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ANALYZING THE IMPACT OF THE 2023 GENERAL ELECTIONS ON LAND PRICES USING MACHINE LEARNING: A CASE STUDY IN ÇANAKKALE, TURKEY

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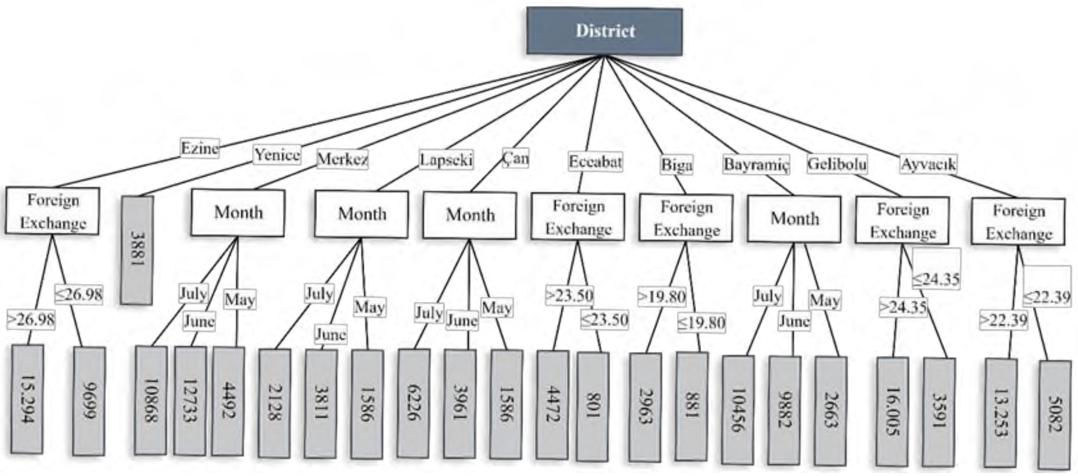
Highlights

- This study analyses the impact of the 2023 Turkish elections on Çanakkale land prices.
- The 'Regression Tree' model, one of the machine learning models, is used to estimate land unit prices.
- Changes in foreign exchange and gold values during the election period affected land unit prices.
- According to the machine learning price prediction model, changes in exchange rates after the elections increased land unit prices.
- Regression trees show how district, gold and exchange rates affect prices.
- Regression tree model, one of the machine learning methods, performs better than linear regression in price prediction.

Graphical Absract



An example of a tree branch from regression tree models

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ABSTRACT: This study analyses the impact of the general elections to be held on 14 May 2023 on the real estate market in Turkey. The aim of the study is to develop a model to predict land unit prices (₺/m²) by analysing land prices, exchange rates and gold values observed before (February-March-April) and after (May-June-July) elections for Ayvacık, Bayramiç, Biga, Çan, Eceabat, Ezine, Gelibolu, Lapseki, Merkez and Yenice districts of Çanakkale province. Daily fluctuations in foreign exchange and gold values, which are the main economic parameters in the study, were recorded during the election period. The findings of this research, which predicts price movements in the property market using machine learning methods such as regression trees, reveal that unit prices of land generally tend to increase with increases in exchange rates, but in some districts where gold prices increase, the unit price shows a reverse trend. This is attributed to the fact that investors prefer gold as a safer asset in times of economic uncertainty. The results obtained can help investors and buyers to predict future trends in property prices, as well as contribute to the development of economic policies by experts to stabilise fluctuations in investment instruments.

Keywords: *Election, Sustainabilty Land Price, Economic Parameters, Regression Tree, Machine Learning*

1. INTRODUCTION

Real estates, which make a great contribution to the country's economy, are at the forefront of today's study topics. The type, characteristics and method searches of real estates are on the agenda of many different professional disciplines in the literature. In real estate valuation, methods and principles should be applied by taking into account current market values. Current market values are also important in sales or construction, mortgages and taxation. Real estate market values are shaped by supply and demand in free market conditions. For this reason, it is difficult to determine current market values. Different methods and techniques are used for this. These techniques have developed with the increase in artificial intelligence applications in today's conditions. Another element as effective as methods in estimating the value of real estates is the type of real estate and the factors (features) affecting its value according to its type. These features vary according to location or lifestyle. They are grouped according to the purpose of use as locational, local, physical, legal and structural [1]. In addition, affecting current market values; It is known that the existence of micro and macroeconomic variables, political events and current force majeure (unexpected sudden events such as earthquakes, disease outbreaks, etc.) also affect the real estate market.

The valuation approach should be expected to be in line with economic theory and to be prone to producing reliable predicts for transaction prices. The valuation process should be in line with economic

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theory and should produce values that are good predicts of observed transaction prices (market value). In general, the approaches used to predict real estate value (comparative, income and cost methods) are not sufficient to predict market value. Determining whether the real estate features affecting the value are actually effective or the degree of effect is one of the primary operations for a real estate valuation system to be created. In general, it has been observed that in the studies conducted in the literature, the local characteristics of real estate are addressed and used in the value predict model [2]. It has been determined that the studies conducted on economic and political effects are more limited. Therefore, the purpose of the article is designed to determine how real estates are affected by economic factors and political events using machine learning methods.

Elections, which are political events that are on the country's agenda and repeated at certain periods of time, play a crucial role in selecting administrators who represent diverse viewpoints within a community [3],[4]. These important decision-making events directy relate to social and economic dynamics and affect various sectors that impact the living conditions of the community. Economic uncertainties related to election processes can influence preferences and prices for real estate investments in developing countries, with noticeable variations in preferences for types of real estate such as housing, parcels, and land before and after elections. It has been observed that studies in the literature generally focus on the effect of changes in housing prices during election periods. It has been concluded that the effect of the election on the market values of houses is generally negative due to the uncertainty involved [5], [6], [7], [8]. In other words, it is understood that citizens are cautious for a management situation whose outcome can change at any time. In studies, it is generally seen that statistical methods (logistic regression, two-way fixed effects, Difference-Difference) are preferred in order to understand the correlation relationship in the pre-election and post-election market comparison [9], [5], [10], [11].

Aizenman [12], also examined the relationship between economic parameters and real estate prices in 20 international countries using a panel data regression model. They found that international economic indicators such as Gross Domestic Product (GDP), interest rates, inflation rates and exchange rates played a determinant role on real estate prices. In another study, the effects of macroeconomic variables on housing prices in Turkey for the period 1990-2006 were analyzed using Johansen Cointegration and Granger Causality Test. They found that house prices had a bidirectional causality with interest rates and exchange rates, while GDP had a unidirectional relationship with house prices [13]. Two studies conducted in South Africa and Lithuania showed that inflation, interest rates GDP and political risk have both short-term and long-term effects on housing prices. In South Africa, political risks were associated with a long-term decrease in housing prices, while high interest rates and inflation were associated with an increase in housing prices. In Lithuania, they concluded that inflation and interest rates do not affect housing prices, and GDP depends on housing prices [14],[15].

The effect of the exchange rate on the value of housing built in China, Japan and Taiwan has been examined [16], [17]. According to the studies, it has been concluded that the increase in housing prices led to a decrease in the exchange rate. When Komşuoğlu [18], analyzed the exchange rates and gold prices between 2013 and 2019 in Turkey with housing sales, it was determined that there was no causality between gold and exchange rates. In another study, it was found that housing prices interacted with exchange rates and caused price changes [19].

It is understood that the effect of exchange rates on housing prices is generally accepted. In the studies conducted, as the exchange rate increases, housing sales prices also increase [20], [21], [22],[23]. Unlike these methods, [24], investigated the effect of economic parameters on real estate investments in Kenya using the Arbitrage Pricing Theory (APT). Accordingly, they found that a one percent increase in the exchange rate led to a 1.995 percent decrease in real estate prices, while a 1 percent increase in inflation led to a 2.248 percent increase in housing prices.

There are many different methods to determine the effect of economic factors on the value of real estate. In recent years, with the developing technological applications, it is seen that machine learning techniques are used in the studies conducted on this subject in the literature. The results of the studies have concluded that machine learning techniques are effective in developing accurate prediction models by analyzing large data sets [25], [26], [27], [28]. It is also predicted that the inclusion of such economic factors, especially exchange rates, in machine learning-based real estate price prediction models can increase predict accuracy and market predicts [29].

This study was conducted to examine the impact of political events on real estate values. The 2023 Turkish Presidential election was held on May 14, 2023. The changes in the purchase and sale values of lands were examined according to the expectations and economy of the country's administration that changed according to this date. According to the data of the Turkish Statistical Institute (TUIK), while the pre-election GDP increased by 4.0% compared to the same quarter of the previous year, it is seen that real estate activities had a share of 1.4% in this rate. After the election, the GDP increased by 3.8% compared to the same quarter of the previous year, and when the components constituting the GDP were taken into account, it was determined that real estate activities increased by 3.2% [30]. These values explain the uncertainty effect of the election on real estate values. It is understood that citizens are cautious about the changes that will occur in the administration, and therefore they are hesitant to enter into real estate purchase and sale.

There is also a strong relationship between exchange rates and GDP. The economic size of a country determines exchange rates by affecting the value of its currency in international markets. It is known that exchange rates fluctuate during election periods. It is thought that the increase in exchange rates due to these fluctuations may affect real estate prices. High exchange rates attract foreign investors, which causes an increase in demand and real estate prices in the real estate market. Depending on the economic structure and cultural perspective of the country before and after the election, economic indicators may cause excessive increases or decreases in land and housing prices as a result of imbalances in purchasing preferences.

Economic parameters often fluctuate, particularly as election periods approach. Addressing these fluctuations is crucial for creating resilient societies and economies, as emphasized by the 11th United Nations Sustainable Development Goal (UN-SDG). Election-induced hikes in land prices can undermine sustainable urban development. Notably, there have been no studies using machine learning decision tree algorithms to predict land prices before and after election periods. This study aims to develop a model for predicting land unit prices (₺/m^2) by analyzing observed land prices, exchange rates, and gold values for the districts of Ayvacık, Bayramiç, Biga, Çan, Eceabat, Ezine, Gelibolu, Lapseki, Merkez, and Yenice in Çanakkale province, both before (February-March-April) and after (May-June-July) the elections. The goal is to predict future land prices during election periods, providing valuable insights for investors and buyers at both local and national levels.

2. MATERIAL AND METHODS

2.1. Study Area

Çanakkale province has witnessed significant changes in terms of economic and social dynamics. In particular, the opening of the 1915 Çanakkale Bridge to traffic on 18 March 2022 strengthened Çanakkale's transport infrastructure and made the region attractive for investors. This led to an increase in the demand for land for sale. In addition, fluctuations occurred in economic parameters across the country due to the general elections held in 2023. These fluctuations caused differences in the intensity of real estate purchases and sales and in the supply-demand balance of land stocks.Çanakkale offers an important area of investigation to analyse the effects of both the strategic importance it gained with the opening of the 1915 Çanakkale Bridge and the economic parameters during the election period on land prices.

The province of Çanakkale is situated in the northwestern region of Turkey, positioned at coordinates 40.073°N latitude and 26.6225°E longitude, and spans the two coastlines that separate the continents of Europe and Asia (Figure 1).

The surface area of the province is 9995 km^2. Its neighboring provinces are Balıkesir, Tekirdağ and Edirne. The population is 559,383, and it is a province with 12 districts and 576 neighborhoods [31]. The districts of Çanakkale are Ayvacık, Bayramiç, Biga, Bozcaada, Çan, Eceabat, Ezine, Gelibolu, Gökçeada, Lapseki, Merkez and Yenice. These districts, Biga has the largest surface area of 1,354 km², while the district with the largest population is Merkez (Central) district [32].

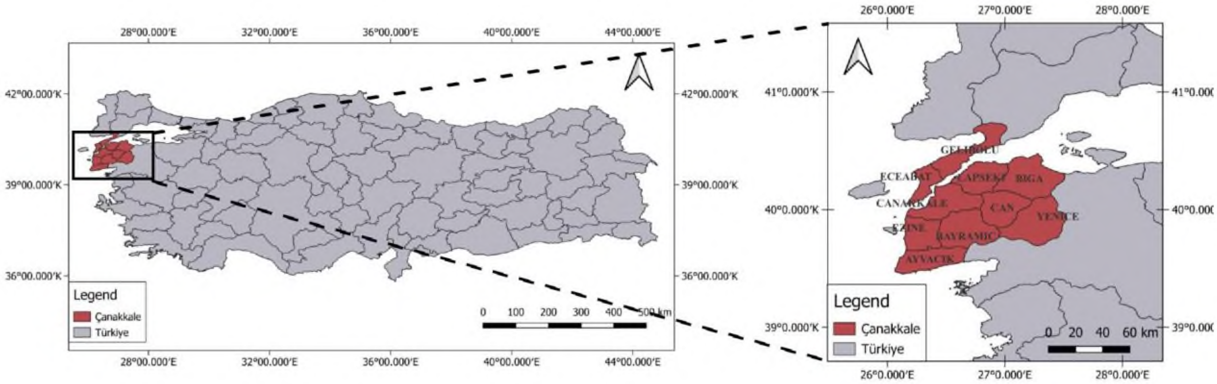

Figure 1. Location of the workspace.

2.2. Materials

To construct a price predicting model, data on land sales in various districts of Çanakkale (Ayvacık, Bayramiç, Biga, Çan, Eceabat, Ezine, Gelibolu, Lapseki, Merkez and Yenice) excluding Bozcaada and Gökçeada were collected from the open access website www.hepsiemlak.com using a web scraper developed using the Python Scrapy library. The land data in these districts were created through two separate datasets: pre-election (February-March-April 2023) and post-election (May-June-July 2023). There were 474 land sales data in the pre-election dataset and 424 land sales data in the post-election dataset. Each land sale data had 7 variables. These variables and data types are given in Table 1.

Table 1. Variables and data types

Variables	Data Type
Unit Price (₺)	Numeric
Foreign Exchange Rate	Numeric
Gold	Numeric
Neighborhood	Categorical
Month	Categorical
District	Categorical
Area Size (m²)	Categorical

Two different data types were used in the related study. In these data types, unit price, foreign exchange rate and gold values were used as numerical data types, while district, neighborhood, area size and month data types were used as categorical data types in the model. Although the area size (m²) is a numerical variable, it was transformed into a categorical variable in order not to cause too much branching in the decision tree. Accordingly, area size (m²) was categorized into 3 classes as 'High, Medium and Low'. Standard deviation (σ), mean ($\bar{x}$), and minimum and maximum area sizes were used for the value ranges in these classes (Eq. 1,2,3), [33].

Low $= [\text{MinUnit\_Price}, \text{MinUnit\_Price} + \sigma]$ (1)
Medium $= [\text{MinUnit\_Price} + \sigma + 1, \bar{x} + \sigma]$ (2)
High $= [\bar{x} + \sigma + 1, \text{MaxUnit\_Price}]$ (3)

After the transformation, the dataset for the pre-election period (February-March-April) consisted of 342 areas with low size, 75 areas with medium size, and 57 areas with high size. Similarly, the post-election dataset (May-June-July) comprised 295 low-sized areas, 59 medium-sized areas, and 70 high-sized areas. The daily values of gold and foreign exchange rates on the dates when the lands were advertised for sale on the real estate website were recorded and included in the dataset.

The minimum exchange value ($) in the dataset before the election was 18.74₺ and the maximum exchange value was 19.46₺. The minimum gold value (gr) before the election was 1103.57₺ and the maximum gold value was 1273.78₺. After the election, the minimum foreign exchange ($) value was 19.21₺ and the maximum foreign exchange value was 26.99₺. After the election, the minimum gold (gr) value was 1219.64₺ and the maximum gold value was 1724.27₺.

In the dataset created for the pre-election and post-election periods, area size (m^2) was determined in the districts of Çanakkale. In February, the highest average unit price was 4924₺ in Ayvacık and the lowest was 1409₺ in Biga (Figure 2). In March, the highest average unit price was 954₺ in Merkez district and the lowest was 129₺ in Biga. In April, the highest average unit price was 2777₺ in Ezine and the lowest was 511₺ in Eceabat.

In May, the highest average unit price was 7698₺ in Ezine and the lowest was 205₺ in Eceabat (Figure 2). In June, the highest average unit price was 8731₺ in Merkez district and the lowest was 1560₺ in Eceabat. In July, the highest average unit price was 8519₺ in Ezine and the lowest was 2065₺ in Biga.

Accordingly, while the pre-election value averages were low in March and April, in May (election time), mobilisations are observed in real estate prices in the districts. It is understood that there is an increase in values in the market in June and July after the elections. The highest land value change is observed in Ezine, Merkez and Ayvacık districts after the elections (Figure 2).

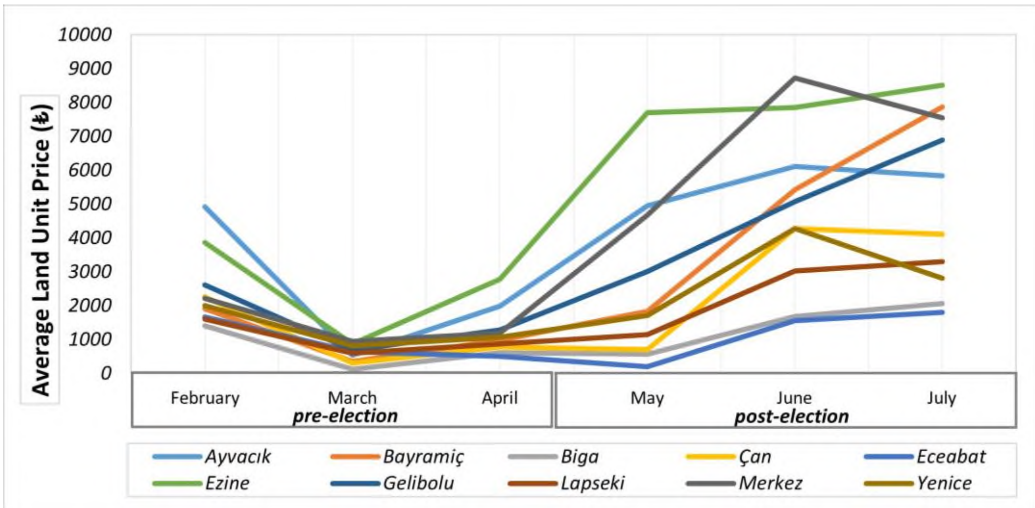

Figure 2. Average land unit price (₺) in pre-election and post-election districts.

In the dataset created for the pre-election and post-election periods, daily foreign exchange and gold values were entered according to the announcement dates on the relevant website of the land data obtained with the Python Scraby Library. Among the economic variables, gold and foreign exchange rates were included in the model as descriptive variables. The main reason for choosing these variables is that they have daily data and thus provide time compatibility according to the announcement dates. Other economic variables, especially those with monthly or longer-term data, were not included in the model.

Figure 3a illustrates the fluctuations in exchange rates ($) during the 2023 election period in Turkey. There was a significant increase in the exchange rates from May to July following the election period. Therefore, it demonstrates that the real estate sector was also affected by this increase in exchange rates ($) (Figure 3a, Figure 3b). The relationship between real estate prices and exchange rates has been an important topic frequently discussed in the literature [34]. The rate of change in the value of gold in Turkey increased between February 2023 and July 2023 (Figure 3b). During this six-month period, there were notable fluctuations in gold values, especially following the elections and more prominently after May

2023.

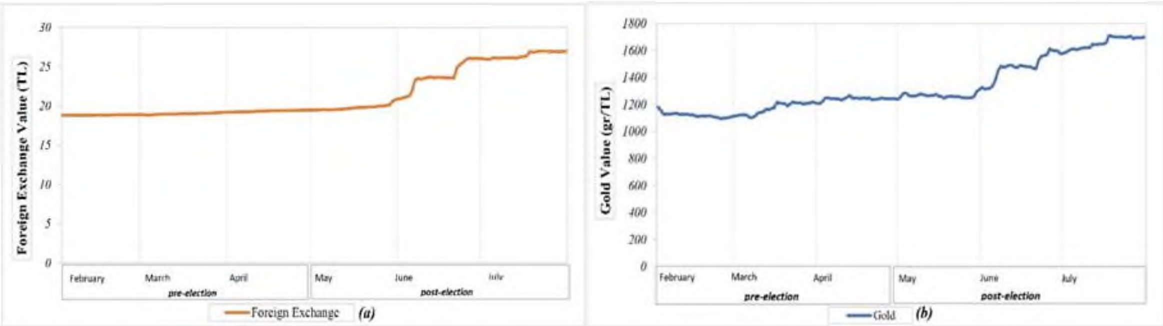

Figure 3. (a) Foreign exchange (1$) versus ₺ and (b) gold (gr) versus ₺ values in the election period in Turkey.

2.3. Method

In the study, regression trees, one of the machine learning methods and multiple linear regression methods, were used to predict the unit price of land before and after the elections and to determine the features affecting this price. The regional effects of these features determined within the scope of the study and their impact paths on the decision-making mechanism were determined. It was aimed to compare both model performances and to find the impact rates of economic and political features by comparing the situation before and after the election with the multiple linear regression method.

2.3.1 Multiple Linear Regression (MLR)

Multiple Linear Regression is the most basic labelled learning method among machine learning methods. It basically works with the logic of the least squares method. It is used to determine the connection between variables. In this method, it consists of 2 different variables as dependent and independent variable. In Formula 1, y_i is the dependent variable in the dataset (the value we predict), the x_i variable is the features in the dataset, i independent variables, β_1 is the effect coefficients of the features, j is the number of features, and n is the number of rows [35], (Eq. 4,5). In the linear regression used to compare the performance values in this study, the minimum tolerance interval was set as 0.05. The ridge value, which prevents the complexity of the model, was set as 1.0E-8.

$$\boldsymbol{y_i} = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_n x_{ji} + \varepsilon_i, \qquad i = 1.. \tag{4}$$

$$\boldsymbol{y} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{pmatrix},\ X = \begin{pmatrix} x_1^T \\ x_2^T \\ x_3^T \\ \vdots \\ x_n^T \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \dots & x_{1l} \\ \vdots & x_{21} & \vdots & \vdots \\ 1 & x_{n1} & \cdots & x_{nl} \end{pmatrix},\ \boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix},\ \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{pmatrix} \tag{5}$$

2.3.2 Regression Tree

The most widely used algorithm among machine learning methods is decision trees [36]. However, decision trees are used for classification. Regression trees, which are similar to decision trees, are preferred as a more appropriate method for this study because they predict numerical variables. In this study, regression decision tree is used to analyse the land prices in Çanakkale districts before and after the elections. The main advantage of regression trees is that they can model complex and non-linear relationships. It is preferred because it is visually more descriptive and easier to interpret. This algorithm uses measures such as variance reduction to split the data set and thus improve prediction accuracy [37]. The splitting is done in such a way as to minimise the variance of the target variable, and at each leaf node the prediction value is calculated as the average of the data at that node. In this model, each internal node represents a decision about a variable, each branch represents the outcome of a decision, and leaf nodes represent classes. [38]. The variable μ in the formula indicates the mean of the features, n indicates the number of data in the features, and c indicates the different values that the relevant feature will take (Eq. 6,7,8). The regression tree is constructed by first calculating the standard deviation of the datasets. Then, binary standard deviation is calculated for each feature in the dataset. Standard deviation reduction is obtained by subtracting the binary standard deviation value for each feature from the obtained standard deviation values. The feature with the largest standard deviation reduction is selected as the first branch. The process continues until all leaves are obtained [35]. The formulas containing these stages are as in 6,7 and 8.

$$\boldsymbol{S} = \sqrt{\frac{\sum(x-\mu)^2}{n}} \tag{6}$$

$$\boldsymbol{S}(\boldsymbol{T},\boldsymbol{X}) = \sum_{C\in X} S(T) - S(T,X) \tag{7}$$

$$\boldsymbol{SDR}(\boldsymbol{T},\boldsymbol{X}) = S(T) - S(T,X) \tag{8}$$

The purpose of the regression tree is to predict the continuous dependent variable (target variable) by utilizing continuous and categorical independent variables [39]. It helps predict the results based on an existing dataset.

The decision tree starts branching out according to the least square prediction variable. To develop the prediction model, 0.60 of the dataset was used as a training set for the learning phase of the algorithm. In this study, the maximum depth for the decision tree was set as 4 and pre-pruning was applied. The minimum gain variable for pre-pruning was 0.01. The minimum number of data for a leaf was set as 2.

The dataset includes numerical and categorical data. Among the numerical data, the 'Field Curvature' feature increases the branching in decision trees, making it difficult to read the tree. Therefore, this data feature was converted to categorical data type. The other numerical data were left as numerical data since they are the main factors in predicting the numerical unit price.

2.3.3 Performance Metrics

Root Mean Square Error (RMSE) is used to measure the predictive ability of a model. RMSE is calculated as the square root of the mean square of the difference between the predicted value and the true value. According to Formula 9, n is the number of observations, y_i is the true value, and $\hat{y}_i$ is the predicted value.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\boldsymbol{y}_i - \hat{\boldsymbol{y}}_i)^2} \tag{9}$$

The fit of the regression equation to the model is indicated by the coefficient of determination(R^2). It shows how well the predictions of the model match the actual data [40]. According to Formula 10, $\hat{y}_i$ is the predicted value for observation i, $\bar{y}$ is the mean value of the dependent variable, y_i is the true value of the observation, and n is the number of observations in the data set.

$$\boldsymbol{R}^2 = \boldsymbol{1} - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2} \tag{10}$$

3. RESULTS AND DISCUSSION

3.1 Multiple Linear Regression (MLR) Modelling

In the study, the effects of variables on unit price in the pre- and post-election periods are analysed using the MLR model. In the pre-election period, area size (β= -0.394) and foreign exchange value (β= -0.247) have a negative effect on unit price, while gold (β=0.113) and district (β=0.329) variables have a positive effect on unit price. In the post-election period, the negative effect of area size (β= -0.455) on unit price continues, but the effects of gold (β= 0.052), foreign exchange (β= 0.178) and district (β=0.23) variables change positively (Table 2).

Table 2. Results of Multiple linear regression model

	İntercept	Coefficient	Std. Error	Std. Coefficient
Pre-Election	Area Size	-0.394	0.042	-0.364
	Gold	0.113	0.032	0.141
	Foregin Exchange	-0.247	0.177	-0.053
	District	0.329	0.036	0.371
Post- Election	Area Size	-0.455	0.033	-0.548
	Gold	0.052	0.128	0.082
	Foregin Exchange	0.178	0.147	0.245
	District	0.230	0.037	0.240

When the pre- and post-election periods are compared, it is observed that the effect of district, gold value and area size on unit price decreased in the post-election period. In particular, while the foreign exchange value had a negative effect on the unit price in the pre-election period, it was found that this effect changed positively in the post-election period. This shows that the effect of foreign currency value on unit price tends to increase in the post-election period.

Although a large change in land values was observed in regional terms after the elections (Figure 2), there was a decrease in the change in value of the region according to MLR after the elections. When looked at in general, it is seen in Figure 3 that there was an increase in the foreign exchange and gold values after the elections compared to before the election. Although the change in the country's economy is in the direction of increase, it is revealed by modeling that these have different effects on the purchase and sale values of the lands (Table 2).

3.2 Regression Tree Modelling

In this section, decision tree models constructed with the pre-election (a) and post-election (b) data using gold and foreign exchange values are presented (Figure 4-Figure 10.) Due to the large size of the decision trees, the sub-branches of the trees are shown separately.

The regression trees indicated that the initial branching for both pre-election and post-election periods was based on the area size (Figure 4). In both trees, if the area size is small, the district factor becomes crucial in determining the unit price of the land. For medium and large areas, the foreign exchange rate is more significant in determining the land unit price. However, after the elections, the gold value becomes more important than the foreign exchange rate for medium-sized areas.

Figure 4. First branch of the decision tree (a: Pre-election b: Post-election).

For land plots with small pre-election area sizes, the regression tree shows that the district characteristic is the most important variable in price determination, as it appears at the root of the tree (Figure 5). This district characteristic branches out differently for the 10 districts in Çanakkale. For Ayvacık district, if the gold value is less than 1217₺, the unit price of land is 2456₺. If the gold value is greater than 1217₺, foreign exchange values gain importance, and the land unit price becomes 4747₺. For Gelibolu district, if the gold value is less than 1128, the land unit price is 2332₺, and if it is greater than 1128, the land unit price is 5273₺. In Bayramiç district, the most important feature in determining the land unit price is the gold value, as in Gelibolu and Ayvacık. If the gold value is less than 1135, it is predicted as 1235₺; if it is greater than 1135, it is predicted as 573₺. In Eceabat district, the foreign currency value stands out in determining the land unit prices; if the foreign exchange value is less than 18.82₺, the unit price of the land is 653₺, and if it is higher, it is 2088₺. In Çan, the month feature stands out in determining the unit price of land. It is 745₺ in February, 1991₺ in March, and 873 ₺ in April. In Biga, if the gold value is less than 1150, it is 281₺, and if it is greater than 1150, it is 769₺. Gold value is important in determining land prices in Lapseki. If the gold value is less than 1157, the final price of the land is 949₺, and if the gold value is greater than 1157, it is 3078₺. Similarly, gold value is important in Merkez district. If the gold value is less than 1121, it is predicted as 6542₺, and if it is greater than 1121, it is predicted as 3571₺. In Yenice, foreign exchange value is important in determining the unit price of land. If the foreign exchange value is less than 18.84, the unit price of land in the district is 1893₺, and if it is greater than 18.84, it is 4472₺. In Ezine district, as in Ayvacık, Gelibolu, Bayramiç, Biga, Merkez, Lapseki districts, the most important feature in determining the land unit price is the gold value. If the gold value is less than 1268, the land unit price is 2974₺, and if it is greater than 1268, the land price is predicted as 7917₺ (Figure 5).

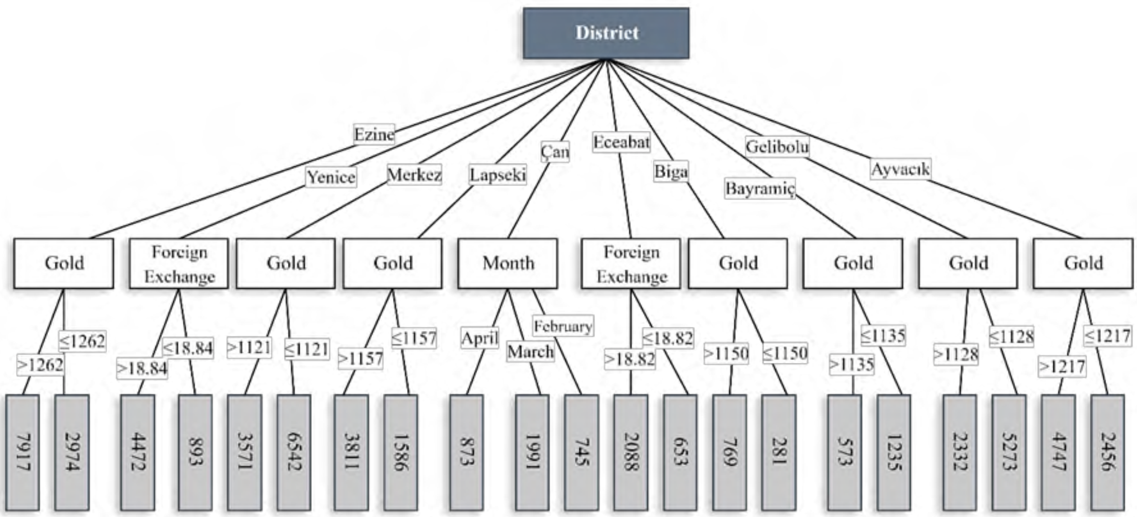

Figure 5. Regression tree for land with low pre-election area size.

In the context of low post-election area size, the district feature is the most important feature in price determination according to the regression tree, as it is located at the root of the tree (Figure 6). The district attribute branches out differently within the 10 districts in Çanakkale, as shown in Figure 8 from the regression trees formed before the elections. For Ayvacık district, the most important feature in determining the post-election price is the foreign exchange value. If the foreign exchange value is less than 22.39, the land unit price is predicted as 5082₺, and if the foreign exchange value is greater than 22.39, the land unit price is predicted as 13,253₺. The most important feature for Gelibolu district is the foreign exchange value. If the foreign exchange value is less than 24.35, the unit price is 3591₺, and if it is greater than 24.35, it is 16.005₺. In Bayramiç district, the most important feature in determining the unit price of land is the month feature at the first level. According to the regression tree, the unit prices in May, June and July are 2663 ₺, 9882 ₺ and 10.456 ₺, respectively. In Biga and Eceabat districts, the foreign exchange value at the first level of the tree gains importance in determining the price. If the foreign exchange value is less than 19.80, the unit price in Biga district is 881₺, and if it is greater than 19.80, it is 2963₺. If the foreign exchange value is less than 23.50, the unit price of land in Eceabat district is 801₺, and if it is greater than 23.50, it is 4472₺. In Yenice district, the post-election land unit price is predicted as 3881₺. According to the regression tree, the post-election month feature stands out in the land unit price predict of Merkez, Çan and Lapseki districts. In Lapseki district, the land unit price predict is 1586₺ in May, 3961₺ in June, and 2128₺ in July. In Çan, it is 844₺ in May, 3961₺ in June, and 6226₺ in July. In Merkez district, according to the decision tree model, the unit price of land is predicted as 4492₺ in May, 15,733₺ in June, and 10,868₺ in July. Finally, in Ezine district, the foreign exchange value gains importance in determining the price. If the foreign exchange value is less than 26.98, the land unit price is 9699₺, and if it is greater than 26.98, it is 16,294₺ (Figure 6).

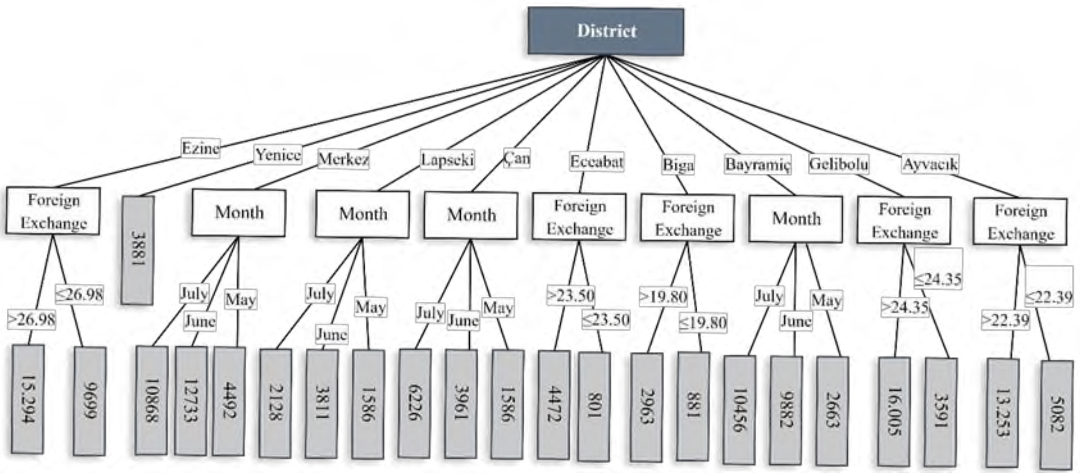

Figure 6. Regression tree for land with post election low area size.

For pre-election medium-sized plots, the foreign exchange value is the most important feature as it is at the root of the tree. When the foreign exchange value is greater than 19.38, the unit price for a medium-sized plot is set at 992₺. If the foreign exchange value is less than 19.38, the foreign exchange value becomes important again. When the foreign exchange value is less than 18.85, the pre-election land unit price for a medium-sized plot is 108₺, and when it is greater than 18.85, it is predicted to be 192₺ (Figure 7).

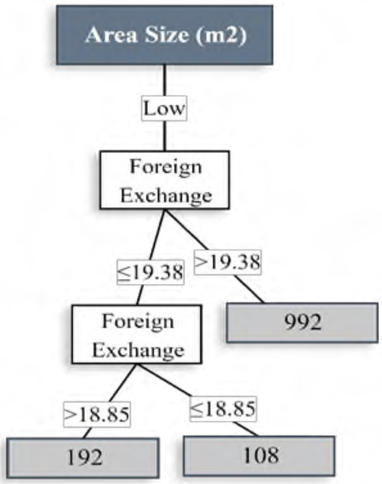

Figure 7. Regression tree for land with pre-election meedium area size.

The most important determinant of unit price for medium-sized land after the elections is the gold value (Figure 8). If the gold value is less than 1489, the foreign exchange value becomes important. If the foreign exchange value is less than 19.54, the unit price is 86₺, and if it is greater than 19.54, the projected unit price is 263₺. If the gold value is greater than 1489, the foreign exchange value becomes important again. If the foreign exchange value is less than 25.83, the unit price of the land is 1056₺, and if it is greater than 25.83, the unit price is 573₺ (Figure 8).

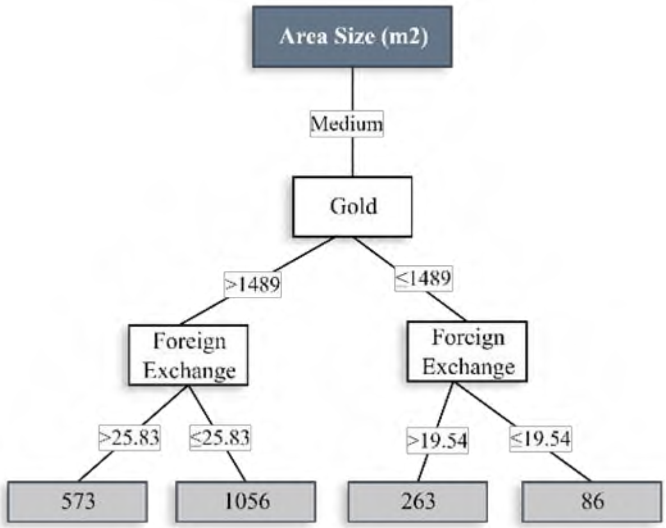

Figure 8. Regression tree for land with post election medium area size.

Before the election, the most important feature in the regression tree for land with high area size is the change value (Figure 9). If the value of foreign exchange is less than 19.27, the month feature gains importance in determining the unit price. Before the election, the unit price for land with high area size was 94₺ in February, 106₺ in March, and 45₺ in April. If the foreign exchange value is greater than 19.27, the gold value gains importance. If the gold value is less than 1250₺, the unit price of the plot is 205₺, and if it is greater than 1250₺, it is 340₺ (Figure 9).

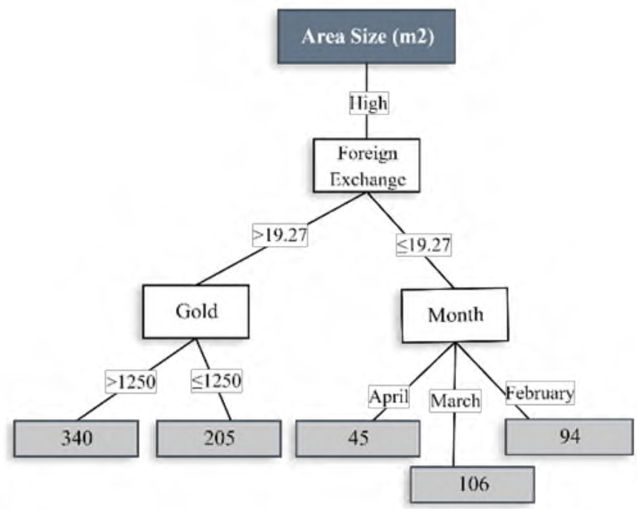

Figure 9. Regression tree for land with pre-election high area size.

When there is a high post-election area size, according to the model, the foreign exchange value gains importance in unit price estimation (Figure 10). If the foreign exchange value is less than 26.07, the gold value gains importance, and if the foreign exchange value is greater than 26.07, the foreign exchange value is considered again.

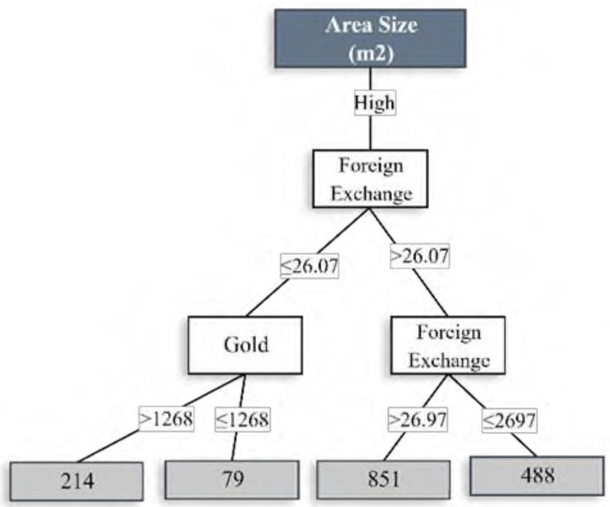

Figure 10. Regression tree for land with post election high area size.

3.3 Evaluation of Regression Tree Models

Regression trees, a machine learning technique, are employed to predict unit prices of land based on various characteristics including pre- and post-election periods, foreign exchange rates, and gold prices. As the size of the area changes, the characteristics that determine the unit price also change. The features that become important in determining the price in each tree model are given in Figure 11. The importance of the attributes decreases from the root to the lower levels. According to the regression tree, before the elections, district and foreign exchange values were the most important features in determining the price as they were at the root of the tree. After the elections, district, gold, and foreign exchange values were the most important characteristics affecting the price. The pre- and post-election branching of the tree according to district characteristics enabled the estimation of unit prices of land in Çanakkale. Thus, land unit prices for the districts in Çanakkale (excluding Bozcaada and Gökçeada) were predicted based on daily changes in gold and foreign exchange values. Before the elections, gold value was generally important in determining prices (Figure 5), whereas after the elections, foreign exchange values (Figure 6) became important in determining prices (Figure 11). According to the regression trees constructed before the elections, an increase in gold values led to an increase in prices in certain districts, while a decrease in gold values led to a decrease in prices in certain districts. However, this was not the case in Gelibolu, Bayramiç, Merkez and Çan districts. In these districts, land unit prices decreased with the increase in the value of foreign exchange and land unit prices increased with the decrease in the value of foreign exchange values (Figure 5). According to the regression trees for the pre-election period, unlike the other districts, the month feature was important in determining the price in Çan district of Çanakkale (Figure 5). It was observed that the unit price of land increased in March compared to February and April.

According to the regression trees for the post-election period, currency value was more effective in determining the unit price of land (Figure 9). When the low-sized land was evaluated according to district characteristics, it was observed that foreign exchange values and month characteristics were important. While an increase in foreign exchange values increases the unit price of land, a decrease in foreign exchange values decreases the unit price of land (Figure 6). According to the regression tree model, the most expensive lands after the elections were located in Gelibolu, Merkez, Ezine and Ayvacık districts of Çanakkale. In the branching of low-sized land by month, the unit price of land increased after the elections, especially in June, in Merkez, Bayramiç, Lapseki and Çan districts of Çanakkale (Figure 6). This confirms the post-election increase in land prices.

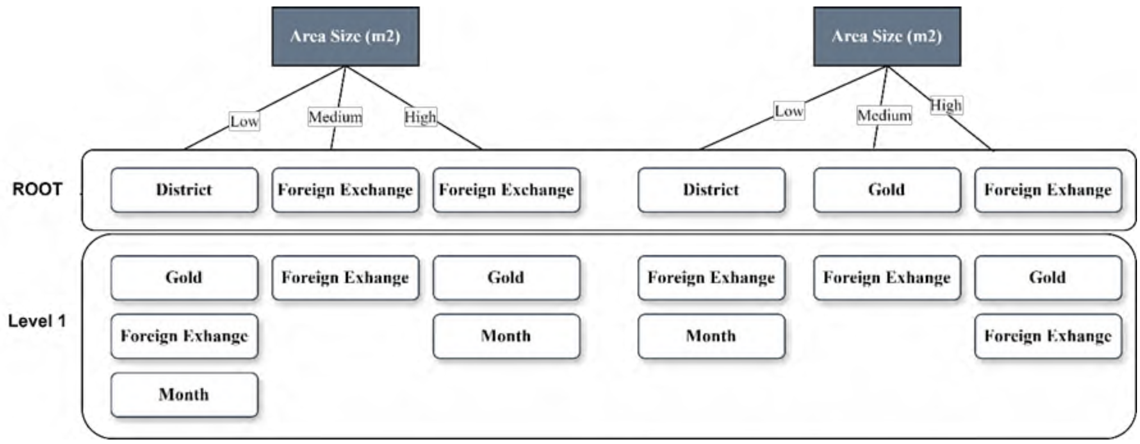

Figure 11. General representation of branching in regression trees.

3.4 Performance Evaluation of the Models

Root mean square and R^2 deviation is used to compare the performance of regression tree and MLR models used for land unit price predicting. These performance values were compared separately for pre-election and post-election price predicts (Table 3).

The datasets used to determine the performance of the two models were the same. For the MLR model, the RMSE value was 2118 for the pre-election dataset and 5343 for the post-election dataset. According to the regression tree model, it was 4984 before the election and 1863 after the election. In this case, the error rate was higher in the linear regression model. The unit price prediction performance of the regression tree model was more successful.

When the R^2 values of the models are analysed, the pre-election R^2 value of the MLR model is 0.326 and the post-election R^2 value is 0.389. The pre-election R^2 value of the regression tree model is 0.326 and the post-election R^2 value is 0.183. In this model, the R^2 values range between 0.326 and 0.389, which indicate an acceptable level of explanatory power considering the dataset and the nature of the problem studied.

In the post-election period, the RMSE value of the Multiple Linear Regression model decreased to 4300 and the R^2 value increased to 0.389. This shows that the fit of the model has improved significantly. In the post-election period, the RMSE of the Regression Tree model decreased to 1863, which is lower than the RMSE of the Multiple Linear Regression model (4300). This indicates that the Regression Tree model provides better accuracy in unit price predicting. Since RMSE measures the prediction errors of the model, a lower RMSE value indicates a better prediction performance.

Table 3. Performance values of the models.

Models	Performance Metrics	Pre-Election	Post- Election
Multiple Linear Regression	**RMSE**	1739	4300
	R^2	0.326	0.389
Regression Tree	**RMSE**	4984	1863
	R^2	0.326	0.183

3.5 Discussion

Elections affect political, economic, and social life in a country. Economic parameters change with the changes in economic policies at the time of elections, and the real estate market is also affected by this situation. Changes in economic parameters such as foreign exchange and gold also affect real estate investment demands and prices. In Turkey, elections took place in the first round on May 14, 2023, followed by the second round on May 28, 2023. During this election period, foreign exchange rates exhibited a stable trajectory from February to May but surged post-May. Conversely, gold values experienced a modest rise in March, escalating further in May. Inflation, which is another parameter, showed a balanced decrease until the election period and an increase after the election. No study was found in Turkey that analyses the real estate price change with these changing economic parameters during the election period. According to this study, the change in land unit prices before and after the elections in 10 districts of Çanakkale (excluding the islands) was predicted using gold and foreign exchange values through a regression tree from machine learning models. The regression tree model was employed to analyze the pre-election and post-election land unit price predictions, along with the influential features affecting the price. Additionally, multiple linear regression was utilized to assess and compare the performance of the model. The Regression Tree model has a lower RMSE value in the post-election and pre-election periods, indicating that the machine learning method is better at predicting unit prices. One of the main objectives of the study is to predict the unit prices of land. Although post-election R^2 values are higher in the multiple linear regression model, RMSE values evaluating the accuracy of unit price predicts show that the regression tree model gives more accurate results after the election. Accordingly, in the post-election period, the regression tree model predicts comparative land unit prices more accurately than the linear regression model. Regression tree models were created to predict the unit prices of land with economic parameters such as gold and foreign exchange before and after the elections and to find the features that affect the price. Upon reviewing various studies in the literature, it is apparent that research on housing values predominantly employs financial methods rather than machine learning techniques [5], [9], [10], [11], [14], [41]. According to the regression tree model, the first branching in predicting the unit price of land before and after the elections was shaped according to the area size feature. This can be explained by the fact that the change in area size directy affects the unit price. Afterwards, district, foreign exchange and gold characteristics came to the fore. The fact that the district feature was effective in land unit price estimation enabled the district-based change to be analysed according to gold and foreign exchange values. According to the regression tree model, it was determined that the unit prices of land increased in Ayvacık, Biga, Eceabat, Ezine, Lapseki, Yenice districts with the increase in gold values before the election. The increase in gold values can be explained in relation to the socioeconomic status of the districts in Çanakkale. Especially Biga and Lapseki districts have become attractive regions for investors due to their proximity to the 1915 Çanakkale Bridge, which opened on 18

March 2022. This suggests that the increase in gold values may have affected land prices in Biga and Lapseki districts more than other regions. On the other hand, Ayvacık district stands out as one of the regions with high tourism potential in Çanakkale. The fact that the increase in gold values resulted in an increase in land prices in Ayvacık, a touristic region, supports this relationship. However, in contrast to this situation, in Bayramiç and Merkez districts, the land unit prices decreased with the increase in gold prices, and the unit prices increased with the decrease in gold prices.Bayramiç district can be considered as a region with lower attractiveness in terms of the real estate market compared to Biga and Lapseki districts, whose popularity increased with the opening of the 1915 Çanakkale Bridge. This may have caused investors to turn to alternative investment instruments instead of real estate. In this case, with the increase in gold prices, investors turned to gold, which is considered to be safe. In other words, investors preferred the investment tool with the highest return.

In this case, it reduced the demand for land and caused the unit price of land to decrease. When gold prices fall, investors turn to alternative investment tools. The reverse is also the case. The decline in gold prices increases the demand for real estate, which is one of the investment tools, and increases land prices. According to the regression tree, there was a significant increase in the unit price of land in Çan district, especially in March. This increase can be interpreted as a result of the impact of the earthquakes centered in Kahramanmaraş on 6 February. According to the regression tree, there was a significant increase in the unit price of land in Çan, especially in March. The decline in gold prices increases the demand for real estate, which is one of the investment instruments, and increases land prices. According to the regression tree, there was a significant increase in the unit price of land in Çan, especially in March. This increase can be interpreted as a result of the impact of the Kahramanmaraş-based earthquakes that occurred on 6 February 2023. Due to the safety concerns caused by the Kahramanmaraş earthquakes, a migration trend from big cities or high-risk areas to safer and rural areas also supported this increase. This may have increased the demand for land in safe areas by raising awareness of the earthquake risk and thus contributed to the price increase.It is also an indication that this earthquake affected not only the regional properties but also the property prices in Turkey as a whole.

According to the post-election regression tree model, the most important feature affecting the unit price of land is the foreign exchange value. As the foreign exchange value increased, the land unit prices increased, and as the foreign exchange value decreased, the land unit prices decreased. The districts with the highest land unit prices are Gelibolu, Ayvacık, Merkez and Ezine. These districts support this claim, as they are among the districts with the highest buying and selling density in Çanakkale [42].

In addition, in some districts, the month feature also came to the fore in determining the unit price of land. The increased significance of the month factor in influencing prices during the post-election period can be attributed to the gradual manifestation of changes in economic, political, and market conditions. Notably, May, June, and July emerge as critical months in determining unit prices. The summer period is traditionally characterized by heightened real estate activity. This seasonal surge in demand, along with an influx of foreign investors during the summer months, exerts upward pressure on land prices. The model corroborates the finding that May, June, and July significanty impact unit prices. According to the model, Lapseki, Bayramiç and Çan districts, which are predicted to have high land unit prices in June, also support the fact that prices increased in these districts after the elections. In addition, the intensification of real estate sales in Lapseki district with the construction of the 1915 Çanakkale Bridge and its opening to vehicle traffic [42], [43]. confirms that prices have also increased with the increase in demand for the region.

4. CONCLUSIONS

This study, which covers 10 districts in Çanakkale province, is a pioneering study that demonstrates that machine learning can be used successfully in determining price predicts for pre- and post-election periods and determining the economic characteristics that affect them. In this study, not only the effect of the elections but also economic parameters such as gold and foreign exchange, which change before and after the election, were used to predict the unit price of land. Obtaining district-specific results in the model allows predicting the change in real estate prices during periods of important events such as future elections. It can demonstrate important results for those who would like to invest in real estate in a region. While helping investors and buyers make decisions, it can also increase confidence in the real estate market. It can also help control real estate price increases by shaping the economic policies of governments. In addition, real estate prices are not in constant increase with economic parameters such as foreign currency and gold. Events that are important for a country or region affect changes in real estate prices. In order to see the general situation in a country, larger datasets can be used to predict the unit price of land. In parallel with the increasing data size, studies have also started to be modeled with different machine learning methods. Thus, it is possible to obtain different results in different regions.

Declaration of Ethical Standards

The authors conducted this study in accordance with all ethical standards.

Credit Authorship Contribution Statement

Author 1: Played a key role in developing the research design, performing the analysis, drafting the manuscript. Actively participated in the discussion of the results and contributed significantly to the final version.

Author 2: Formulated the main idea, contributed significantly to its development and helped to write the manuscript while finalising the overall concept.

Author 3: Focused on contributing to the description of the analyses, editing the manuscript and interpreting the results.

Author 4: Performed the analyses, revised the manuscript and contributed to the final version by actively participating in the discussion of the results.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

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