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Estimation of Residential Land Price in the Suburban Region of India, A Comparison between Artificial Neural Network and Hedonic Price Model

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Abstract: The real estate land price valuation is a global issue, and its importance is not limited to the real estate market but also in the banking sector, insurance sector, and governing bodies for taxation and acquisitions. This paper compares the accuracy of the Hedonic Pricing Model (HPM) and Artificial Neural Network (ANN) model in predicting the residential land price for Chengalpattu district, a suburban region in the southern part of India. Residential land prices and data for the variables affecting land prices were collected and used to develop the HPM and ANN models. Subsequently, both models predicted land prices for newer land parcels, and their accuracy was compared. The performance evaluation indices of root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), R-square and accuracy were calculated for the predicted results of both the models. The HPM predicted the residential land prices with an accuracy of 75 %, whereas the ANN model predicted the prices with an accuracy of 91 %. The study showed that the ANN model is reliable and accurate in residential price prediction for suburban regions.

Keywords: *Artificial neural network, Hedonic pricing model, Prediction performance evaluation, Sub urban residential land price*.

1. Introduction

Estimating the price of real estate property is crucial not only for investment decision-making but also for accusations, taxation, and secured loans where the property is the collateral. It is also vital to calculate the immovable property value to determine the asset value of the business entities. Due to variances within the perspective of valuers, valuation error is inevitable in property appraisal (Shapiro, 2019). It was identified that fiscal and prudent decisions are based on the observed appraisal of the property values [1], [2]. The real estate market is unstable and subject to extreme variations. Therefore, it is more important to analyze these variations in the market to support sellers, buyers, and investors in the decision-making process. For accurate estimation of the prices, a large set of data is required for analysis and modeling [3].

Several methods were employed to estimate the market prices of real estate property. The traditional methods like the comparison method, profits method, contractor's cost method, and hedonic models were employed to estimate the real estate prices [4]. The hedonic pricing model (HPM) is convenient, trusted, and frequently used tool for predicting real estate property prices [5], [6] and rent appraisals [7]. HPM is a regression analysis based model where the real estate property price is estimated by the summation of the value contributed by each attribute of the property.

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In 1974, Sherwin Rosen introduced HPM, stating that a product's price is the sum of the price of the individual attributes. Regression analysis can be used to assess the significance, weight, and impact of the individual attributes on a product's overall value [8]. The hedonic pricing theory asserts that an asset, like a dwelling, could be conceived as a bundle of discrete attributes like property features, location characteristics, and environmental factors [9]. The hedonic pricing approach enables us to determine the merit generated by any of the asset's attributes and to draw conclusions about the performance of the remaining variables if some of these characteristics are altered [10].

Regression strategies such as linear regression, support vector regression (SVR) or k-nearest neighbors, and random tree regression for property market forecast have been widely employed and have produced acceptable outcomes [11]. However, the regression approach's drawbacks are its expensive, nonlinearity, multicollinearity, and heteroscedasticity characteristics [12].

In contrast to hedonic models, several other nuanced forecasting approaches, like spatial lag and spatial error models, were emphasized for the non-linear association amongst extracted features [13]. The relationship between the property price and the features is non-linear, and ANN has proven to be suitable for modeling nonlinearity [14]. Because of its ability to surpass the traditional valuation methods, the ANN model has gained widespread acceptance in the property valuation process [15].

The ANN model mimics the human brain's functionality [16]. Neural networks are computational networks that simulate how the brain conducts a specific activity. A neural network comprises layers of interconnected elements called neurons that learn by altering the weights of the connection between them [17], [18]. The network processes the commands the user gives through the interaction of the neurons in the network, which resemble the neurons in the human brain [19]. A basic ANN model consists of an input layer through which the data enters the network, hidden layer(s), and an output layer that produces the result. All the layers of the ANN are interconnected by nodes representing the neurons in the human brain. There can be more or fewer layers and more or fewer neurons per layer. The objective of an ANN is to produce a response equivalent to the response that exists in the relationship between the input and output variables [20]. They are made up of simple processing units and can store prior information.

A comparison of traditional approaches and ANN for property valuation found that ANN produces more reliable predictions [3], [18]. The ANN model works better when a data set has many values. The ANN technique can deal with non-linear relationships, allowing for a broader range of variations [21]. It can also adapt to changing surroundings, deal with noisy and ambiguous input and generalize previously unknown scenarios [22]. Comparing ANN and hedonic models showed that the ANN model predicted more accurately than the hedonic pricing model [23].

Most of the studies with ANN models are based on house/apartment valuation [24], rent appraisal, and office valuations [25]. However, its application in land and commercial properties is minimal [26], [27]. These studies have mainly concentrated on urban agglomeration [28], [29] or farmlands [30], but land price prediction for the suburban region is sparse. Similarly, many studies were carried out on housing price prediction comparison between the HPM and ANN [31], but performance comparison of the models for residential land price prediction is limited, and further such studies in the suburban region are rare. This study aims to compare the performance of the HPM and ANN for a larger suburban study area of the Chengalpattu district in India. The larger study area in the suburban region possesses varied land use patterns and a varied range of land prices.

2. Study area

The Chengalpattu district was selected as the suburban study area because it is adjacent to Chennai city, one of India's fastest growing metropolitan cities. Since the urban development in Chennai has exhausted the available lands within its boundary, it has witnessed rapid spatial urban development in its adjacent districts, with Chengalpattu witnessing maximum development. The study area of Chengalpattu district covers an area of 2945 sq. km, located on the southeast coast of India in the state of Tamil Nadu. The Chengalpattu district is surrounded by Chennai in the north, Bay of Bengal in the east, Villupuram district in the south, and Kancheepuram district and Tiruvannamalai district in the west. Agriculture is the main occupation of most people, but because of the proximity to Chennai, the district has seen an inevitable rise in urban related economic activities. The Siruseri SIPCOT (largest IT park in Asia), several other IT and BPO related companies, automobile companies like Ford motors, Hyundai, Rane TRW, Mahindra world city, Madras atomic power station, and Chennai International airport, the primary airport serving the city of Chennai are situated in Chengalpattu district. The district has a good road system connecting all major districts and towns. An important National Highway, NH32, traverses through Chengalpattu district, connecting with many state districts. The district has excellent railway connectivity. Suburban trains from Chennai run through the district's length, providing a day-to-day commutation facility for the working people. (Source: https://chengalpattu.nic.in/about-district/)

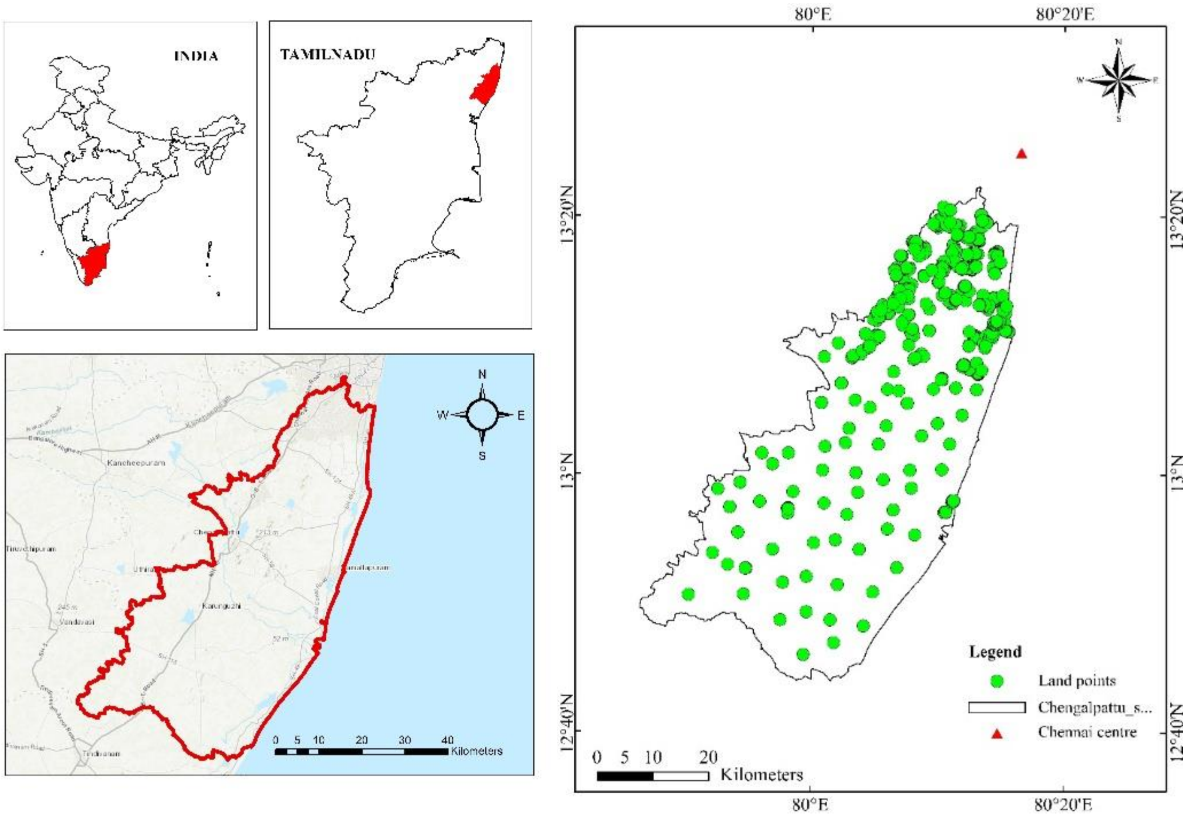

Fig 1 a. Location of Chengalpattu district represented in India **b.** Location of residential plots considered for the study.

3. Methodology and Data collection

Data collection of land prices in India is challenging as data is not readily available for the study. The market prices of the residential land were considered. Sixteen variables were identified through a literature survey and expert interviews. The variables were selected best to represent the suburban nature of the study area. Initially, 1034 residential lands were considered. The land price and the data of 16 factors were collected for all the land plots. Data filtration was carried out manually by removing land prices that are not reasonable with reality, missing data, and repetition of data. Finally, 980 residential land prices were finalized for the study. The considered residential plot locations are mapped in the Chengalpattu district map and shown in Fig. 1. Among the sixteen variables, 13 variables belong to the distances measured from nearest urban agglomeration, National Highways, bus stops, healthcare centers, commercial amenities, industries, agriculture, forest, Mass Rapid Transport Systems (MRTS), places of worship, Central Business District (CBD), universities and parks. The CBD was taken as the center of Chennai city rather than the center of Chengalpattu district. Because the rapid urbanization happening in the Chengalpattu district is due to the spatial expansion of Chennai city. The center of Chennai city is represented with a red triangle in Fig. 1. All distances were measured in kilometers. The description of the variables is given in Table 1. The collected data were preprocessed, visualized, and further utilized in developing the HPM and ANN models.

Table 1. Details of the variables

Sl. No.	*Variables*	*Description*	*Mean*	*Std. Deviation*
1	Distance to the nearest town	The distance from land to the nearest town center or village center.	4.75	2.49
2	Distance to National Highways	The nearest distance from land to the National Highway or important arterial roads.	3.35	4.89
3	Distance to bus stop	The distance between the land and the nearest bus stop.	1.11	1.09
4	Distance to hospital	The distance from land to the nearest healthcare facility.	2.54	2.40
5	Distance to commercial amenities	The distance from land to the nearest location with a cluster of commercial shops.	1.69	1.45
6	Distance to industries	The distance from land to the nearest micro or small or medium industry.	3.30	2.36
7	Proximity to agricultural lands	The distance from the land to the nearest farmlands	2.27	2.02
8	Distance to forest	The distance from the land to the designated forest areas	3.64	3.16
9	Distance to MRTS	The distance from the land to the suburban metro train stations or railway junction	24.33	14.84
10	Proximity to the place of worship	The distance from the land to places of worship.	1.16	1.14
11	Orientation of land	The direction in which the land is connected to the accessing road. It is a categorical variable which values ranging from 1 to 8. 1 - north, 2 - northeast, 3 - east, 4 - southeast, 5 - south, 6 - southwest, 7 - west, and 8 - northwest.	-	-
12	Distance from CBD	The distance from the land to the center of Chennai city.	37.29	14.59
13	Distance to Universities	The distance from the land to the nearest educational facility.	4.27	3.25
14	Distance to park/garden	The distance from the land to the nearest play area, park, or garden.	1.59	1.23
15	Location of site	It is a categorical variable that indicates the type of surrounding in which the land is located, with values ranging from 1 to 3. 1 -standalone site, 2 - gated community, and 3 - special economic zone.	-	-
16	Type of approval	It is a categorical variable with values ranging from 1 to 3. 1 - unapproved land, 2 – approved by the Directorate of Town and Country Planning (DTCP), and 3 – approved by Chennai Metropolitan Development Authority (CMDA).	-	-

3.1 Model specification: Hedonic Pricing Model (HPM)

The HPM is a regression model determining the relationship between response and explanatory variables. The multivariate regression model determines the relationship between the response variable and multiple explanatory variables. The response variable (Y) is the land price, and the explanatory variables (X_i) are the sixteen factors affecting the price of the land.

$$Y = a_0 + a_1X_1 + a_2X_2 + \ldots\ldots + a_iX_i \quad (1)$$

Where Y is the land price, X_1, X_2…. X_n – factors affecting landprice, a_0 - Constant, a_1, a_2,.a_n – Regression coefficients.

3.2 Model specification: Artificial Neural Network (ANN)

One of the most pressing issues in the hedonics literature is the functional form to be used, and ANNs are being considered in this regard. In the designing phase of the ANN, the number of layers and neurons in the layers have to be specified. There are no hard and fast rules, and designs are altered through testing. The appropriate number of input variables, data size, and network architecture would significantly impact the outcome produced by the model [24]. There is no consensus in the previous research on the number of neurons provided in the hidden layers [14]. Worzala et al. (2009) claim that one of the complications was determining the ideal number of hidden layers and the number of nodes to be employed in each hidden layer. This complication is rectified by trial and error. An ANN model for real estate valuation typically has an input layer with the same number of neurons, a hidden layer with the same number of neurons (even though the number of variables might range from half to twice), and an output layer with a single neuron. After training with a dataset, an ANN model estimates the prices of new properties in the same market [4]. The property's features or attributes are fed into the input layer, weightage allocation and transformation materialize in the hidden layer, and the predicted property price is produced in the output layer [4]. Allowing a trained neural network model to anticipate responses from new input measurements can be used to verify its accuracy [16]. The accuracy of the neural network model's predictions can then be compared to the actual output. [20].

The ANN model is trained with 70 % of data and tested with 30 % of data. A trial and error method was followed to finalize the architecture of the ANN model. The architecture components of the ANN model were changed, and the loss function was observed. The model which produced the least loss function was selected. The selected ANN model has a first layer containing 16 nodes equal to the number of explanatory variables. The second layer contains 32 nodes, the third layer of 10 nodes, and the final layer contains one output node. The ANN model is of architecture 16 x 32 x 10 x 1, containing one input layer, two hidden layers, and one output layer. The architecture of ANN is presented in Fig. 2. Rectified linear activation function (ReLu) and Adam optimizers were utilized in the model. The developed model was utilized to estimate land prices for the newer inputs. Finally, the efficiency of the price estimation was assessed through performance evaluation metrics.

The developed models of HPM and ANN are compared for their performance efficiency via evaluation metrics. A new set of land data of ten residential land parcels were utilized for estimating residential land prices through the developed models, and their performance was compared.

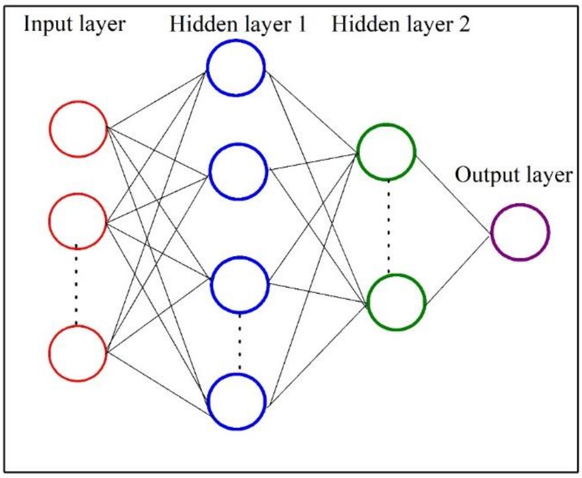

Fig 2. Schematic of ANN used in the study

3.3 Evaluation Metrics

The different evaluation metrics considered to evaluate the performance of both the models are Mean Absolute Error (MAE), Mean absolute percentage error (MAPE), Root mean squared error (RMSE), and R-square (R^2).

3.4 Mean Absolute Error (MAE)

MAE is the mean absolute difference between the actual and predicted land prices. The MAE is calculated using the given formulae

$$MAE= \frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \quad (2)$$

3.5 Mean absolute percentage error (MAPE)

MAPE is a measure of accuracy with which a model can predict. It is the mean ratio between the absolute deviation and the actual land price.

$$MAPE= \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (3)$$

3.6 Root mean squared error (RMSE)

RMSE is the square root of the mean of the square deviation between the actual price and the predicted price.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}} \quad (4)$$

3.7 R-square (R^2)

R-squared (R^2) is a statistical measure that depicts the proportion of variance for a dependent variable in a regression model that is explained by one or more independent variables.

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (5)$$

Where $\bar{y}$ is the mean of target values.

4. Results and Discussion

The influencing variables (other than the categorical variables) are plotted against the land price and represented in Fig. 3. It is evident that the land price decreases as the distance from CBD, MRTS, the nearest town, university, and bus stop increases (Fig. 3a, 3b,3c,3d, and 3e). Land prices increase when the distance between land, forest, and agricultural lands increases (Fig. 3f and 3g). The residential land for sale in the vicinity of forest and agricultural land has lesser value as these places are generally away from urban development. This indicates that the residential land price in the study region is influenced by urbanization. The plots of residential land price versus distance from hospitals, commercial amenities, and industry show identical trends (Fig. 3h,3i, and 3j). Initially, the plot shows a positive correlation, but the trend exists only for a small price range in the lesser-priced plots. This reaction could be because the industries of different scales (micro, small, and medium), commercial amenities of various scales, and hospitals of all nature are distributed throughout the suburban study region. The residential plots existing at the same distance from these amenities command varied prices depending on the distance from the main urban zones and other attributes. The attributes of distances from the place of worship and park/gardens indicate a mixed price influencing trend in the study region (Fig. 3k and 3l). The study region encompasses some of the traditionally important places of worship surrounding which an old rural town already exists. Therefore, the price variation also depends on the nature and size of the old rural towns.

The land near the national highways will command higher prices, but in this study, some residential plots far from the National Highways also command higher prices. On the outlook, the National Highways seem to show a different behavior on the real estate pricing (Fig. 3m). Nearby the city, the open spaces are shrinking along the highways, so few lands are available for sale. Therefore, the land prices are costlier for the plots available along the road at right angles to the highways and nearby the city. Another important reason is that the land parcels along the highways are primarily used for commercial purposes rather than residential plots.

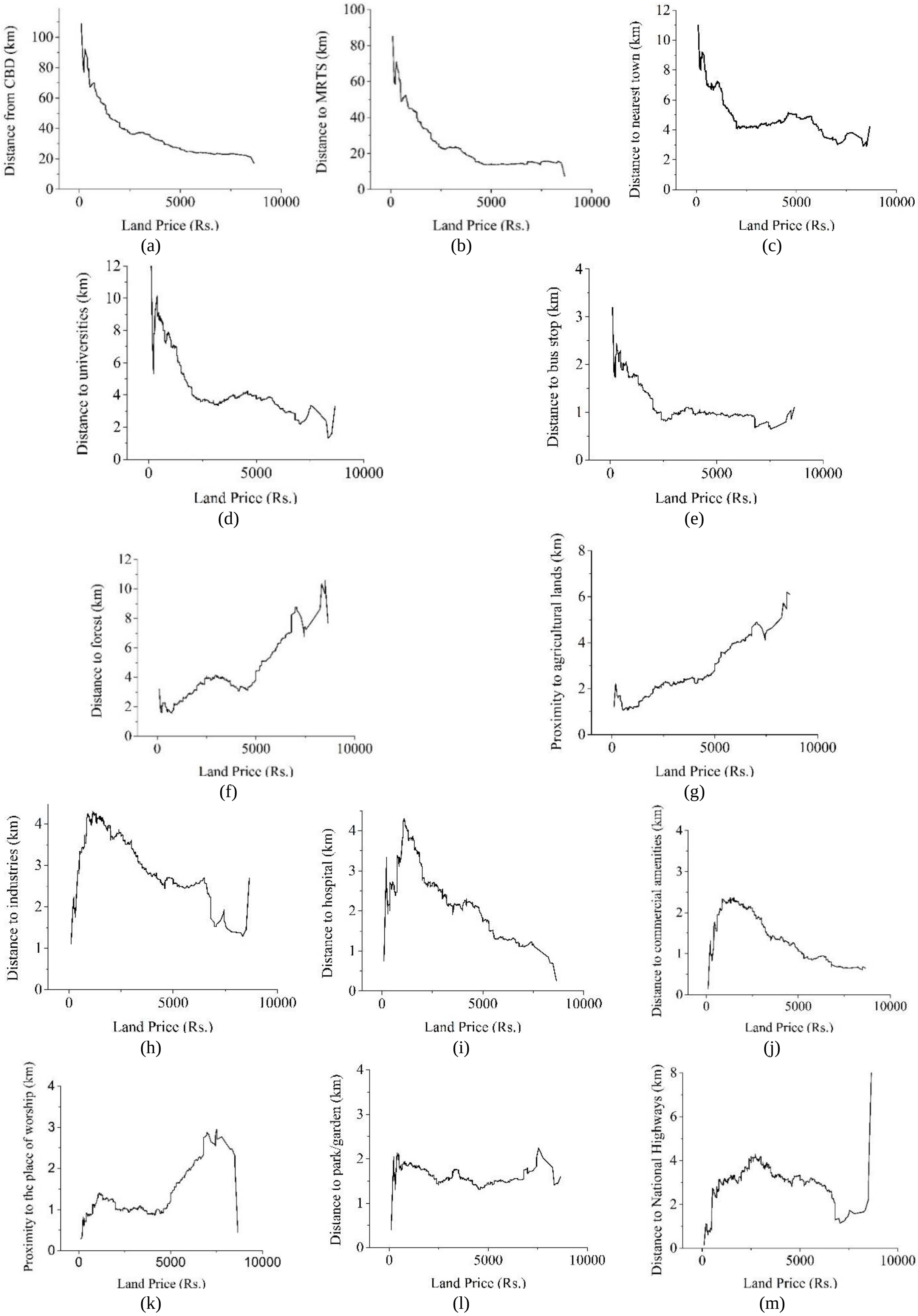

Fig 3. Relationship plot between land price and variables

4.1 Pearson Correlation

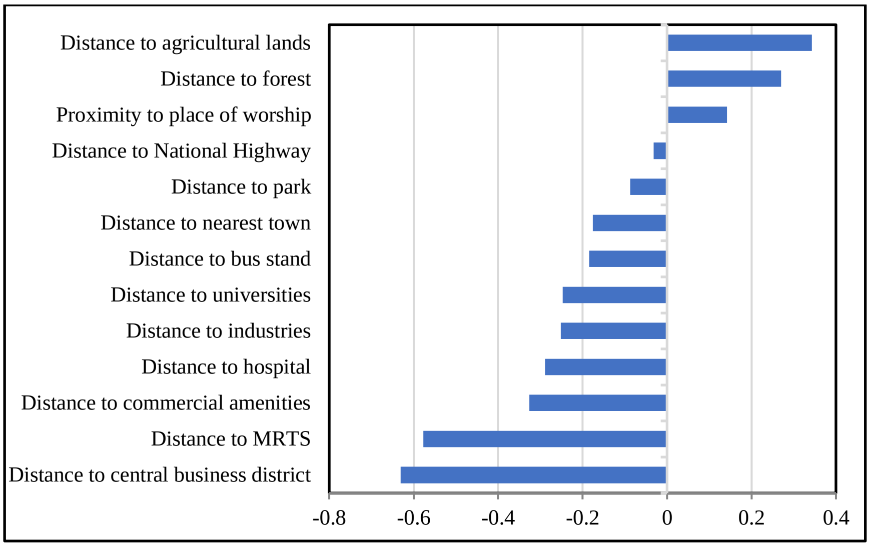

Fig 4. Pearson correlation between land price and variables

The Pearson correlation coefficient measures the correlation between explanatory and response variables. Its value ranges from -1 to 1. The value closer to -1 indicates a maximum negative correlation, and the value closer to 1 indicates a maximum positive correlation between variables and the land price. The correlation between the variables and the land price is represented in Table 2 and Fig. 4.

Table 2. Correlation coefficient between variables and land price

Sl. No.	*Variables*	*Pearson Correlation*	*Sig. (2-tailed)*
1	Distance to the nearest town	-0.182	0
2	Distance to National Highways	-0.039	0.220
3	Distance to the bus stop	-0.182	0
4	Distance to hospital	-0.296	0
5	Distance to commercial amenities	-0.310	0
6	Distance to industries	-0.230	0
7	Proximity to agricultural lands	0.315	0
8	Distance to forest	0.225	0
9	Distance to MRTS	-0.542	0
10	Proximity to the place of worship	0.113	0
11	Orientation of land	-0.022	0.478
12	Distance from CBD	-0.601	0
13	Distance to Universities	-0.221	0
14	Distance to park/garden	-0.088	0.006
15	Location of site	0.014	0.647
16	Type of approval	-0.265	0
	Price	1	

4.2 The efficiency of HPM

The HPM model was generated by analyzing the collected land data. A multiple regression analysis was performed on the study data; the results are displayed in Table 3, and subsequently, an equation was framed by utilizing the coefficients. The analysis revealed a R^2 of 0.53, indicating that the explanatory variables could explain only a 53 % variation in the land price. The explanatory variables other than the distance to the National Highway, distance to industries, distance to agriculture, the orientation of land, and distance to parks were all significant. The variables like distance to hospital, distance to commercial amenities, distance to MRTS, distance to CBD, and distance to universities had negative coefficient values, meaning the land price decreases with the increase in distance between the variable and land parcel. The developed model was utilized to determine the land prices of newer residential plots represented in Table 4. For the land prices predicted using the HPM model, the RMSE is INR 743.85 per sq. ft, and MAPE is 24.71 %. The accuracy of land prices predicted was 75.86 %. The results suggest that the errors were high in the land price prediction model using HPM. The plot showing the actual price and the predicted price of the residential land prices are shown in Fig. 5.

Table 3. Result of Regression Analysis

Sl. No.	*Variables*	*Coefficient*
1	Distance to the nearest town	38.46
2	Distance to National Highways	6.43
3	Distance to the bus stop	223.28
4	Distance to hospital	-174.16
5	Distance to commercial amenities	-86.16
6	Distance to industries	-29.85
7	Proximity to agricultural lands	39.71
8	Distance to forest	48.05
9	Distance to MRTS	-25.48
10	Proximity to the place of worship	226.72
11	Orientation of land	-10.36
12	Distance from CBD	-39.23
13	Distance to Universities	-50.59
14	Distance to park/garden	19.59
15	Location of site	180.23
16	Type of approval	-18.12
	(Constant)	5159.70

Table 4. Estimation of the land price through HPM

Actual price (Rs./sq. ft.)	*HPM Predicted price (Rs./sq. ft)*	*Variation*
2590	3459.31	869.31
4400	3690.32	-709.68
2850	3359.00	509.00
3500	2849.64	-650.36
6110	4940.72	-1169.30
2400	3496.49	1096.49
3333	3929.00	596.00
6800	6527.22	-272.78
2600	3239.71	639.71
975	546.72	-428.28

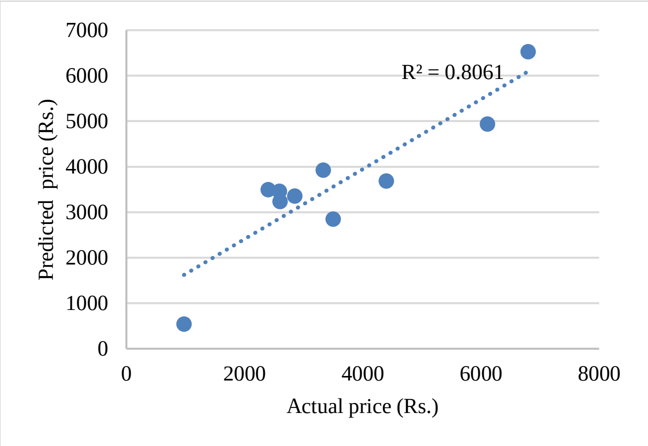

Fig 5. R-Square for regression

4.3 Efficiency of Artificial Neural Network

The data set was divided into two sections. 70% of the data was used for training the model, whereas 30% of the data was utilized for testing the model. The developed model was utilized to predict the land prices of the new residential plots. The results are represented in Table 5. For the developed ANN model, the RMSE is INR 603.19 per sq. ft, and MAPE is 11.26 %. The accuracy of land prices predicted was 92.69 %. Therefore, the results suggest that the ANN model is highly accurate in determining residential land prices. The plot showing the actual price and the predicted price of the residential land prices are shown in Fig. 6. The prediction performance comparison between the land prices predicted by HPM and ANN is given in Table. 6.

Table 5. Estimation of the land price through ANN

Actual price (Rs. /sq. ft)	*ANN Predicted price (Rs./sq. ft)*	*Variation*
2590	2243.32	346.68
4400	3844.43	555.57
2850	2785.72	64.28
3500	3223.18	276.82
6110	5440.29	669.71
2400	2478.33	78.33
3333	3914.54	581.54
6800	6404.24	395.76
2600	2627.81	27.81
975	1101.65	126.65

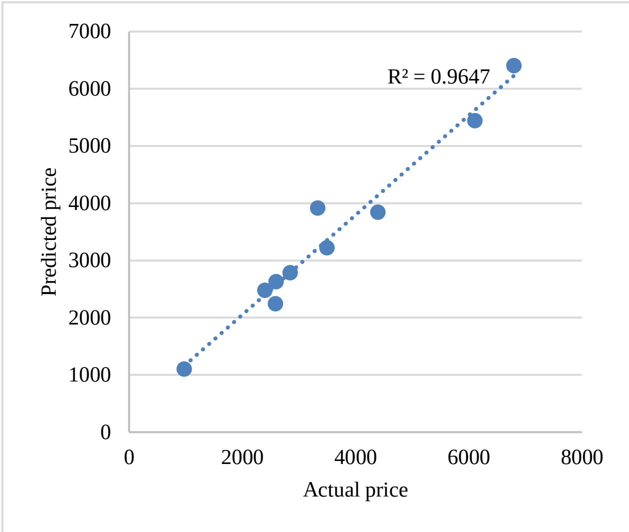

Fig 6. R square for ANN

Table 6. Prediction performance comparison between HPM and ANN

Performance Evaluation Metrics	*HPM*	*ANN*
MSE	553317.80	147588.20
RMSE	743.85	384.17
MAE	694.08	312.30
MAPE	24.14	8.77
R^2	0.80	0.96
Accuracy (%)	75.86	91.23

The residential land prices predicted using HPM and ANN model are given in Table 7. The predicted value is compared with the actual land price. It was observed that the ANN can predict the land prices more accurately than that of an HPM. The study results support the findings established by other researchers in housing real estate studies [12], [29], [32]. The land prices in the study area had a larger range; additionally, the ambiguous and noisy data set reduces the HPM model's prediction ability. The HPM model also suffers an accuracy loss when the price and variable behavior do not follow a trend. The HPM model fails to envisage the combined influence of the multifaceted variables. Wider variations exist between the actual residential land price, and the HPM predicted prices, suggesting that HPM has shortcomings in the land price prediction that could be overcome by using ANN. A 10 % error plot for the actual land price is considered and compared with the predicted land prices from HPM and ANN model and represented in Fig. 7. From the plot, it is evident that the ANN model predicted prices are nearer to the actual price, whereas the HPM model predicted prices are further away. Furthermore, almost all the ANN model predicted prices fall within the 10% range of the actual price. Comparatively, one out of ten HPM predicted prices fall within the 10% range of the actual price.

Table 7. Comparison of actual land price with predicted land price by HPM and ANN methods

Actual price (Rs./sq.ft)	*HPM Predicted price (Rs./sq.ft)*	*Variation*	*ANN Predicted price (Rs./sq.ft)*	*Variation*
2590	3459.31	869.31	2243.32	346.68
4400	3690.32	709.68	3844.43	555.57
2850	3359.00	509.00	2785.72	64.28
3500	2849.64	650.36	3223.18	276.82
6110	4940.72	1169.30	5440.29	669.71
2400	3496.49	1096.49	2478.33	78.33
3333	3929.00	596.00	3914.54	581.54
6800	6527.22	272.78	6404.24	395.76
2600	3239.71	639.71	2627.81	27.81
975	546.72	428.28	1101.65	126.65

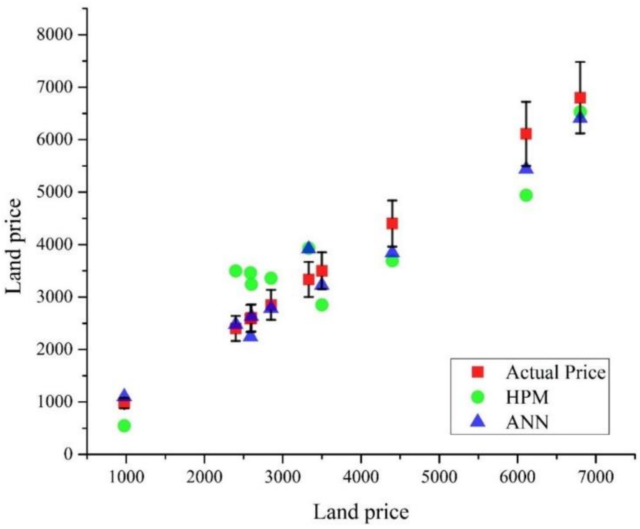

Fig 7. Land prices predicted by HPM and ANN Vs. Actual land price

5. Conclusion

This study analyses the prediction capability of the artificial intelligence model using ANN and the traditional hedonic model using the regression method. The performance comparison was carried out for the residential land price in suburban regions where the urban and rural characteristics were considered. Therefore, the study considered an extensive list of factors that would increase the performance of the models, both HPM and ANN. This paper analyzed the application of ANN for residential land price prediction for the Chengalpattu district, a suburb of Chennai. The ANN model achieved higher accuracy in land price prediction with performance indicators of RMSE = INR 384.24, R^2 = 0.96, Accuracy = 91.23 % and MAPE = 8.766. The same land price when predicted with HPM produced results with performance indicator of RMSE = INR 743.85, R^2 = 0.80, Accuracy = 75.86 % and MAPE = 24.13. The results indicate the better prediction capability of ANN models in land price prediction. This work explores the ANN approach for property appraisal in a developing country with a non-transparent and unstructured real estate market. Hence ANN models are recommended to be utilized in investment decision making, land price calculation in taxation, and acquisition processes.

An important limitation for applying ANN in property valuation will be the availability of robust and quality data. ANN being a data-intensive model, requires sufficient data for proper functioning. However, more reliable and high-quality data could increase the model's credibility and reliability [33], [34]. In the future, the study can be extended further to check the efficacy of land price prediction through support vector machine (SVM), fuzzy logic, and random forest prediction methods.

Conflicts of Interest

Authors would like to make it clear that this publication has no conflicts of interest, and this research received no external funding.

Author contributions

Sridhar M B: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation, Visualization. **Sathyanathan R:** Investigation, Writing-Reviewing and Editing.

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