanslarını ölçmek için Additive Regression ve Random Committee topluluk öğrenme algoritmalarından yararlanılmıştır. Ayrıca arsa fiyatlarına etki eden değişkenler Chi-Squared öznitelik seçim algoritması ile belirlenmiştir. Analizler sonucunda Random Committee topluluk öğrenme algoritması, Additive regression topluluk öğrenme algoritmasına göre daha başarılı sonuçlar verdiği görülmüştür. Arsa fiyatına etki eden değişkenler olarak 'Metre kare fiyatı', 'Metre kare' ve 'Kredi durumu' değişkenleri bulunmuştur.

[a] enes.filiz@balikesir.edu.tr 0000-0002-8006-9467

1. INTRODUCTION

Economic developments around the world are closely monitored. Countries are required to act in accordance with these developments to raise the standard of living of their people and reduce the number of those in need. Great importance is attached to economic steps in order to live a more comfortable life and avoid difficulties in the future. Since important investment tools such as houses and cars are no longer viewed as investments but rather as necessities, new investment tools are increasingly sought. In this regard, the interest in the stock market and precious metals is considered an undeniable fact. Lives are directed entirely towards investment for various reasons, such as keeping individuals and families secure and preventing the wasting of financial resources. Land has emerged as another prominent investment tool in recent years. Interest is attracted to land due to rising prices and the notion that it could offer an alternative living space in the future. Generally, a connection is established regarding expectations between land prices and investment. The valuation of land is generally influenced by a wide array of dynamic factors, which suggests that its market value does not emerge in isolation. Rather than viewing land prices as a direct indicator of investment potential, it is often suggested that various underlying conditions should be considered. Characteristics such as location, infrastructure capabilities, zoning status, and regional expectations are frequently observed to play a significant role in shaping the overall price structure of land.

Like other real estate assets, land is often characterized by its resistance to physical depreciation, which contributes to its status as a preferred investment vehicle. Unlike structures or vehicles that typically wear and tear over time, land generally maintains its physical presence and structural value. Consequently, it is frequently regarded as a resilient investment source. Furthermore, the finite nature of land as a limited resource is considered a significant factor in its attractiveness to investors. As a fundamental component of the economy, land plays a critical role in production processes, thereby influencing broader economic stability and public welfare. While serving as a source of raw materials for various industries, land also provides the necessary physical space for industrial operations. In the contemporary era, the vast amount of data generated regarding land including prices, size, location, zoning, and credit status facilitates the creation of comprehensive datasets. The analysis of these datasets is expected to provide valuable insights into future investment strategies and real estate price assessments. Data mining techniques are often prioritized for the evaluation of such extensive information. The influence of these methods continues to grow, with machine learning, ensemble learning, and deep learning algorithms yielding more granular and robust results. These algorithms enable the construction of classification and prediction models, allowing for the systematic measurement of performance and the detailed presentation of land-related price dynamics.

Within the literature, various studies on land prices have been conducted. Potepan (1996) determined and estimated prediction equations for rent, housing, and urban land prices using the two-stage least squares method. Ihlanfeldt (2007) investigated the effects of restrictions in land use regulations on housing and vacant land prices. Latruffe & Le Mouël (2009) provided a general theoretical and empirical overview of the conversion of agriculturally suitable land into higher-value areas. Du et al. (2011) examined the dynamic relationship between housing and land prices in China in light of land policy developments. Sauer & Pereira

Leite (2012) analyzed the reasons for increased investment and the consequences for land prices. Ciaian et al. (2021) reviewed the literature regarding the inclusion of agricultural subsidies in land prices. Roestamy et al. (2022) aimed to analyze the establishment of a land bank for fairer distribution and sustainable management. Zhou et al. (2023) examined the impact of land resource mismatch on urban energy efficiency using panel data. Bai et al. (2024) investigated how large-scale industrial land transfers affected pollution emissions in China. Qi et al. (2025) focused on improving industrial land use efficiency through the lens of price deviation. Agosta et al. (2025) aimed to identify the key factors affecting agricultural land prices at micro and macroeconomic levels. Studies using data mining methods for land prices have also been examined. Chen et al. (2016) proposed the use of online rental listings as a reliable data source for mapping. Derdouri & Murayama (2020) presented a comparative study of spatial estimation using geostatistical methods and machine learning. Marandu et al. (2023) aimed to develop an optimized ensemble learning algorithm for grid-level RLP mapping. Qiao et al. (2024) used ensemble learning algorithms to examine the relationships between land turnover and carbon emissions. Ren (2024) examined various machine learning and deep learning algorithms to predict housing prices. Gao et al. (2024) proposed a data science approach synthesizing machine learning and deep learning for predictive modeling. Jafary et al. (2024) investigated the performance of four Automated Valuation Models and compared the results. Im et al. (2025) estimated land prices in Sejong City using a weighted average ensemble model. Deng & Zhang (2025) used a new three-level ensemble learning model to improve valuation accuracy. Qiao (2025) proposed an ensemble learning model within a Monte Carlo Simulation framework. Hibatulloh et al. (2025) aimed to evaluate and compare ensemble learning algorithms for price prediction.

When the literature is evaluated in general terms, it is observed that there is a significant gap in academic studies regarding the analysis of land prices through ensemble learning algorithms. Furthermore, the absence of such a comprehensive study specifically focused on Turkey enhances the significance and original contribution of this research. In this context, the study aims to address this gap and focuses on interpreting local market dynamics by utilizing advanced analytical methods. In this study, land prices are focused upon within the framework of the literature and current issues. Ensemble learning algorithms, specifically Additive Regression and Random Committee algorithms, will be utilized to estimate land prices specifically in Istanbul, a province characterized by high population and economic density. In this regard, the comparison of the performance of classification and prediction models is intended. Furthermore, the significant variables affecting land prices will be identified, and the performance of these models will be examined using these variables. Thus, an ensemble learning algorithm with superior performance will be identified, and successful results will be obtained with a reduced number of variables. In line with these objectives, this study seeks to address several key research questions. First, it investigates which ensemble learning algorithm demonstrates the highest performance in estimating land prices specifically within the province of Istanbul. Second, the study evaluates the comparative effectiveness of Additive Regression and Random Committee algorithms in both classification and prediction contexts. Furthermore, it explores the most critical variables that significantly influence land prices. Finally, the research examines whether high predictive accuracy can be maintained using a reduced set of effective variables to minimize model complexity.

2. MATERIAL AND METHODS

The Material and Methods section is developed in alignment with the core purpose of the research and within the context of the literature. The study employs the Additive Regression and Random Committee algorithms, which are recognized as contemporary and robust ensemble learning methods. Both the classification and prediction models of these algorithms are examined to evaluate their performance. In order to identify the key variables affecting land prices, the Chi-Square Feature Selection algorithm is utilized, consistent with the findings in the literature.

2.1. Data Set

In accordance with the research objectives, land prices in Istanbul are analyzed through machine learning algorithms using a dataset current as of December 2024. Istanbul is selected as the study area due to its role as a leading economic indicator and its high market volatility. The dataset comprises 40 representative land listings, equally distributed with 20 plots from the European side and 20 from the Asian side, sourced from the Sahibinden platform. The price variable serves as the dependent variable in the study. To minimize the impact of outliers and ensure data consistency, the analysis focuses on listings within a price range of ₺2,750,000 to ₺20,000,000. For classification purposes, the mean value of the price variable is calculated; listings above this average are coded as '1', while those below are coded as '0'. Furthermore, the definitions and descriptive statistics of the 13 independent variables utilized in this pilot study are presented in Table 1.

Table 1. Basic statistical information and definitions of the variables used in the study

Variable	***Min***	***Max***	***Average***	***Standard Deviation***	***Definition***
Continent					1: Europa, 2: Asia
District					1: Büyükçekmece, 2: Silivri, 3: Arnavutköy, 4: Çatalca, 5: Sarıyer, 6: Şile, 7: Beykoz, 8: Ümraniye, 9: Çekmeköy, 10: Pendik
Zoning status					1: Residential, 2: Farmland, 3: Warehouse, 4: Villa, 5: Commercial + Residential, 6: Land
Square meter	81	2761	577,98	510,7	
Price per square meter	2674	45016	17381,4	11052	
Block number	2	10463	2152,38	3060,78	
Parcel number	1	8079	247,28	1275,4	
Floor Area Ratio	0,05	2,07	0,5118	0,496	
Building Height Limit	3,5	18,5	8,68	3,54	
Credit Status					1: Yes, 2: No, 3: No information available
Title Status					1: Freehold Title, 2: Shared Title, 3: Allocation Title
Who is the seller?					1: Real Estate Agency, 2: From Owner, 3: Construction Company
Exchange status					1: Yes, 2: No
Price					0: Below Average, 1: Above Average

2.2. Ensemble Learning

In line with the objective of the study, the status of land prices in Istanbul province is examined. The performance of classification and prediction models for land prices is investigated. In this regard, ensemble learning algorithms are utilized. Ensemble learning algorithms represent a powerful class of machine learning that combines predictions obtained from multiple models. Instead of using a single classification algorithm for target classification, a series of algorithms is combined to obtain superior results. Although ensemble learning is applied in various fields such as gene expression, economics, and education, it performs successfully in all areas where machine learning is applicable (Dietterich, 2002; Zhou, 2009; Filiz, 2023). Since ensemble learning algorithms are frequently preferred in price-related studies in literature, they are also employed in this study (Yu et al., 2008; Li et al., 2021; Bouteska et al., 2024). Additionally, the k-fold cross-validation method is used with specified algorithms. In addition to this, although the dataset consists of 40 observations, ensemble learning algorithms are specifically preferred due to their robust performance in mitigating overfitting risks within small sample sizes. According to Dietterich (2000), ensemble methods offer a significant statistical advantage by combining multiple hypotheses, which effectively reduces the risk of selecting an inaccurate model when the training data is limited. This approach ensures more stable and reliable results in studies with constrained observation numbers.

2.2.1. Additive Regression Algorithm

This method, recognized as one of the ensemble learning algorithms, is a classifier that enhances the classification and prediction performance of regression-based models. In each iteration, it operates by fitting a model to the residuals left by the algorithm in the previous iteration. Prediction is performed by adding the results of each model. Reducing the shrinkage parameter helps prevent overfitting and provides a smoothing effect, although it extends the learning time (Friedman, 2002). The Additive Regression algorithm is selected for this study as it is effectively utilized in the literature for pricing across various fields (Martins-Filho & Bin, 2005; Brunauer et al., 2013; April et al., 2024).

2.2.2. Random Committee Algorithm

The Random Committee algorithm is recognized as an effective ensemble learning method. This algorithm yields successful results in both prediction and classification tasks. It utilizes a framework that generates a set of base classifiers, where each base algorithm is constructed using a unique random number of seed. The final prediction is determined as the simple average of the predictions produced by these individual base classifiers (Weka website). Given its proven effectiveness in pricing predictions across diverse fields in the literature, the Random Committee algorithm is specifically preferred for this study to ensure reliable estimations (Guo & Luh, 2004; Braouezec, 2010; Serrano, 2022).

2.2.3. Chi-Squared Feature Selection Algorithm

One of the most critical aspects in fields such as ensemble learning, machine learning, deep learning, and artificial intelligence is identifying the variables that influence prediction or classification success. The methods utilized to determine these effective variables are referred to as feature selection algorithms. The primary objective of feature selection is to operate with a reduced number of variables while achieving a performance level that is comparable to, or even higher than, the results obtained using all available variables. The Chi-Square feature selection algorithm, a prominent method in this category, calculates the chi-square statistic relative to the class and evaluates the significance of each feature accordingly. Within the Weka software, this process is executed using the 'ChiSquaredAttributeEval' module (Weka website). Given its successful application across various domains in the literature, the Chi-Square algorithm is preferred as the feature selection method in this study (Rustam et al., 2018; Thaseen et al., 2019; Mengash et al., 2022).

2.2.4. Classification Model Performance Criteria

Within the scope of the study's objective, the performance metrics of the classification models obtained from different ensemble learning algorithms for land prices are determined and the results are compared. In this regard, various classification performance metrics are utilized to facilitate a comprehensive comparison. The study employs the correlation coefficient, Kendall's tau, Spearman's rho, mean absolute error (MAE), and root mean squared error (RMSE) metrics. A high correlation coefficient is anticipated as an indicator of model success. It is generally established that algorithms yielding higher values represent more successful models. Kendall's tau and Spearman's rho are considered the most significant rank correlation coefficients for measuring classification performance. In this context, both are used for comparison on the same dataset. It is determined that the algorithm with higher Kendall's tau and Spearman's rho values produces a more successful classification model. Conversely, MAE and RMSE values measure the errors of the classification model; accordingly, it is concluded that the algorithm with lower values demonstrates a more successful performance.

2.2.5. Prediction Model Performance Criteria

Just as specific metrics are utilized to evaluate the performance of classification models, certain metrics are also employed to investigate the performance of prediction models. These metrics serve to determine which algorithm demonstrates superior predictive performance. In this regard, the study utilizes Root Relative Squared Error (RRSE), Direction Accuracy (DAC), Relative Absolute Error (RAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) metrics. The RRSE, RAE, MAPE, and MSE values represent errors associated with the prediction model; therefore, algorithms with lower values are considered to demonstrate better predictive performance. Similarly, the DAC value measures the percentage of correct matches between the predicted and actual changes in direction. It is established that algorithms with a high DAC value demonstrate more successful prediction performance.

3. APPLICATION

The study focuses on land prices in Istanbul. In this context, classification and prediction performances are examined using different ensemble learning algorithms. The application consists of three primary steps:

Step 1: Using all variables included in the study, the performance of classification and prediction models for land prices is investigated through ensemble learning algorithms.

Step 2: The effective variables influencing land prices and their respective importance levels are determined using a feature selection algorithm.

Step 3: Utilizing the effective variables identified in the previous step, the performance of classification and prediction models for land prices is re-examined through ensemble learning algorithms, and the results are compared.

The flow chart illustrating this research process is presented in Figure 1.

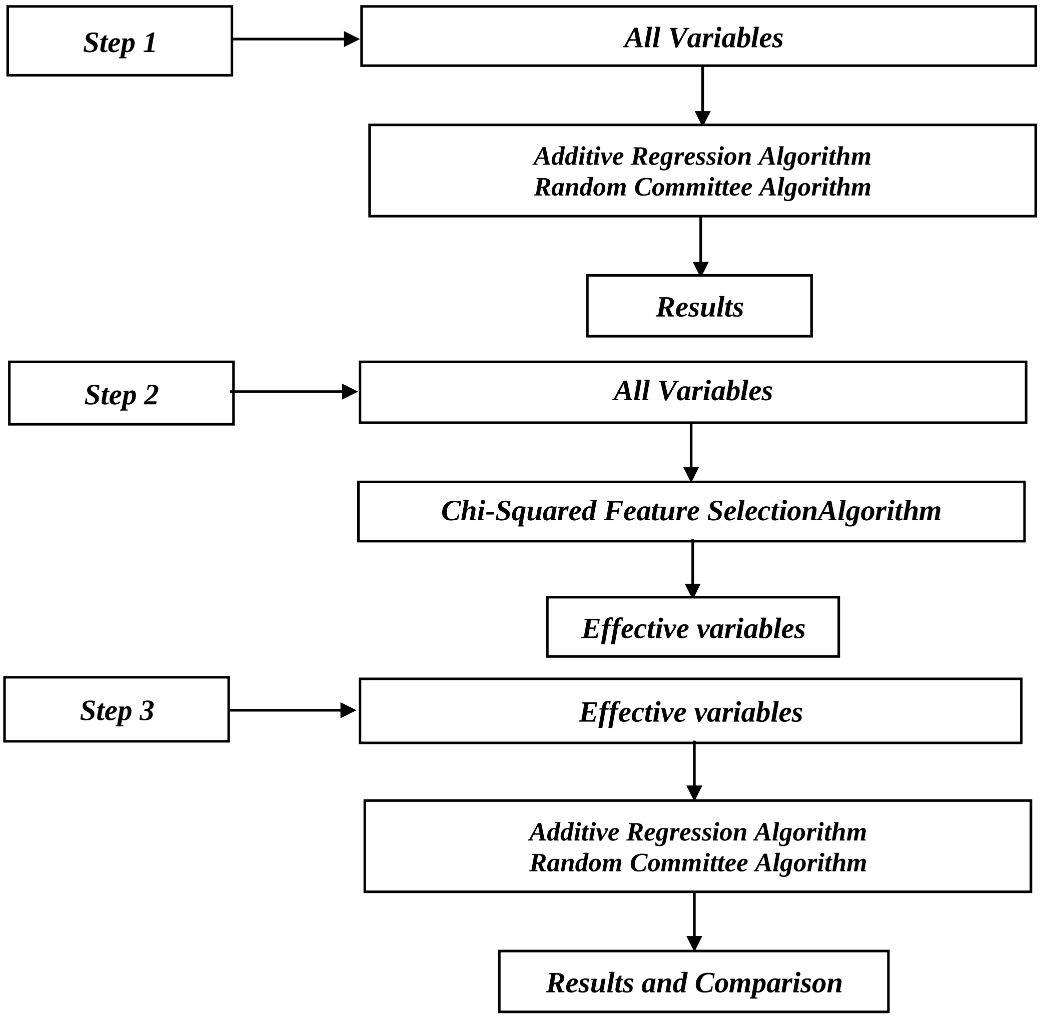

Figure 1. Flow chart of the study

4. FINDINGS

In line with the purpose and implementation steps of the study, the status of land prices in Istanbul is examined. The performance of classification and prediction models for land prices is investigated using ensemble learning algorithms. Ensemble learning algorithms do not require any prior assumptions regarding the statistical distribution of the data, which allows for more flexible analysis of complex datasets. All analyses within the scope of the study are conducted using the Weka software.

In accordance with the first step of the study, classification model performance metrics are determined using ensemble learning algorithms with all variables, and the results are presented in Table 2.

Table 2. Classification model performance values for land prices using all variables and ensemble learning algorithms

	Additive Regression	*Random Committee*
Correlation coefficient	0,6326	**0,6737**
Kendall's tau	0,5288	**0,5705**
Spearman's rho	0,6397	**0,6570**
Mean absolute error	0,3090	**0,2475**
Root mean squared error	0,4314	**0,3711**

According to Table 2, the Random Committee algorithm demonstrates more successful performance than the Additive Regression algorithm across all criteria for the classification models obtained using all variables. In this evaluation, the algorithm characterized by lower error metrics and higher values in other performance areas is identified as the superior model.

In line with the first step of the study, prediction model performance criteria are determined using all variables through ensemble learning algorithms, and the results are presented in Table 3.

Table 3. Prediction model performance values for land prices using all variables and ensemble learning algorithms

	Additive Regression	*Random Committee*
RRSE	6,1532	**1,5507**
DAC	**77,7778**	66,6667
RAE	6,5863	**1,0799**
MAPE	4,7938	**0,7890**
MSE	0,0022	**0,0001**

According to Table 3, the Random Committee algorithm demonstrates superior performance in error metrics compared to the Additive Regression algorithm for the prediction models obtained using all variables. In this context, only within the DAC metric does the Additive Regression algorithm (77.7778) exhibit more successful performance.

In line with the second step of the study, the effective variables influencing land prices are determined through the feature selection algorithm, and the results are presented in Table 4.

Table 4. Effective variables land price determination and their importance levels

Effective variables	*Importance levels*
Price per square meter	17,3778
Square meter	14,0670
Credit status	6,3158

According to Table 4, the effective variables in the determination of land prices are identified as 'Price per square meter' (17.3778), 'Square meter' (14.0670), and 'Credit status' (6.3158).

In line with the third step of the study, classification model performance metrics are determined using these effective variables through ensemble learning algorithms, and the results are presented in Table 5.

Table 5. Classification model performance values for land prices using effective variables and ensemble learning algorithms

	Additive Regression	*Random Committee*
Correlation coefficient	0,6632	**0,7919**
Kendall's tau	0,5355	**0,7373**
Spearman's rho	0,6463	**0,7740**
Mean absolute error	0,2880	**0,1200**
Root mean squared error	0,3952	**0,3186**

According to Table 5, the Random Committee algorithm demonstrates more successful performance than the Additive Regression algorithm across all criteria for classification models obtained using effective variables. In this evaluation, the algorithm characterized by lower error rates and higher values in other performance metrics is identified as the superior model. Additionally, all performance criteria exhibit improvement for both algorithms compared to previous steps.

In line with the third step of the study, prediction model performance criteria are determined using ensemble learning algorithms with the effective variables, and the results are presented in Table 6.

Table 6. Prediction model performance values for land prices using effective variables and community learning algorithms

	Additive Regression	*Random Committee*
RRSE	9,2131	**1,2672**
DAC	**74,0741**	66,6667
RAE	9,1512	**0,3956**
MAPE	6,6977	**0,9817**
MSE	0,0049	**0,0001**

According to Table 6, the Random Committee algorithm demonstrates superior performance in error metrics compared to the Additive Regression algorithm for the prediction models obtained using effective variables. Within this scope, only in the DAC metric does the Additive Regression algorithm (74.0741) exhibit more successful performance. Furthermore, it is determined that the performance criteria of the Additive Regression algorithm generally yield acceptable results in terms of overall improvement. Regarding the Random Committee algorithm's criteria, DAC and MSE remain constant, RRSE and RAE exhibit improvement, while MAPE shows an increase.

In line with the third step of the study, Figure 2 presents comparisons of classification model performances obtained using all variables versus effective variables.

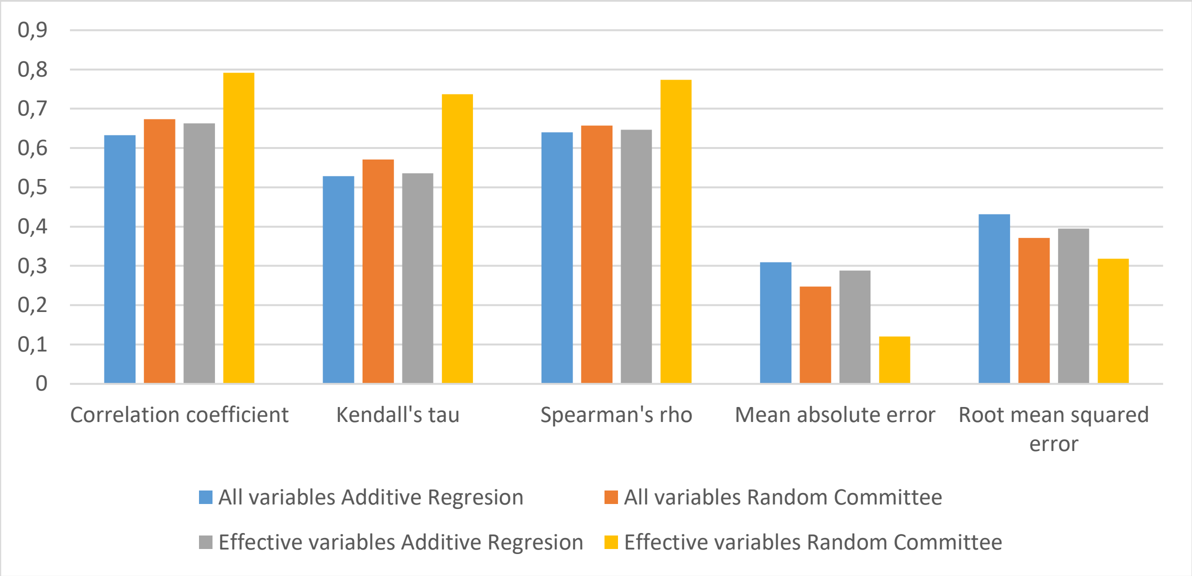

Figure 2. Comparisons of classification model performances obtained using all variables and effective variables

In line with the third step of the study, Figure 3 presents the comparisons of prediction model performances obtained using all variables versus those obtained using effective variables.

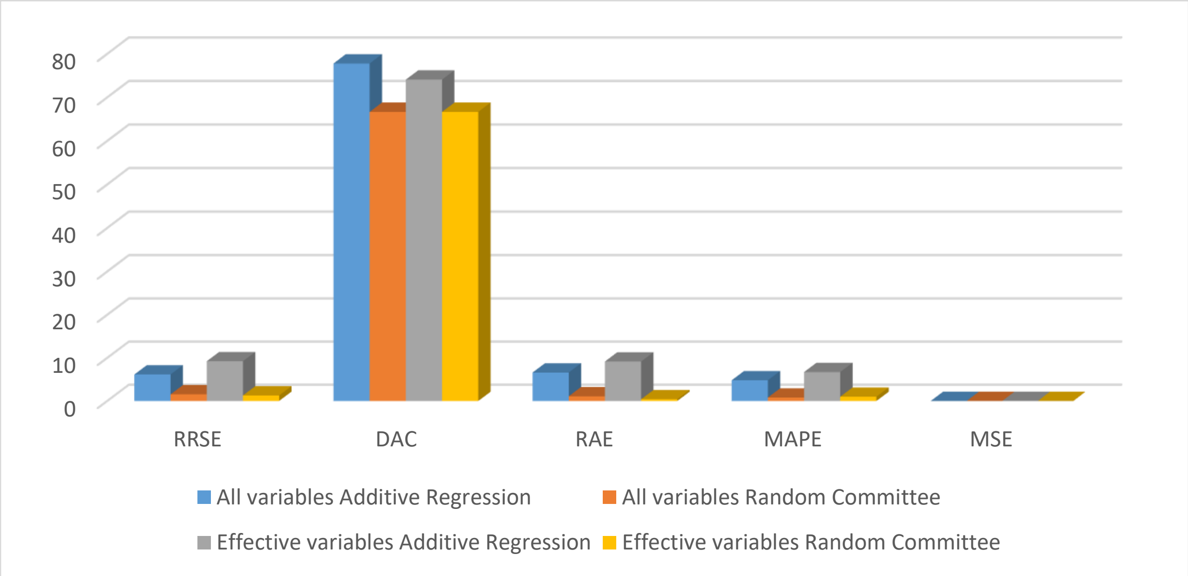

Figure 3. Comparisons of prediction model performance obtained using all variables and effective variables

5. RESULTS AND DISCUSSION

In line with the objective of the study, land prices in Istanbul are examined. The classification and prediction model performances for land prices are investigated and analyzed comparatively using Additive Regression and Random Committee ensemble learning algorithms. Furthermore, the effective variables influencing land prices are determined using the Chi-Squared feature selection algorithm.

Results are obtained and analyzed according to the specified application steps. In the first step, the performance of classification models is examined using all variables. It is observed that the Random Committee algorithm yields more successful results than the Additive Regression algorithm. Similarly, when the performance of models obtained through feature selection is evaluated, the Random Committee algorithm again demonstrates superior performance. For prediction models, the Random Committee algorithm shows successful performance regarding error metrics, while the Additive Regression algorithm performs better only in terms of the DAC value (77.8%). These findings are consistent with successful results in the literature regarding land prices and ensemble learning (Chen et al., 2016; Kim et al., 2021; Qiao et al., 2024). Based on the feature selection results, the variables ‘Price per square meter’, ‘Square meter’, and ‘Credit status’ stand out. Similar results for the ‘Square meter’ variable are also reported in various studies in the literature (Gülmez, 2006; Çiçek & Hatırlı, 2014; Dayı & Gencan, 2024; Agosta et al., 2025).

Based on these results, it is concluded that changes in land prices serve as a realistic indicator of the national economy and individual investments. As land is a non-producible and limited investment tool, such analyses provide crucial insights for investors. This subject is considered essential for both the economy and the public regarding investment planning and future needs. The significance of this study is evident, as land price dynamics vary across regions and periods. Furthermore, the study demonstrates that land prices are not merely real estate figures but critical indicators of general economic expectations. It is also shown that the utilized ensemble learning algorithms are effective for classification and prediction tasks on similar datasets. The study offers significant theoretical and practical contributions to the field. Theoretically, it proves that robust and reliable models can be established using ensemble learning algorithms, such as Random Committee, even with small-scale datasets, thereby expanding the applicability of machine learning in real estate economics. Practically, the results provide a strategic framework for stakeholders; policymakers and regulators utilize these findings to develop transparent land valuation standards and urban planning strategies, while firms and investors leverage the identified effective variables to optimize capital allocation and risk management.

The study has certain limitations. The results are analyzed exclusively using Additive Regression and Random Committee algorithms, and feature selection is restricted to the Chi-Squared method. The dataset consists of 40 land plots in Istanbul (20 European, 20 Asian side).

RESEARCHERS' CONTRIBUTION RATE STATEMENT

This study has been prepared entirely by the author from start to finish.

FUNDING AND ACKNOWLEDGMENTS

This study received no financial or institutional support.

CONFLICT OF INTEREST STATEMENT

No conflict of interest has been declared.

REFERENCES

Agosta, M., Schimmenti, E., Di Franco, C. P., & Asciuto, A. (2025). Agricultural Land Markets: A Systematic Literature Review on the Factors Affecting Land Prices. Land, 14(5), 978.

April, B. K., Oluoch, L., & Awe, O. O. (2024). Novel Applications of Bayesian Additive Regression Model for Predicting Diamond Prices: A Comparative Study of Tree-Based Ensemble Techniques. In Practical Statistical Learning and Data Science Methods: Case Studies from LISA 2020 Global Network, USA (pp. 127-164). Cham: Springer Nature Switzerland.

Bai, C., Xie, D., & Zhang, Y. (2024). Industrial land transfer and enterprise pollution emissions: Evidence from China. Economic Analysis and Policy, 81, 181-194.

Bouteska, A., Abedin, M. Z., Hajek, P., & Yuan, K. (2024). Cryptocurrency price forecasting–a comparative analysis of ensemble learning and deep learning methods. International Review of Financial Analysis, 92, 103055.

Braouezec, Y. (2010). Committee, expert advice, and the weighted majority algorithm: An application to the pricing decision of a monopolist. Computational Economics, 35(3), 245-267.

Brunauer, W., Lang, S., & Umlauf, N. (2013). Modelling house prices using multilevel structured additive regression. Statistical Modelling, 13(2), 95-123.

Chen, Y., Liu, X., Li, X., Liu, Y., & Xu, X. (2016). Mapping the fine-scale spatial pattern of housing rent in the metropolitan area by using online rental listings and ensemble learning. Applied Geography, 75, 200-212.

Ciaian, P., Baldoni, E., Kancs, D. A., & Drabik, D. (2021). The capitalization of agricultural subsidies into land prices. Annual Review of Resource Economics, 13(1), 17-38.

Çiçek, U., & Hatırlı, S. (2014). Factors Affecting Housing Prices in Isparta Analysis Using Hedonic Price Model. Mehmet Akif Ersoy University Journal of Social Sciences Institute, 1(13), 98-114.

Dayı, F., & Gencan, M. Y. (2024). Investigation of Factors Affecting House Prices: The City of Samsun. Gümüşhane University Journal of Social Sciences, 15(2), 348-364.

Deng, L., & Zhang, X. (2025). Boosting the accuracy of property valuation with ensemble learning and explainable artificial intelligence: The case of Hong Kong. The Annals of Regional Science, 74(1), 32.

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(5), 794-822.

Dietterich, T. G. (2000, June). Ensemble methods in machine learning. In *International workshop on multiple classifier systems* (pp. 1-15). Berlin, Heidelberg: Springer Berlin Heidelberg.

Dietterich, T. G. (2002). Ensemble learning. In M. A. Arbib (Ed.), The handbook of brain theory and neural networks (Vol. 2, pp. 110–125). MIT Press.

Du, H., Ma, Y., & An, Y. (2011). The impact of land policy on the relation between housing and land prices: Evidence from China. The Quarterly Review of Economics and Finance, 51(1), 19-27.

Filiz, E. (2023). Evaluation of match results of five successful football clubs with ensemble learning algorithms. Research quarterly for exercise and sport, 94(3), 773-782.

Friedman, J. H. (2002). Stochastic gradient boosting. Computational statistics & data analysis, 38(4), 367-378.

Gao, F., Yi, S., Li, X., & Chen, W. (2024). Ensemble intelligence algorithms and soil environmental quality to model economic quantity of land resource allocation and spatial inequality. Land Use Policy, 141, 107147.

Guo, J. J., & Luh, P. B. (2004). Improving market clearing price prediction by using a committee machine of neural networks. IEEE Transactions on Power Systems, 19(4), 1867-1876.

Gülmez, A. (2006). Adapazarı Metropolitan Municipality Examination of Land Price Changes. BİLGİ Journal of Social Sciences, (1), 115-124.

Hibatulloh, M. N., Prakoso, G. D., Yunus, A. D. P., & Putra, T. D. (2025). Prediksi Harga Rumah di Bandung 2024 Menggunakan Ensemble Learning: Analisis Komparatif dan Interpretabilitas. Jurnal Informatika: Jurnal Pengembangan IT, 10(2), 484-493.

Ihlanfeldt, K. R. (2007). The effect of land use regulation on housing and land prices. Journal of urban economics, 61(3), 420-435.

Im, S., Kim, K., Lee, G., & Lim, H. J. (2025). Development of a Weighted Average Ensemble Model for Predicting Officially Assessed Land Prices using Grid Map Data and SHAP. IEEE Access.

Jafary, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2024). Automated land valuation models: A comparative study of four machine learning and deep learning methods based on a comprehensive range of influential factors. Cities, 151, 105115.

Kim, J., Won, J., Kim, H., & Heo, J. (2021). Machine-learning-based prediction of land prices in Seoul, South Korea. Sustainability, 13(23), 13088.

Latruffe, L., & Le Mouël, C. (2009). Capitalization of government support in agricultural land prices: what do we know?. Journal of economic surveys, 23(4), 659-691.

Li, H., Jin, F., Sun, S., & Li, Y. (2021). A new secondary decomposition ensemble learning approach for carbon price forecasting. Knowledge-Based Systems, 214, 106686.

Martins-Filho, C., & Bin, O. (2005). Estimation of hedonic price functions via additive nonparametric regression. Empirical economics, 30(1), 93-114.

Marandu, G. T., Tarimo, B., & Mushi, V. (2023). Fine-scale mapping of residential land price using machine-learning: An experimental study in the city dominated by informal land markets. African Journal of Land Policy and Geospatial Sciences, 6(4), 759-778.

Mengash, H. A., Hussain, L., Mahgoub, H., Al-Qarafi, A., Nour, M. K., Marzouk, R., ... & Hilal, A. M. (2022). Smart cities-based improving atmospheric particulate matters prediction using chi-square feature selection methods by employing machine learning techniques. Applied Artificial Intelligence, 36(1), 2067647.

Potepan, M. J. (1996). Explaining intermetropolitan variation in housing prices, rents and land prices. Real Estate Economics, 24(2), 219-245.

Qi, Y., Lin, R., & Zhu, D. (2025). Impact of rising industrial land prices on land-use efficiency in China: A study of underpriced land price. Land Use Policy, 151, 107490.

Qiao, R., Wu, Z., Jiang, Q., Liu, X., Gao, S., Xia, L., & Yang, T. (2024). The nonlinear influence of land conveyance on urban carbon emissions: An interpretable ensemble learning-based approach. Land Use Policy, 140, 107117.

Qiao, R., Zhao, Z., Wu, T., Zhou, S., Ao, X., Yang, T., ... & Wu, Z. (2025). Unveiling the nonlinear drivers of urban land resources on carbon emissions: The mediating role of industrial upgrading and technological innovation. Resources, Conservation and Recycling, 212, 108000.

Ren, Y. (2024, December). Ensemble learning models for house price prediction: A case study in king county, USA. In AIP Conference Proceedings (Vol. 3194, No. 1, p. 020004). AIP Publishing LLC.

Roestamy, M., Martin, A. Y., Rusli, R. K., & Fulazzaky, M. A. (2022). A review of the reliability of land bank institution in Indonesia for effective land management of public interest. Land use policy, 120, 106275.

Rustam, Z., Nadhifa, F., & Acar, M. (2018, November). Comparison of SVM and FSVM for predicting bank failures using chi-square feature selection. In Journal of Physics: Conference Series (Vol. 1108, No. 1, p. 012115). IOP Publishing.

Sahibinden Web Page, www.sahibinden.com, Access Date: 30.12.2024.

Sauer, S., & Pereira Leite, S. (2012). Agrarian structure, foreign investment in land, and land prices in Brazil. The Journal of Peasant Studies, 39(3-4), 873-898.

Serrano, W. (2022). The random neural network in price predictions. Neural computing and applications, 34(2), 855-873.

Thaseen, I. S., Kumar, C. A., & Ahmad, A. (2019). Integrated intrusion detection model using chi-square feature selection and ensemble of classifiers. Arabian Journal for Science and Engineering, 44(4), 3357-3368.

Weka Web Page, https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomCommittee.html, Access Date: 20.11.2025.

Weka Web Page, https://weka.sourceforge.io/doc.stable/weka/attributeSelection/ChiSquaredAttributeEval.html, Access Date: 20.11.2025.

Yu, L., Wang, S., & Lai, K. K. (2008). Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy economics, 30(5), 2623-2635.

Zhou, Z. H. (2009). Ensemble learning. Encyclopedia of Biometrics, 1, 270– 273. Springer.

Zhou, D., Hu, Y., Sun, Q., & Xie, D. (2023). Land resource mismatch and energy efficiency: Evidence from 243 cities in China. Energy Policy, 183, 113800.